In Search of Seasonality in Intraday and Overnight Option Returns*

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JEL Classification: G12, G13, G14, G11

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Abstract

We uncover momentum and reversal patterns in half-day option returns that persist for up to at least 20 business days, with economic magnitudes of 0.22% to 0.45% per half-day. Specifically, returns show strong momentum within the same period (e.g., intraday-to-intraday) but reverse sharply across opposite periods (e.g., intraday-to-overnight). These patterns increase over time, are robust to various delta-hedging schemes and option selection criteria, and persist across different subsamples. Momentum and reversal strengthen when market makers actively manage capacity constraints during intraday-overnight transitions, indicating supply-side constraints drive predictability.

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1 Introduction

The study of return predictability in financial markets has long been central to understanding of market efficiency and price formation. While extensive literature documents various patterns in stock returns at different horizons, one of the most pervasive and widely studied phenomena is momentum – the tendency for assets with high past returns to continue outperforming in the future. Originally documented by Jegadeesh and Titman (1993) in U.S. stocks at monthly frequencies, momentum has since been found across global equity markets (Rouwenhorst 1998), corporate bonds (Jostova, Nikolova, Philipov, and Stahel 2013), commodities (Erb and Harvey 2006), and currencies (Okunev and White 2003). Beyond documenting momentum across asset classes, recent research has also pushed toward higher frequencies, with studies examining intraday momentum in stocks (Heston, Korajczyk, and Sadka 2010), bonds, commodities, and currency futures (Baltussen, Da, Lammers, and Martens 2021). More recently, Heston, Jones, Khorram, Li, and Mo (2023) find evidence for momentum in monthly straddle returns on individual equities. However, the intraday behavior of option returns remains largely unexplored.

We examine whether past option returns predict future option returns at the intraday frequency. This approach allows us to test whether the momentum phenomenon documented in monthly option returns by Heston, Jones, Khorram, Li, and Mo (2023) extends to much higher frequencies, and whether intraday patterns differ from those observed in monthly data.

Our analysis yields four key facts about momentum and reversal in half-day option returns. First, we document strong momentum effects in both intraday and overnight option returns, with returns from the same half-day period in previous days positively predicting current returns. This momentum persists for up to at least 20 business days. Second, we find evidence of reversal effects, where returns from the opposite half-day period (overnight vs. intraday) negatively predict current returns. Third, while reversal effects are strongest at the first lag, momentum effects dominate at longer horizons. Momentum remains statistically significant even at 20 days, while reversal effects, though persistent, are considerably weaker at extended lags, demonstrating that longer-term momentum is substantially stronger than reversal. Fourth, an important question is whether these high-frequency option patterns simply inherit the well-known intraday and overnight periodicity of the underlying stock market (Lou, Polk, and Skouras 2019; Lu, Malliaris, and Qin 2023). Delta-hedged option returns remove first-order exposure to underlying price movements each half-day, so any inherited predictability would have to operate through higher-order effects. We show that the inclusion of past stock returns leaves the option return predictability patterns unchanged. Furthermore, spanning tests demonstrate that option strategies formed on the underlying stock return periodicity cannot replicate the returns to option strategies formed on the option return periodicity. Thus, the half-day oscillations we uncover constitute a genuinely option-specific phenomenon rather than a mechanical transformation of stock-level patterns.

The economic magnitude of these effects is large. Long-short portfolios formed on past average option returns over the last five business days generate significant profits for both momentum and reversal strategies. Reversal strategies, based on returns from the opposite half-day period, yield average half-day returns of −0.25% for intraday and −0.28% for overnight holding periods. Momentum strategies, based on returns from the same half-day period, yield average half-day returns ranging from 0.22% to 0.45%. These patterns are robust to alternative approaches to constructing option returns, including alternative delta-hedging schemes, open-interest weighting, and selection of different option contracts, and persist after controlling for various option factor models as well as stock and option characteristics such as trading volume, volatility, and bid-ask spreads.

Examining three-year rolling windows reveals that strategy returns have increased strongly over the sample period. Intraday momentum returns grew from nearly 0.20% to 0.60% per half-day, while overnight momentum returns increased from approximately 0.10% to 1.00% per half-day. Reversal strategies show a similar temporal strengthening, with the absolute magnitude of their returns having more than quadrupled over time.

We investigate the economic mechanisms underlying these patterns and find that they are most pronounced in options on stocks that are typically costlier to arbitrage. For example, the overnight momentum effect is 0.46% per half-day stronger for options on stocks with the highest limits-to-arbitrage compared to those with the lowest, suggesting a role for mispricing. We rule out explanations based on simple volatility risk premia. For example, the ratio of day-to-night volatility of the underlying stock (Muravyev and Ni 2020) does not explain the conditional patterns in option returns. Indeed, the long-short momentum portfolios generate nearly identical returns of 0.26% and 0.27% per half-day for stocks with the lowest and highest volatility ratios, respectively.

The core of our explanation centers on a disconnect between option demand and option returns. We find that investor demand, proxied by order imbalances, exhibits strong and positive persistence across all time lags. Buyers tend to remain buyers, and sellers remain sellers, regardless of whether the period is intraday or overnight. This finding contrasts sharply with the alternating pattern of momentum and reversal that we document in returns, indicating that demand-side pressure (see, e.g., Gârleanu, Pedersen, and Poteshman 2009; Goyenko and Zhang 2019) alone is an insufficient explanation.

At first sight, this empirical disconnect between demand and returns mirrors the pattern documented in equities by Lu, Malliaris, and Qin (2023). These authors show that stock portfolios exhibiting strong night-minus-day return spreads also display persistent, one-directional order imbalances. Similar to our case, the authors reject explanations based solely on price pressure or demand cycles. However, they rely on a shift in the marginal liquidity provider over the trading day—from fast inventory-constrained arbitrageurs who operate at the open to slow deep-capitalized arbitrageurs who trade later in the session. This fast-slow segmentation is plausible in equities, but we do not find confirming evidence for options. In particular, we show that momentum and reversal remain equally strong where such segmentation is the least plausible. Hence, while our empirical evidence on demand persistence parallels theirs, the mechanism in our setting is different.

Hence, the disconnect between persistent demand and alternating returns points instead to supply-side frictions, particularly the capacity constraints and inventory management practices of option market makers. Recent evidence emphasizes that the supply side plays an important role in explaining option trading volume, liquidity, and returns

(Cao, Jacobs, and Ke 2024; Pederzoli, Doshi, and Sert 2025a; Pederzoli, Jacobs, and Mai 2025b). Our evidence supports this hypothesis, as we show that the momentum and reversal patterns strengthen significantly when market makers actively manage their capacity, proxied by periods with larger adjustments to the bid-ask spread. This supply side effect is substantial. The difference in long-short returns for the overnight momentum strategy between the most active and least active quote setting environments is 0.45% per half-day. Moreover, we find that predictability is stronger when option trading is concentrated on fewer exchanges consistent with market makers facing more concentrated order-flow risk and tighter inventory constraints.

These findings add an additional dimension to the literature on demand-based asset pricing. Although prior work shows how persistent demand can generate price momentum, our results demonstrate that the structure of market making and liquidity provision can inject sharp reversals, creating more complex, alternating return dynamics even in the face of one-directional demand pressure.

Our paper contributes to different streams in the literature starting, quite evidently, with the literature on momentum in asset prices, and, specifically, in option returns. Heston, Jones, Khorram, Li, and Mo (2023) document an initial reversal and subsequent momentum in monthly straddle returns. Heston, Jones, Khorram, Li, and Mo (2024) document a quarterly seasonality in option returns. Käfer, Mörke, and Wiest (2025b) document cross-sectional and time-series momentum in option factors which subsumes momentum at the single-option level. Käfer, Mörke, Weigert, and Wiest (2025a) utilize Bayesian model averaging to estimate a stochastic discount factor for single-stock options. Option momentum is one of the most likely included factors.

We also add to the growing literature studying intraday stock returns. Heston, Korajczyk, and Sadka (2010) find strong evidence in favor of return periodicity in 30-minute returns. Gao, Han, Li, and Zhou (2018) show that the first half-hour return on the market as measured from the previous day's close price has predictive power for the last half-hour of the trading day. Baltussen, Da, Lammers, and Martens (2021) find evidence of intraday momentum due to the gamma hedging demand from market participants across a broad set of equity, bond, commodity, and currency futures. Bogousslavsky (2021) finds that a mispricing factor earns positive returns throughout the day but performs poorly towards market close. Lou, Polk, and Skouras (2019) and Akbas, Boehmer, Jiang, and Koch (2022) document a strong intraday-overnight reversal effect in the cross-section of U.S. stocks and link investor heterogeneity to its causes. Relatedly, Lu, Malliaris, and Qin (2023) show that equity portfolios exhibiting strong night-minus-day return spreads display highly persistent, one-directional order imbalances throughout the trading day, despite alternating overnight and intraday returns. While their empirical pattern resembles ours, the mechanism they propose is conceptually distinct from the supply-side explanation we document for option markets.

Another stream of the literature emphasizes the importance of the supply side in shaping trading volume, liquidity, and returns in options markets. Pederzoli, Jacobs, and Mai (2025b) document that although end users are typically net long volatility, they reduce these positions precisely in high-volatility periods. This apparent puzzle can be explained by option market makers' behavior according to the authors. They show that the demand curve of option market makers shifts more strongly than that of end users in high-risk states, tightening effective supply, widening spreads, and raising the required compensation for absorbing volatility exposure. Additionally, Pederzoli, Doshi, and Sert (2025a) show that exchanges facing more volatile intraday order flow widen spreads even for the same stock and day, indicating that concentrated flow risk exacerbates intermediary constraints. In options written on the S&P 500 index, Cao, Jacobs, and Ke (2024) document systematic variation in derivative spreads with volatility and inventory conditions. Furthermore, Hu, Kirilova, Muravyev, and Ryu (2025) show that option dealers primarily manage risk through rapid inventory rebalancing rather than continuous delta-hedging. Together, these studies underscore that intermediary supply elasticity is a critical determinant of short-horizon option dynamics.

Finally, our paper adds to the relatively scant literature on high-frequency option returns. Closest to our paper, Muravyev and Ni (2020) find that close-to-open returns are negative on average, whereas open-to-close returns are positive. However, these authors look at unconditional averages while we study conditional patterns in returns,[1]

Two recent papers also analyze momentum and reversal patterns in intra-day option returns. Da, Goyenko, and Zhang (2025) show that straddle's return during a particular 30-minute trading interval today positively predicts its returns during the same 30-minute interval on the subsequent day. Beckmeyer, Filippou, Zhou, and Zhou (2025) document that returns reverse half-hourly during the trading day. Moreover, the overnight return negatively predicts the half-hour intraday return from 10:00 am to 10:30 am.

Our work complements these intraday analyses within the trading day by adopting a different lens. Rather than investigating the market frictions that drive return dynamics within 30-minute intraday intervals, our analysis focuses on the lower-frequency interaction between two distinct economic regimes: the entire open-to-close trading day and the close-to-open overnight period. We choose this horizon for three complementary reasons. First, prior research documents that option markets exhibit fundamentally different behavior in intraday and overnight periods. Muravyev and Ni (2020) show that average overnight option returns are negative, while intraday returns are positive, implying distinct pricing dynamics across the trading break.

Second, high-frequency intervals are characterized by limited and uneven trading activity, especially in individual equity options. In our sample, averaging across years, the median stock exhibits a roughly 50-percentage-point higher probability that a trading day has positive option volume in both half-day periods than the probability of observing positive volume in all 30-minute intervals.[2] Pederzoli, Doshi, and Sert (2025a) document similarly that intraday option volume is substantially lower than stock volume even among the constituents of the S&P 500 index.

Third, microstructure evidence indicates that liquidity supply evolves smoothly during the continuous trading session but shifts sharply at the close-open boundary. Empirically, bid-ask spreads in both equities (McInish and Wood 1992; Chan, Chung, and Johnson

[1]An additional stream of the literature studies intraday risk-neutral measures on the index level (Birru and Figlewski 2012; Andersen, Bondarenko, Todorov, and Tauchen 2015; Dalderop 2020), highlighting the forward-looking content in option prices.

[2]Following the literature, we model the overnight period until 10:00 am EST, and hence, include the first 30 minute of the trading day towards the overnight period.

1995) and options remain stable intraday (Cao, Jacobs, and Ke 2024). Consistent with this evidence, we show in the Internet Appendix that liquidity conditions for individual equity options measured by bid-ask spreads are highly persistent within the trading session but propagate much less to the next trading day, producing a clear kink in spread dynamics at the day transition. Specifically, we run stock-level autoregressions of 30-minute bid-ask spreads for bid-ask spreads for within-day observations and separately for observations including the overnight transition.[3] Figure A.1 in Internet Appendix A shows that intraday coefficients are large and highly persistent. The average first autoregressive lag amounts is approximately 0.86, while the fifth lag has a coefficient of 0.74. On the other hand, the corresponding overnight estimates are materially lower and nearly constant at around 0.66 for the first five lags. Taken together, these considerations justify our use of half-day periods as the empirically relevant frequency at which option-market liquidity constraints, hedging frictions, and price pressure meaningfully manifest.

The remainder of the paper proceeds as follows. Section 2 describes our data and methodology for constructing delta-hedged option returns. Section 3 presents our main findings on intraday and overnight momentum and reversal. Section 4 investigates potential explanations for momentum and reversal at half-day periods, including demand pressures, and supply-side factors. Section 5 concludes.

2 Data

Our primary data provider is CBOE that provides quotes, trade volumes, and Greeks at intraday frequencies for all options on individual U.S. stocks over the period from January 2004 to December 2021. The intraday prices and quotes for the underlying stocks are also provided by CBOE. Historical daily prices and stock data are obtained from CRSP. We gather stock characteristics from the publicly available data set of Jensen, Kelly, and Pedersen (2023). We match CBOE data with CRSP and OptionMetrics by extending the CRSP and OptionMetrics linking algorithm provided by WRDS. We also source option

[3] For each stock and lag $L = 1, \ldots, 5$, we estimate $s_{d,\tau} = \alpha + \beta\, s_{d',\tau-L} + \varepsilon_{d,\tau}$ separately for within-day observations ($d' = d$) and observations including the overnight transition ($d' \neq d$), and then average the coefficients across stocks following Ni, Pearson, Poteshman, and White (2021).

trade data from polygon.io over the period from 2014 to 2021. Finally, we obtain from CBOE the daily volume of options traded at each of the existing option exchanges for each optionable stock over the period from 2012 to 2019.

We retain only options written on common stocks. That is, we keep options whose underlying stocks have share codes 10 or 11 and exchange codes 1, 2 or 3. Moreover, we exclude stocks with a prior month's closing price below \$5 to avoid options on highly illiquid underlying stocks.

To compute intraday and overnight option returns, we follow Muravyev and Ni (2020). The delta-hedged option dollar profit and loss (PnL_t) for an option contract with price C_t between times $t-1$ and t is given as:

$$PnL_t = C_t - C_{t-1} - \Delta_{t-1} \times (S_t - S_{t-1}), \tag{1}$$

where Δ_{t-1} is option delta at time $t-1$ and S_t denotes the price of the underlying at time t. Finally, the return is given as:

$$Ret_t = \frac{PnL_t}{C_{t-1}}. \tag{2}$$

Closing prices are based on quote midpoints at 4:00 pm Eastern Standard Time (EST). The open price is the quote midpoint at 10:00 am EST, although the equity option markets open at 09:30 am. As bid-ask spreads are especially wide immediately after markets open (Chan, Chung, and Johnson 1995), we skip the first 30 minutes. A similar approach is used by Muravyev and Ni (2020). For the intraday period, delta-hedges are revised every 30 minutes.

We apply standard filters (see, e.g., Muravyev and Ni 2020) to our intraday options data. In particular, we exclude option contracts for which the option mid-quote violates no-arbitrage bounds. Second, we exclude options where the bid price is greater or equal to the ask price, the bid price is not available, or below 50 cents. Third, we discard options with quoted bid-ask spread greater than 70% of the midpoint or three dollars. Fourth, we skip options with missing delta. Fifth, we retain only options with implied volatility strictly above 2%. Sixth, we discard options with zero open-interest. Finally, we keep only at-the-money (ATM) options. That is, we strict our analysis to options with an absolute standardized moneyness below one, and time-to-maturity between 5 and 50 days.[4] All filters are applied only at portfolio initiation date following Bali, Beckmeyer, Mörke, and Weigert (2023). This mitigates any forward-looking bias, which can significantly impact option returns, as shown by Duarte, Jones, Mo, and Khorram (2025).

Finally, we construct one intraday and one overnight return for each stock-day observation based on single-option contract returns. Concretely, we compute overnight and intraday returns for each option contract. Subsequently, we average them daily for each underlying stock. For simplicity, we will denote the stock and half-day level average option return as the option return.

2.1 Summary Statistics

Table 1 presents summary statistics of the intraday option returns. Panel A shows statistics across the entire sample, while Panel B reports the time series average of the cross-sectional statistics. The average delta-hedged call and put option returns are slightly positive, ranging between 2 and 6 basis points per half-day period. The median half-day period option return is negative. Moreover, it is higher in absolute magnitude for the overnight period compared to the intraday period. The median overnight return is -23.2 basis points, whereas it is -20 basis points for the intraday return.

Muravyev and Ni (2020) document that the overnight option returns are negative on average, but positive intraday. We, on the other hand, find positive average returns, though economically close to zero. The difference might be due to one of the following reasons. First, the intraday period in Muravyev and Ni (2020) starts at 9:45 am instead of 10:00 am as in our case. Second, we revise the delta-hedge every 30 minutes, whereas Muravyev and Ni (2020) re-hedge every 80 minutes. Third, Muravyev and Ni (2020) pool all options per underlying and half-day, whereas we concentrate on ATM options.

[4]Standardized moneyness is calculated as $m^{stand} = \log(K/S)/(\sigma^{atm}\sqrt{\tau})$, where σ^{atm} is the 30-day at-the-money implied volatility, τ is the time to expiration, S is the spot price of the underlying asset, and K is the strike price.

Finally, our sample ends in 2021, but the sample period of Muravyev and Ni (2020) ends in 2013. Figure B.1 indicates that the difference in sample periods plays an important role. The figure shows the three-year rolling average of the cross-sectional median for overnight and intraday delta-hedged option returns. The returns of the half-day periods show opposing behavior. While the average intraday median option return is positive until 2012, it turns negative for the rest of the sample. In contrast, the overnight average median return is lowest at 8 basis points around 2010 and 2012 and starts to increase until the rest of the sample. Importantly, though, our median half-day returns line up in sign with the corresponding statistics in Table 1, Panel B, of Muravyev and Ni (2020). Both are negative, and the overnight return is larger in absolute magnitude compared to intraday returns.

3 Main Results

This section establishes our main findings in which we conduct parametric and nonparametric tests to assess the predictive power of past option returns on future option returns. First, we study momentum and reversal effects by regressing half-day option returns on previous half-day option returns. Second, we add various option return predictors to the cross-sectional regressions and show that our results are robust to their inclusion. Third, and similar to the standard literature on asset price momentum (see, e.g., Heston, Jones, Khorram, Li, and Mo 2023 for momentum in monthly straddle returns), we study momentum and reversal when the formation period is not confined to a single past option return, but based on return over multiple lags. Fourth, we study the performance of aforementioned investment strategies over time. Finally, we consider alternative cross-sectional and time-series momentum strategies.

3.1 Cross-sectional Regressions

We start analyzing momentum and reversal in intraday and overnight option returns via cross-sectional regressions. Following the procedure in Heston, Korajczyk, and Sadka

(2010) and Heston, Jones, Khorram, Li, and Mo (2023), for each lag k, we run cross-sectional regressions of half-day (either intraday or overnight) option returns on returns lagged by k half-day periods:

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + \epsilon_{i,t}, \tag{3}$$

where $r_{i,t}$ is the delta-hedged option return on stock i in the half-day period t. The slope coefficient $\gamma_{k,t}$ is the response of returns in the half-day period t to returns over a previous interval lagged by k half-day periods. We run return regressions in Equation (3) separately for intraday and overnight periods. Hence, the approach is different to simply computing half-day period return autocorrelations by removing market-wide effects, thereby reducing variance and isolating individual option returns relative to other underlyings (Heston, Korajczyk, and Sadka 2010).

Figure 1 displays the return responses for lags up to 20 business days, i.e., 40 half-day lags.[5] Panel A shows results for intraday option portfolios, and Panel B shows results for overnight periods. Both panels document similar effects, which can be summarized as follows. First, the slope coefficients are positive and statistically significant at even lags of previous half-day periods. Hence, intraday and overnight option returns display significant momentum on the daily level up to 20 business days in the past. Option intraday (overnight) returns until day $t-19$ positively predict intraday (overnight) returns at day t. Moreover, there is a gradual decay in the magnitude of the slope coefficient $\gamma_{k,t}$. It is close to 0.09 for second lag and flattens out at about 0.04 by lag 10. However, the coefficients are statistically significant at all even lags, demonstrating persistent momentum effects even at lags of 20 trading days. Second, intraday and overnight option returns exhibit reversal for uneven lags of past half-day periods as the slope coefficient is negative for all uneven lags up to and including lag 39. Third, the first lag shows the strongest reversal effect by a large margin. The slope coefficient is close to -0.15 (-0.23) and is highly statistically significant when intraday (overnight) returns are regressed on

[5] We winsorize returns at 0.05% in each tail to mitigate the influence of data errors. Jensen, Kelly, and Pedersen (2023) uses a similar approach for international stock data.

the previous overnight (intraday) returns. Finally, despite the strong reversal at lag one, momentum effects are stronger than reversal effects.

3.1.1 Additional controls

Next, we study whether the predictive ability of past option returns is resilient to controlling for trading volume, volatility, bid-ask spread, and past stock returns. We modify Equation (3) as follows:

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + \Gamma'_{k,t} X_{i,t-k} + \epsilon_{i,t}, \tag{4}$$

where $X_{i,t-k}$ denotes a vector of controls. We include in $X_{i,t-k}$ trading volume, return of the underlying stock, absolute return of the underlying stock, and relative bid-ask spread of the options as controls.

Table 2 presents the results. For completeness, we also report the slope coefficients in Table 2 without additional controls in Equation (4). As is evident from Table 2, adding controls hardly changes the quantitative and qualitative conclusions on momentum and reversal in half-day option returns. The inclusion of additional controls has almost no economic or statistical effect on the slope coefficients. Hence, momentum and reversal in half-day option returns are fairly distinct from trading volume, bid-ask spreads, and volatility of the underlying. Our results are similar to those of Heston, Korajczyk, and Sadka (2010) who find that momentum and reversal in the cross-section of 30-minute stock returns are also largely unrelated to trading volume, volatility, and bid-ask spreads, even though these variables show similar periodicity as stock returns.

3.2 Portfolio Sorts

Besides cross-sectional Fama-MacBeth regressions, we also conduct portfolio sort analyses, which allow for a non-linear relation between returns of different half-day periods (Lou, Polk, and Skouras 2019). In line with the previous literature on momentum in asset prices at lower frequency, we allow the formation period to contain multiple returns. Following Heston, Jones, Khorram, Li, and Mo (2023), we aggregate multiple returns using simple averaging. Recall that Figure 1 shows momentum and reversal at even and uneven lags of past half-day option returns, respectively. Consequently, we aggregate returns over even lags to study cross-sectional momentum in half-day option returns, whereas we use uneven lags of past option returns for studying cross-sectional reversal effects. In case of half-day momentum, we consider the same half-day periods over the last five, 10, and 20 business days as the formation period. Additionally, we study long-term signals by excluding the most recent periods. That is, we consider the last 10 or 20 business days excluding the most recent five business days and the last 20 business days excluding the most recent 10 business days. In case of half-day reversal, we proceed similarly with uneven lags. We sort option returns into decile portfolios based on past average returns over the formation period and calculate the mean and t-statistic of each decile portfolio using equal-weighting. The holding period is always one half-day period. We require at least 50% non-missing return observations in the formation period for a valid return signal for the holding period. Additionally, we report the long-short portfolio which goes long in the high decile portfolio and shorts the low decile portfolio.

Panel A of Table 3 presents results for intraday returns based on previous half-day periods, and Panel B shows results for overnight returns. Both panels document strong cross-sectional momentum (reversal) based on average returns over past even (uneven) lags. In general, the portfolio-level analyses reported in Table 3 mimic the conclusions from cross-sectional regressions presented in Figure 1. Intraday cross-sectional momentum and reversal yield economically and statistically large average returns to long-short portfolios formed on past average option returns.

However, there are some notable additions. First, considering longer formation periods does not harm the performance of the long-short option portfolios in the case of cross-sectional momentum. The average daily return to the long-short portfolio ranges between 0.22% and 0.23% for intraday holding periods considering the average past option return over the last five, 10 or 20 business days. For overnight holding periods, the average daily long-short portfolio is even slightly higher at 0.45% when the formation period contains more than the last 10 business days compared to the shorter formation period using the last five trading days (0.42%). Second, skipping the most recent lags in the formation period still yields economically and statistically strong long-short portfolio returns for cross-sectional momentum. The daily average returns range from 0.12% to 0.15% (0.28% to 0.34%) for intraday (overnight) holding periods. Third, the performance of cross-sectional reversal strategies is largely dependent on the first lag in the formation period. Either including longer uneven lags or excluding the first lag entirely significantly weakens the performance of the long-short portfolio returns. When the formation period contains the past cross half-day periods over the most recent five business days, the reversal strategy yields average long-short portfolio returns of −0.25% (−0.28%) for intraday (overnight) holding periods. Increasing the formation period to the last 20 business days reduces the absolute magnitude of the long-short portfolio returns by 40–50%. Fourth, the performance of long-short momentum portfolios are nearly equally-driven by the underperformance and outperformance of decile one and ten, respectively. The same applies for cross-sectional reversal based on recent lags in the formation period. On the contrary, cross-sectional reversal using past lags in the formation period is mainly due to the underperformance of options in the highest decile.

Table 3 also reports the abnormal returns (alphas) of the long-short portfolios using different factor models. These include an option market version of the capital asset pricing model (CAPM) with the equal-weighted market factor, the factor model of Tian and Wu (2023),[6] and of Horenstein, Vasquez, and Xiao (2025). Controlling for these risk factors does not change the magnitude and statistical significance of the return spreads.

3.2.1 Effect over Time

In order to assess whether the momentum and reversal patterns are concentrated at specific times during our sample period, we examine three-year moving averages of the returns to long-short option portfolios constructed based on past performances. Instead of showing results for all possible formation periods, we limit our focus on formation

[6] We use only the three primary risks of option market makers outlined in Tian and Wu (2023) in their construction.

periods which contain the last five trading days.

Figure 2 shows that the long-short portfolio returns are positive (negative) for momentum (reversal) in each three-year window. The 95% confidence intervals indicate that the momentum and reversal returns are statistically significant at all times. Furthermore, the figure shows that the strategy returns are becoming larger in absolute magnitude over time. Although the average first three-year return to the reversal strategy is below 0.20% per day in absolute terms, the returns increase in absolute size to more than 0.40% per day for the last three-year rolling window. We observe even stronger increases for the momentum strategy based on the average returns of the past same half-day period returns over the last five business days. For intraday (overnight) holding periods, the average daily returns are approximately 0.20% (0.10%) at the beginning but increase to nearly 0.60% (1.00%) per day at the end of the sample. The increase roughly coincides with the absolute and relative increase in small-volume options in the sample, as depicted in Figure B.2. The latter graphic shows that the share of low-volume options declines towards the end of our sample period but the number of unique underlyings increases slightly. This overlaps with the flattening three-year rolling average strategy returns over the last two years of our sample in the case of overnight holding period returns. Interestingly, such a flattening at the end of the sample is not observed for intraday holding period returns.

3.2.2 Alternative Trading Strategies

So far, we have assessed cross-sectional momentum and reversal by the performance of the long-short portfolios that takes a long position in the highest decile and a short position in the lowest decile of portfolios sorted by past average returns (Jegadeesh and Titman 1993). In this subsection, we consider alternative trading strategies. Specifically, we consider standard time-series and cross-sectional trading strategies of the previous literature on momentum in asset prices (Lo and MacKinlay 1990; Lewellen 2002; Moskowitz, Ooi, and Pedersen 2012; Goyal and Jegadeesh 2018). Formally, the return to time-series (TS) momentum and reversal in half-day period t with the formation period $-t$ is defined as:

$$r_t^{TS} = \frac{2}{N} \sum_{i=1}^{N} \text{sign}(r_{i,-t}) r_{i,t}, \tag{5}$$

and the return for the cross-sectional (CS) strategy in month t is given as:

$$r_t^{CS} = \frac{2}{N} \sum_{i=1}^{N} \text{sign}(r_{i,-t} - \bar{r}_{-t}) r_{i,t}, \tag{6}$$

where $\bar{r}_{-t}$ is the cross-sectional mean formation period return at time $-t$.

Table 4 reports average returns on the CS and TS strategies for the same formation periods considered in Table 3. Table 4 shows that the CS strategy yields lower returns in absolute magnitude, compared to the long-short portfolio returns in Table 3. This is to be expected, as the CS strategy includes approximately half the sample in both long and short positions, compared to using only the extreme deciles. Importantly, this change has little impact on the levels of statistical significance. Hence, Table 4 shows that momentum and reversal are not confined to options with the most extreme past returns, but exist across the entire cross-sectional range of options.

Comparing the returns of the TS strategies with those of the CS strategies shows that both types of strategies yield economically similar results. In particular, in case of intraday holding periods and cross-sectional momentum, the TS strategies tend to yield higher results than CS strategies, albeit the difference is economically small. In general, higher returns to TS than CS strategies has been documented using both monthly straddle returns (Heston, Jones, Khorram, Li, and Mo 2023) and stock returns (Moskowitz, Ooi, and Pedersen 2012). The reason lies in an imbalance between the exposures on the long and short sides of the TS strategy. In stock markets, Goyal and Jegadeesh (2018) show that the overall TS strategy has a net long position due to an average overweight in the stock market, while Heston, Jones, Khorram, Li, and Mo (2023) document a net short position due to an imbalanced exposure in the case of monthly straddle returns. As the cross-sectional mean is close to zero over half-day periods as shown in Table 1, the long and short sides in the TS strategy are nearly balanced in our case. Hence, the performance of our TS strategy is closer to that of the CS strategy compared to the lower-frequency returns.

3.3 Momentum and Reversal in the Underlying

Lou, Polk, and Skouras (2019) document that overnight (intraday) stock returns positively predict future overnight (intraday) returns, while past overnight (intraday) returns negatively predict subsequent intraday (overnight) returns. Hence, the underlying equity market features the same alternating half-day return periodicity that we uncover for option returns.

Even if underlying stock returns display such periodicity, it is not obvious that these dynamics should translate into predictable delta-hedged option returns. By construction, our return measure removes the first-order delta exposure to movements in the underlying each half-day. If stock-level momentum and reversal were to drive the option-level patterns, this influence would need to operate through higher-order channels. Table 2 already provides evidence against such a mechanism. Recall that we include past intraday stock returns as controls in those regressions. As noted in Section 3.1.1, including these controls leaves the slope coefficients for option-return predictability virtually unchanged. This suggests that the option-based signal captures information orthogonal to the behavior of the underlying stock.

To further rule out the possibility that stock-return periodicity indirectly explains our findings, we perform a spanning analysis using long-short portfolios. For each intraday and overnight period, we first sort options into decile portfolios based on past half-day underlying stock returns. Subsequently, we form long-short option portfolios. We then test whether these past half-day stock return based option portfolios can span past half-day option return based option portfolios. This approach assesses whether the predictive content of the option return signal can be replicated by conditioning solely on underlying stock-based information.

Table 5 reports the results. Across all specifications, the intercepts of the spanning regressions remain essentially equal to the raw long-short option portfolio returns formed based on past option returns, indicating that the option-based signal contributes independent predictive power. The slope coefficients on past stock return based option strategy are economically negligible and only sporadically statistically significant. Finally, the R^2s are below 1% throughout, showing that variation in the option return based option portfolio is virtually unrelated to the stock return based option portfolio.

Taken together, these findings demonstrate that half-day momentum and reversal in delta-hedged option returns are not inherited from analogous patterns in the underlying equity market. Underlying returns neither attenuate the predictive ability of past option returns nor help explain long-short option strategy profits. The periodicity in option returns therefore reflects an option-specific return-formation mechanism rather than a transformed reflection of stock-return dynamics.

3.4 Robustness Tests

Bid-Ask Bounce First, we rule out the possibility that intraday momentum and reversal patterns are driven by bid-ask bounces. We estimate the slope coefficients $\gamma_{k,t}$ in Equation (3) using returns computed only from bid or ask prices. If the documented periodicity in half-day periods is due to bid-ask bounces, we should not observe return momentum and reversals using the bid-to-bid or ask-to-ask returns (Heston, Korajczyk, and Sadka 2010). Figure C.1 in Internet Appendix C plots slope $\gamma_{k,t}$ coefficients using ask-to-ask returns, and Figure C.2 shows $\gamma_{k,t}$ coefficients using bid-to-bid returns. As is evident from both panels, bid-to-bid and ask-to-ask returns show the same periodicity pattern. In addition, all return responses are statistically significant. Hence, our main results are not driven by bid-ask bounce.

Weighting by Open-Interest In the main results, we construct the equal-weighted option return for each underlying and each half-day period using all ATM single options contracts, following Muravyev and Ni (2020). To mitigate concerns that the results are driven by single option contracts with low open-interest, we alternatively construct an open-interest weighted average option return per underlying and half-day period.

Figure D.1 and Table D.1 in Internet Appendix D.1 repeat the main results using the alternative return measure. Return responses and performance of the long-short portfolios are quantitatively and qualitatively unchanged.

Initial Delta-Hedged Returns In the main results, we compute intraday option returns by delta-hedging the option position every 30-minute interval, following Muravyev and Ni (2020). An alternative choice is to employ an initial delta-hedge. The difference between the two hedging schemes is essentially a short-term reversal strategy in the underlying stock. Due to their positive Gamma, options require buying more of the underlying asset as its price rises to maintain a replicating portfolio. As the option hedge is short in the replicating portfolio, one must therefore sell the underlying following an increase in the prices of the underlying. Heston, Korajczyk, and Sadka (2010) shows that there is considerable short-term reversal in stocks at 30-minute frequency. This can have an impact on long-short option positions if the reversal effects differ between the long and short positions. To mitigate concerns that our results are driven by such an effect, we repeat our main analyses using initial delta-hedged option returns. Figure D.2 shows return responses to lagged returns produced by running the regression in Equation (3). The figure shows the same periodicity as using frequently delta-hedged returns. Moreover, Table D.2 reports performances of the long-short portfolios constructed based on past option returns. Again, the results are quantitatively and qualitatively similar to those obtained from frequently delta-hedging.

Selecting One or All Options Per Underlying Despite focusing on ATM options with 5 to 50 days-to-maturity, we either pool all options on a single stock to form an aggregate option return or we select the option contract whose time-to-maturity is closest to 30 days and whose moneyness is closest to one in absolute terms for each underlying and each half-day period. Internet Appendices D.3 and D.4 report results for selecting the closest ATM option and using all options, respectively. Both the return responses of Equation (3) and the returns of the long-short portfolios based on past option performances do not change quantitatively or qualitatively.

High vs. Low VIX Levels We next examine whether the documented patterns vary with market-wide stress by splitting the sample into two subsamples based on the median monthly VIX level. Table E.1 reports that the half-day momentum and reversal patterns are present and statistically significant in both low- and high-uncertainty periods, as gauged by the VIX. However, the economic magnitude of the long-short portfolio returns is consistently larger during periods of high market stress. For example, the intraday reversal strategy based on the last five business days yields -0.23% in low VIX months versus -0.28% in high VIX months. A similar strengthening is observed for momentum strategies; the corresponding intraday strategy earns 0.20% in low VIX periods vs. 0.26% in high VIX periods.

Stock Market Momentum Crashes Given that stock market momentum strategies are known to experience periodic crashes (see, e.g., Daniel and Moskowitz 2016), we next test whether our half-day option strategies are influenced by stock market momentum crashes. We identify months where a standard stock momentum strategy performs most poorly (the bottom 20 months in our sample, 2004-2021) and analyze our portfolio returns separately for these "MOM Crash" and all other "No MOM Crash" periods. Table E.2 shows that, far from crashing, our option-based strategies remain highly profitable during these episodes. In fact, both momentum and reversal effects are economically larger during stock momentum crash months. This strengthening is consistent with our previous finding that the strategies' performance is amplified during periods of high market stress.

Across Weekdays To ensure our findings are not driven by mispricing related to non-trading periods, such as the weekend effects in Jones and Shemesh (2018), we test the performance of our strategies across different days of the week. Table E.3 presents the long-short portfolio returns for each weekday. The results show that both the momentum and reversal patterns are remarkably stable and economically large across all five days, from Monday to Friday. The stability of these profits indicates that the half-day periodicity we document is not attributable to a particular day-of-the-week effect and is therefore unlikely to be an artifact of how markets process information over non-trading intervals.

Earnings Announcements Since earnings announcements (EAs) are major informational events potentially impacting option implied volatility (Alexiou, Goyal, Kostakis, and Rompolis 2025), we test whether their presence influences our results. We partition the sample based on whether an earnings announcement for the underlying stock occurred during the strategy's formation period. Table E.4 shows that the half-day momentum and reversal patterns remain statistically significant in both the presence ("w/ EA") and absence ("w/o EA") of an announcement. This confirms the robustness of the core finding.

4 Potential Explanations

Having established robust cross-sectional momentum and reversal in half-day option returns, we next investigate potential economic mechanisms giving rise to these patterns.

4.1 Characteristics of Decile Portfolios

We investigate which option and stock characteristics can explain the cross-sectional momentum and reversal in intraday and overnight option returns. For each half-day period, we sort options into decile portfolios based on formation periods using the most recent five trading days. For each half-day period, we cross-sectionally normalize stock and option characteristics to lie within the interval $[0, 1]$ to ease interpretation. Subsequently, we compute for each half-day period, each decile portfolio, and each formation period the average normalized characteristic. Subsequently, we average over time and half-day period. Table 6 presents the average stock and option characteristics of each decile for the momentum and reversal formation periods using the last five business days. The characteristics include the following stock-based characteristics: the day-night-volatility ratio (Day-Night-Vol-Ratio) which is computed over the last 60 trading days, a proxy for hedging costs (Hedging Costs) of market makers following Tian and Wu (2023), age of the underlying firm (Age), book-to-market ratio (BM), market beta (Beta), idiosyncratic volatility (Ivol), lottery demand (Max5), jump risk (Jump Risk), and the log nominal stock price (Log Price). We also include the open-interest, option volume, and an Amihud (2002)-type illiquidity measure ("Illiq") based on 30-minute intervals and absolute changes in implied volatility scaled by trading volume, averaged over the last 5 business days, as option-based characteristics.

Table 6 shows that small, lottery-like, younger stocks with high beta, high idiosyncratic volatility and high hedging costs often appear in the extreme decile portfolios. This applies to the use of both even and odd lags in the formation period. Similarly, options with high illiquidity are more likely to appear in extreme deciles. In contrast, the day-night volatility ratio does not appear to be related to the formation of options in portfolios based on past performance.

Prior literature has emphasized that investor demand affects option returns (Gârleanu, Pedersen, and Poteshman 2009; An, Ang, Bali, and Cakici 2014; Goyenko and Zhang 2019) and volatility surfaces (Bollen and Whaley 2004). However, we note that our extreme decile portfolios include options with relatively *low* open interest and *low* trading volume. This suggests that demand effects are unlikely to be the main drivers of our results. In the following subsections, we will use the findings from Table 6 to understand the economic underpinnings of the documented intraday and overnight periodicity, in particular the demand (and supply) effects.

4.2 Effects in the Cross-Section

As indicated in the previous section, the cross-sectional momentum and reversal phenomena are strongly associated with certain stock and option characteristics. Motivated by these findings, we study if the documented reversal and momentum effects are confined to specific subgroups of options in the cross-section. Heston, Jones, Khorram, Li, and Mo (2023) conduct a similar analysis in the case of monthly straddle returns. The authors highlight three benefits of such an analysis. First, if the cross-sectional momentum and reversal effects are present in only small and illiquid options, these effects might be deemed less important. Second, documenting momentum and reversal in all subgroups of options would reduce potential data snooping concerns. Third, if these effects are more pronounced in groups of options with higher limits-to-arbitrage, then mispricing might be the underlying cause.

We conduct bivariate portfolio sorts to more rigorously study the impact of stock and option characteristics on cross-sectional intraday and overnight momentum and reversal. For each selected control characteristic, we first sort options at each half-day period into terciles. Subsequently, we sort options into quintiles based on their average return over the formation period for each control tercile. For each control tercile, we finally compute the long-short portfolio return by investing long in the high quintile portfolio and shorting the low quintile portfolio. Additionally, we compute the difference-in-difference return spreads between the long-short portfolios of the high and low control terciles.

We consider the following five conditioning variables: firm size, idiosyncratic volatility of the underlying stock, the average of the top five highest returns for each stock in the previous month, an arbitrage index, and option illiquidity. The arbitrage index is constructed based on the three primary risks of option market makers according to Tian and Wu (2023).[7] Option illiquidity is constructed similarly to Amihud (2002) but using 30-minute interval implied volatility changes scaled by trading volume.

Table 7 presents key findings from the bivariate portfolios. Panel A (B) shows the results when the formation period includes only even (uneven) lags of past half-day periods over the last five business days in the formation period. Cross-sectional momentum is prevalent throughout intraday and overnight holding periods and in all subgroups of options. Thus, we show the existence of momentum and reversal for options for underlying firm with high or low market capitalization, idiosyncratic volatility, past extreme returns, if the option market maker face high or low primary risks when delta-hedging her options book, or if the illiquidity is high or low. At the same time, momentum and reversal effects are stronger for smaller firms with higher idiosyncratic volatility and higher illiquidity and extremely high past stock returns. In addition, momentum and re-

[7] The three primary risks entail delta-hedging costs, volatility risk, and jump risk that are also known to predict the cross-sectional variation in future returns of optionable stocks (see, Bali and Hovakimian 2009; Xing, Zhang, and Zhao 2010; Cremers, Halling, and Weinbaum 2015).

versal in intraday and overnight option returns are more pronounced when option market makers face higher limits-to-arbitrage. Overall, the results in Table 7 suggest that the cross-sectional momentum and reversal patterns at half-day periods are not confined to specific subgroups of options, but strengthens for higher limits-to-arbitrage.

4.3 Day-Night-Volatility Ratio

Muravyev and Ni (2020) provide evidence that the volatility ratio can explain differences in unconditional intraday and overnight option returns. These authors show that the instantaneous excess return of a delta-hedged option portfolio is proportional to the difference between realized and implied instantaneous variances, multiplied by the option Gamma and squared stock price, and integrated over the holding period of the option position. If option prices understate intraday volatility and realized instantaneous variance is higher than its implied counterpart, this would lead to positive delta-hedged option returns. Similarly, if option prices overestimate overnight volatility (because overnight volatility is typically lower than intraday volatility) and realized instantaneous variance is lower than its implied counterpart, this would imply negative delta-hedged option returns. If option prices show such volatility bias, the ratio between overnight and intraday stock volatility would capture such an effect, as documented by Muravyev and Ni (2020) for unconditional overnight and intraday option returns.

Although Table 6 does not show a direct link between the day-night-volatility ratio of the underlying stock in explaining momentum and reversal, in this section, we more formally test if the volatility ratio also explains the momentum and reversal effects via bivariate portfolio sorts, following Muravyev and Ni (2020). For each stock, we compute intraday (overnight) volatility as the standard deviation of open-to-close (close-to-open) underlying returns over the previous 60 days. Subsequently, we form the ratio of the two standard deviations as the volatility ratio. Each half-day period, we sort underlying stocks into terciles based on their day-night-volatility ratio. Within each tercile, we perform quintile portfolio sorts of options using various formation periods and finally compute the high-minus-low quintile portfolio. We also compute the difference in the high-minus-low quintile portfolio between the low and high volatility ratio terciles. If there is an association between the day-night-volatility ratio and periodicity in overnight and intraday returns, we would expect statistically significant difference in the long-short portfolio returns.

Table 8 reports the results for intraday and overnight returns in Panels A and B, respectively. The high-minus-low quintile portfolio returns are nearly identical across the terciles based on the volatility ratio. Hence, the differences in the long-short portfolio returns are economically small (below 0.02%) for most lags, and not statistically significant. This finding reinforces the evidence in Table 6 that intraday and overnight option return periodicity is unrelated to the day-night-volatility ratio of the underlying.

4.4 Demand Effects

Demand by option end-users can push implied volatility higher, leading to positive half-day option returns. Bollen and Whaley (2004) document that changes in implied volatility directly correlate with net buying pressure from option order flow. Similarly, Gârleanu, Pedersen, and Poteshman (2009) model demand-pressure effects on option prices, and show that option demand contributes to the expensiveness of single-stock options. Goyenko and Zhang (2019) show that end-user demand creates significant price pressures that can cause end-of-day option prices to deviate from their fundamental values. If option demand obeys a periodic pattern, it could potentially explain the periodic changes in implied volatility leading to momentum and reversal in option half-day returns.

We begin by asking whether demand-side factors can explain the documented momentum and reversal patterns by analyzing the degree of persistence in trading volume and order imbalances. We utilize signed volume data from three US options exchanges operated by NASDAQ.[8] The data provide signed volumes and the number of trades (open buy/sell; close buy/sell) by non-market makers, including professional customers, firm customers, and all other customers. The overall sample period is from 2009 to 2021. Subsequently, we proxy order imbalances using the volumes of bought and sold contracts

[8]Nasdaq GEMX, Nasdaq Options Market (NOM), and Nasdaq PHLX.

as follows:

$$OIB_{i,t} = \frac{V_{i,t}^{\text{buy}} - V_{i,t}^{\text{sell}}}{V_{i,t}^{\text{buy}} + V_{i,t}^{\text{sell}}}, \tag{7}$$

where $V_{i,t}^{\text{buy}}$ and $V_{i,t}^{\text{sell}}$ denote the volume of bought and sold ATM options on stock i at time t with time to maturity within five and 50 days, respectively.

Figure 3 shows the slope coefficients that predict current order imbalances using past order imbalances at various lags, similar to cross-sectional return regressions in Equation (3). Panel A shows the results from regressing intraday order imbalances on previous half-day order imbalances. The slope coefficients start at approximately 0.09 for lag 2, declining to approximately 0.06 at lag 4, and then gradually decreasing to around 0.02 by lag 20, All coefficients remain positive and statistically significant throughout. Panel B presents the results for overnight order imbalances and displays a similar pattern, but with slightly lower initial values.[9]

Thus, Figure 3 shows that order imbalances exhibit strong positive persistence at all lags. This is in contrast to the patterns that we document for returns in Figure 1. If momentum and reversal in option returns were driven by demand pressure alone, we would expect trading activity to exhibit similar alternating patterns. Instead, we find that buyers today remain buyers tomorrow, regardless of whether we transition from intraday to overnight periods or vice versa. Combined with the evidence of strongly periodic returns, this suggests that while trading interest persists, its price impact varies systematically between intraday and overnight periods. The absence of demand reversal indicates that the return patterns must arise from time-varying frictions in how persistent demand is accommodated rather than from changes in the demand itself.

This pattern in option order imbalance is similar to the equity-market evidence in Lu, Malliaris, and Qin (2023), who also document that order imbalances for stock portfolios with strong night-minus-day return patterns remain positive and persistent throughout the trading day, even though stock returns alternate in sign between the overnight and intraday legs. Our results, therefore, echo their empirical finding that simple price-pressure

[9] Figure F.1 in the Internet Appendix documents high persistence in standardized log trading volume, with slope coefficients on past standardized log trading volume exceeding 0.70 even at 20-day lags.

stories, in which order imbalances mechanically reverse with returns, are inconsistent with the data.

4.4.1 Heterogeneity in Demand

To rule out alternative demand-based explanations, we investigate whether our patterns might reflect a tug-of-war between different trader types. Lou, Polk, and Skouras (2019) argue that investor heterogeneity influences intraday and overnight stock returns. The authors document, similar to our findings in the options market, strong intraday and overnight continuation effects in same half-day periods accompanied by cross-period reversals. Lou, Polk, and Skouras (2019, Figure 3) show that individual investors trade more frequently directly after the open, while institutional investors prefer trading directly before the close. Hence, even though the overall demand for trading is evenly distributed, their allocation with respect to the types of investors differs.

Similar to Lou, Polk, and Skouras (2019), we analyze when do institutional and individual investors trade during the trading day. As in Lou, Polk, and Skouras (2019), we use the size of trades to differentiate between institutional and individual investors where large trade quantities are associated with institutional investors and small trade sizes with individual investors. We use either the trade size or the dollar volume per trade to differentiate between small and large orders.[10] Furthermore, we use the identification mechanism of Bryzgalova, Pavlova, and Sikorskaya (2023) to identify retail option trades.

Figure 4 plots the intraday evolution of trading activity using three proxies to distinguish between retail and non-retail traders: trade size, dollar volume per trade, and the retail-trade identification method of Bryzgalova, Pavlova, and Sikorskaya (2023). Using trade size or dollar volume, we observe a slightly higher share of small trades in the first 30 minutes after the open and a modest increase toward the end of the day. Applying the Bryzgalova, Pavlova, and Sikorskaya (2023) measure suggests slightly higher non-retail activity at the open. Taken together, the three proxies do not provide clear evidence that trader types differ systematically in their intraday trading patterns. In contrast

[10]Small volume is based on less than 2 contracts ($2,000) per trade, large volume is based on more than 10 contracts ($10,000) per trade.

to the patterns documented for equities in Lou, Polk, and Skouras (2019), such timing differences do not appear to be a robust feature of the options market in our setting.

To provide another view on whether the tug-of-war hypothesis is present in options markets, we examine if momentum and reversal patterns persist in extremely low-volume options where institutional participation is minimal by construction. We focus on option contracts where fewer than 10 contracts per underlying and day have been traded on average over the past six-month period. For this subset of options, we form quintile portfolios based on past average returns over various formation periods. Table 9 shows that the momentum and reversal effects remain statistically significant and economically comparable to the full sample of options. These findings challenge the notion that the cross-sectional momentum and reversal dynamics in half-day option returns stem from an institutional-retail tug-of-war, as these patterns persist even where institutional footprint is negligible.

We close by noting that our findings differ from the interpretation proposed by Lu, Malliaris, and Qin (2023). Their model resolves the coexistence of persistent order imbalances and alternating night-minus-day stock returns by incorporating heterogeneous liquidity providers. Fast, inventory-constrained arbitrageurs absorb order flow near the open, whereas slow arbitrageurs gradually take over later in the day. In the option market, especially for contracts with extremely low trading activity, such a segmentation into slow and fast arbitrageurs is empirically implausible. Hence, while our demand-side evidence parallels the findings of Lu, Malliaris, and Qin (2023) that order imbalances do not reverse, our results show that the economic mechanism generating the periodicity in option returns must differ from fast-versus-slow-arbitrageur channel.

4.5 Supply Effects

The previous section shows that persistent investor demand does not, by itself, explain the alternating momentum and reversal patterns in option returns. This points to supply-side frictions as a likely driver of the documented predictability. While the literature has traditionally emphasized demand-based mechanisms in shaping implied volatility surfaces

(Bollen and Whaley 2004) and the impact of end-user demand on option prices (Gârleanu, Pedersen, and Poteshman 2009; Goyenko and Zhang 2019), recent work highlights that the supply side in options markets also plays an economically significant role. Hu, Kirilova, Muravyev, and Ryu (2025) show that option market makers manage risk primarily through rapid inventory rebalancing rather than systematic delta hedging. When capacity constraints tighten, market makers adjust spreads to limit further inventory accumulation. These spread adjustments provide a natural channel through which supply-side frictions may interact with persistent demand to generate short-horizon return patterns. Similarly, Cao, Jacobs, and Ke (2024) document that spreads in SPX options widen systematically when market makers face elevated demand or heightened volatility, consistent with intermediaries requiring greater compensation when their risk-bearing capacity is strained. Complementing these results, Pederzoli, Jacobs, and Mai (2025b) show, using VIX options, that market-maker supply curves shift substantially in volatile periods in ways correlated with dealers' inventory risk and wealth, and Pederzoli, Doshi, and Sert (2025a) demonstrate that exchanges exposed to more volatile order flow quote wider spreads even for the same stock and day. Together, these studies point to option market makers as risk-constrained intermediaries whose quoting behavior varies systematically with volatility, order-flow conditions, and inventory exposures.

Our previous empirical evidence already provides suggestive support for our results using this supply-side interpretation. As shown in Table 7, the bivariate portfolio sorts using ILLIQ reveal that momentum and reversal effects are stronger when ILLIQ is high. ILLIQ is a Kyle's λ based measure of volatility-related price impact and thus reflects the elasticity of liquidity supply. Higher values indicate that volatility and hence prices move more in response to demand shocks. Accordingly, stronger return predictability in instances where λ is high is consistent with intermediary effects in explaining our documented return patterns.

Guided by this evidence, we next study whether variation in bid-ask spreads provides additional information about supply-side conditions. Higher spread volatility reflects more frequent quote adjustments as market makers manage inventory exposure, volatility risk, and order-flow pressure. If such supply frictions interact with persistent end-user demand, then momentum and reversal effects should be stronger when past spread volatility is high. We test this hypothesis by conditioning our return-signal sorts on the volatility of half-day bid-ask spreads.

Table 10 presents the results for momentum and reversal strategies conditioning on the volatility of the relative bid-ask spread. For intraday momentum strategies based on even lags over the past five business days, options in the high volatility tercile generate long-short returns of approximately 0.25% per half-day, compared with 0.05–0.06% in the low volatility tercile. The resulting differences of approximately 0.19–0.20% depending on the formation window are economically meaningful and statistically highly significant. For reversal strategies using odd lags, a similar pattern emerges. High volatility conditions yield long-short returns of about −0.29% versus −0.03% in the low volatility tercile for odd lags over the last 5 business days, implying differences of 0.26%, again highly statistically significant. Overnight momentum and reversal strategies display the same qualitative behavior, with high volatility terciles consistently yielding stronger predictability than low volatility terciles across all formation-period specifications.

4.5.1 Concentration in Trading

To complement the evidence based on spread volatility, we next examine whether cross-sectional differences in how trading is distributed across option exchanges relate to the strength of the documented momentum and reversal patterns. We obtain for each optionable stock the full day trading volume for each of option exchange between 2012 and 2019 from CBOE. Subsequently, we measure exchange concentration using a Herfindahl Hirschman type index (HHI). For each stock-day, HHI is computed as the sum of squared exchange-level market-share weights based on that stock's option trading volume. Higher HHI reflects trading that is concentrated in fewer venues, while lower HHI reflects greater fragmentation. Because HHI might be mechanically correlated with total trading activity, we construct an orthogonalized HHI by regressing HHI on the total daily trading volume and retaining the residual. This residual isolates variation in exchange concentration that is unrelated to the overall level of trading.[11]

We hypothesize that momentum and reversal patterns are stronger for stocks with higher orthogonalized HHI. A high value of orthogonalized HHI indicates that, for a given level of trading activity, order flow is intermediated by fewer exchanges. In this setting, two supply-side channels might be at play. First, when fewer venues absorb the same aggregate order flow, inventory risk becomes more concentrated, making individual market makers more exposed to flow and more sensitive to persistent demand shocks. This mechanism is closely related to the evidence in Pederzoli, Doshi, and Sert (2025a), who show that exchanges facing more volatile signed order flow quote wider spreads for the same underlying asset and day.[12] Second, when trading is handled by fewer venues, competitive pressure among liquidity providers weakens. Market makers can widen spreads more aggressively in response to risk or inventory conditions without immediately losing flow to competing venues, consistent with evidence that increased competition narrows spreads and improves market quality (e.g., Mayhew 2002; De Fontnouvelle, Fishe, and Harris 2003). Taken together, these considerations suggest that persistent demand may interact more strongly with supply-side frictions when trading is concentrated, leading to more pronounced predictability patterns.

Table 11 summarizes the portfolio sorts that condition return predictability on the degree of exchange concentration, measured by the orthogonalized HHI. For intraday momentum strategies (even-lag specifications), portfolios formed in the high-HHI tercile deliver long-short returns of roughly 0.26–0.27% per half-day, whereas the corresponding figures in the low-HHI tercile are approximately 0.10–0.11%. The spread between the low and high tercile amounts to 0.15–0.17% and is highly statistically significant. The odd-lag reversal strategies show a comparable pattern. Long-short option portfolios based

[11]Raw exchange-level HHI mechanically reflects trading activity, as option volume of high-volume and high-attention optionable stocks might be more fragmented. Therefore, we orthogonalize HHI with respect to volume and use the residual, which captures variation in venue concentration not explained by differential trading activity and attention.

[12]Pederzoli, Doshi, and Sert (2025a) exploit OPRA intraday trade messages that identify the executing exchange for each transaction, allowing them to construct exchange-specific order-flow volatility measures. Our data do not provide this level of granularity, so we cannot observe how intraday order flow is distributed across venues. We therefore rely on stock-level measures of exchange concentration rather than direct exchange-level flow risks.

on past performances in the high exchange concentration tercile earn around -0.33%, compared with -0.11% in the low-concentration tercile for odd lags within the last five business days. The difference indicates that reversal effects also intensify in stocks with more concentrated venue activity. A similar increase is obtained for overnight strategies. Hence, exchange concentration is associated with stronger half-day momentum and reversal patterns, in line with the idea that persistent demand interacts more strongly with liquidity provision when a smaller set of venues intermediates order flow.

Taken together, the spread-volatility and HHI results suggest that supply-side conditions impact how persistent end-user demand translates into short-horizon return predictability. In both cases, momentum and reversal effects are more pronounced when liquidity supply appears tighter or more concentrated, indicating that supply frictions contribute to the observed periodicity of these patterns in conjunction with persistent demand.

5 Conclusion

We document robust momentum and reversal patterns in half-day option returns that persist for up to 20 business days. We find that option returns exhibit strong momentum effects within the same half-day periods (even lags) and reversal effects across opposite half-day periods (odd lags), with economic magnitudes ranging from 0.22% to 0.45% per half-day and strengthening considerably over time. These effects are unrelated to the well-documented momentum and reversal in half-day stock returns.

The economic mechanisms underlying these patterns reveal a fundamental disconnect between persistent investor demand and alternating return patterns. While option order imbalances exhibit consistent positive persistence across all lags, option returns display systematic alternating effects. This disconnect points to supply-side constraints as the primary driver of option return predictability. Our analysis demonstrates that momentum and reversal patterns strengthen when option market makers actively adjust spreads to manage capacity constraints, with effects being particularly pronounced when persistent demand transitions between intraday and overnight periods.

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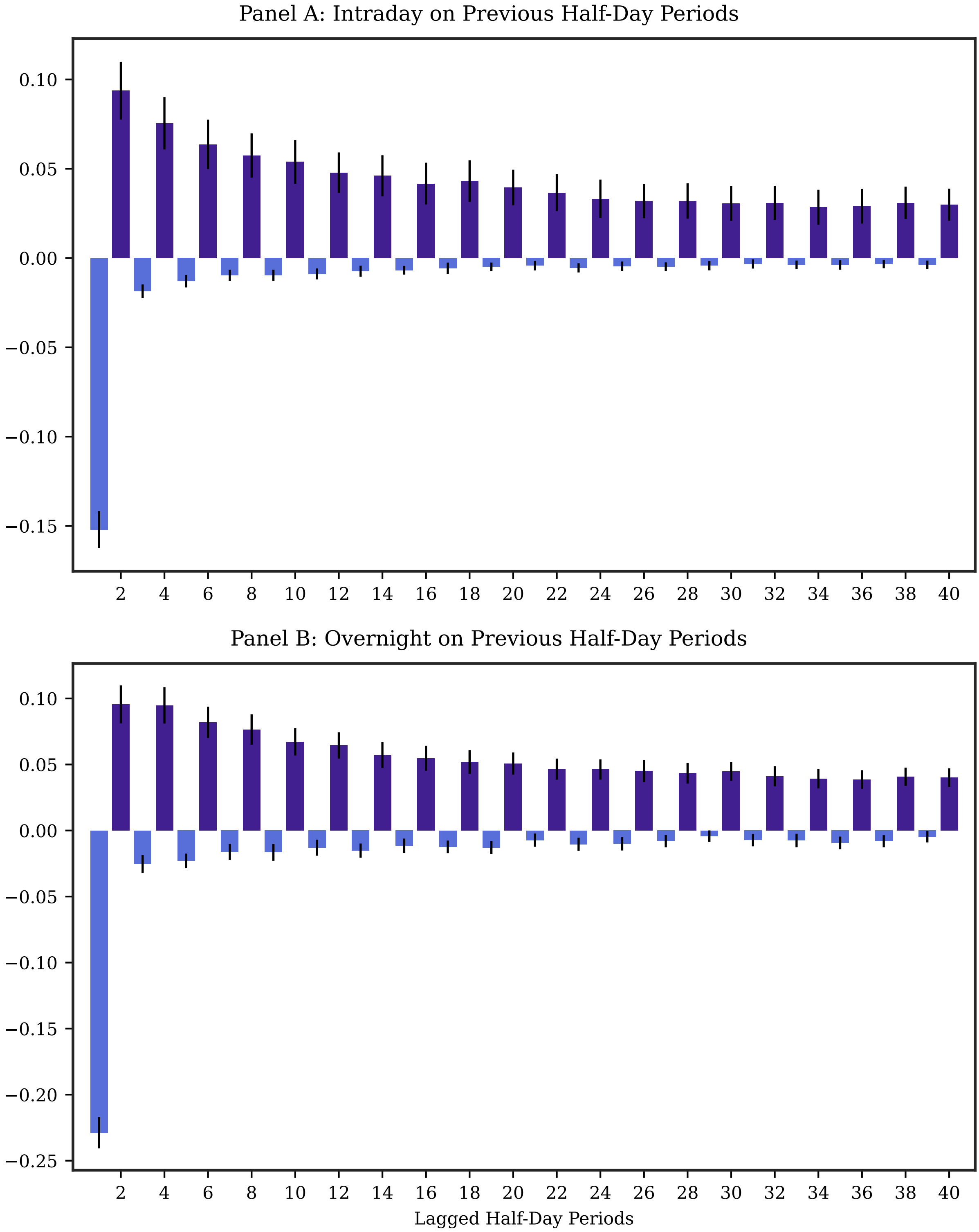

Figure 1: Cross-sectional regressions of intraday and overnight returns on past same half-periods

The figure shows slope estimates of univariate Fama-MacBeth cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ denotes the option return of stock i during interval t and the variable $r_{i,t-k}$ is the option return of stock i in interval $t-k$. We divide the 24h-interval between 16:00 at time t and 16:00 at time $t+1$ into the overnight, i.e., from 16:00 at time t to 10:00 at time $t+1$, and the intraday, i.e., from 10:00 at time $t+1$ to 16:00 at time $t+1$, component. Panel A plots the slope coefficients from regressions of intraday returns on lagged half-day returns. Panel B plots the slope coefficients from regressions of overnight returns on lagged half-day returns. We consider lags k 1 through 40. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

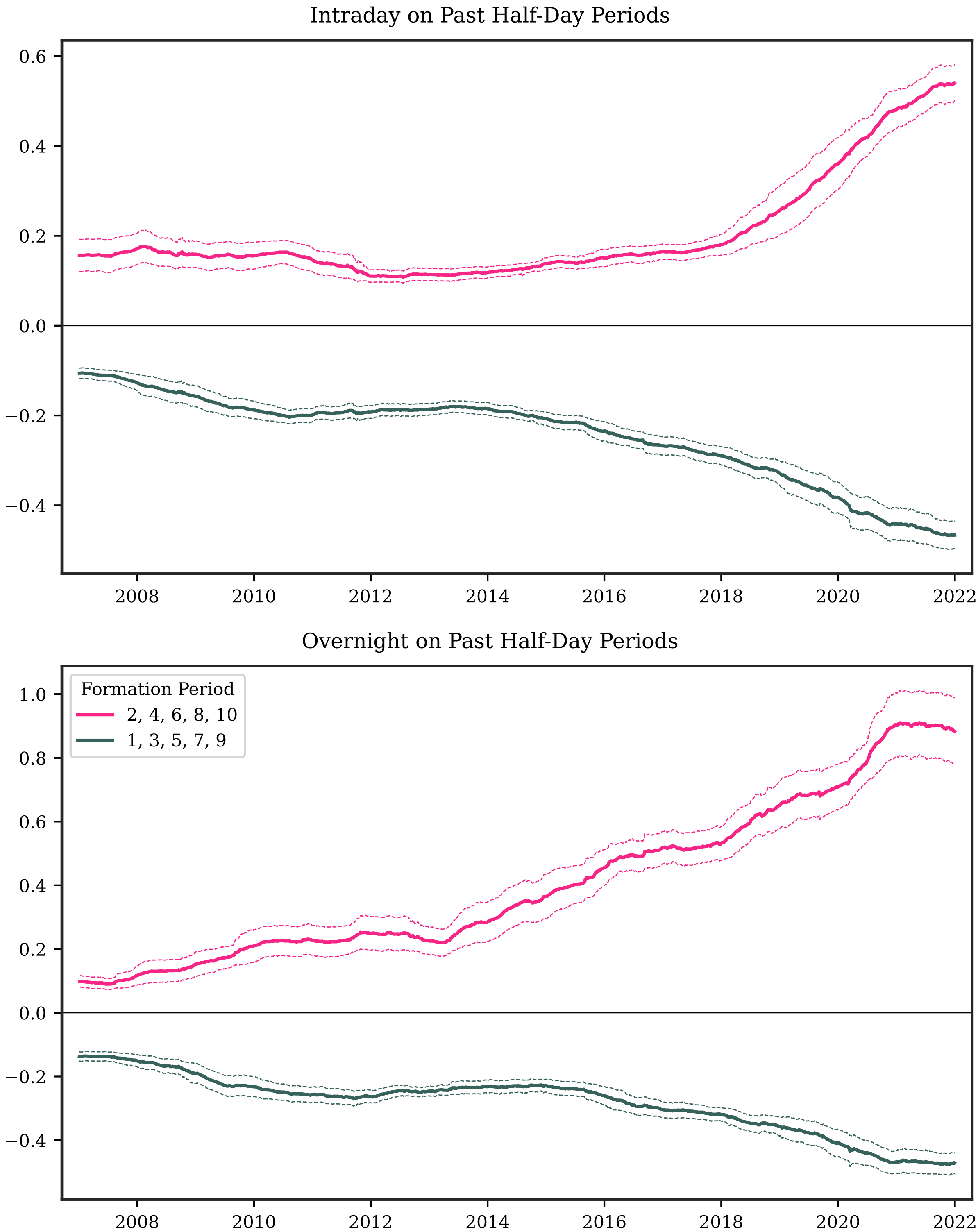

Figure 2: 3-year rolling Performance of Option Portfolios based on Past Performances

The figure shows three-year rolling average option returns of high-minus-low decile portfolios based on past performances. As the signal for decile portfolios, average past option returns over the formation are taken. Panel A shows results for intraday option returns, whereas Panel B reports results for overnight option returns. The dashed lines denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

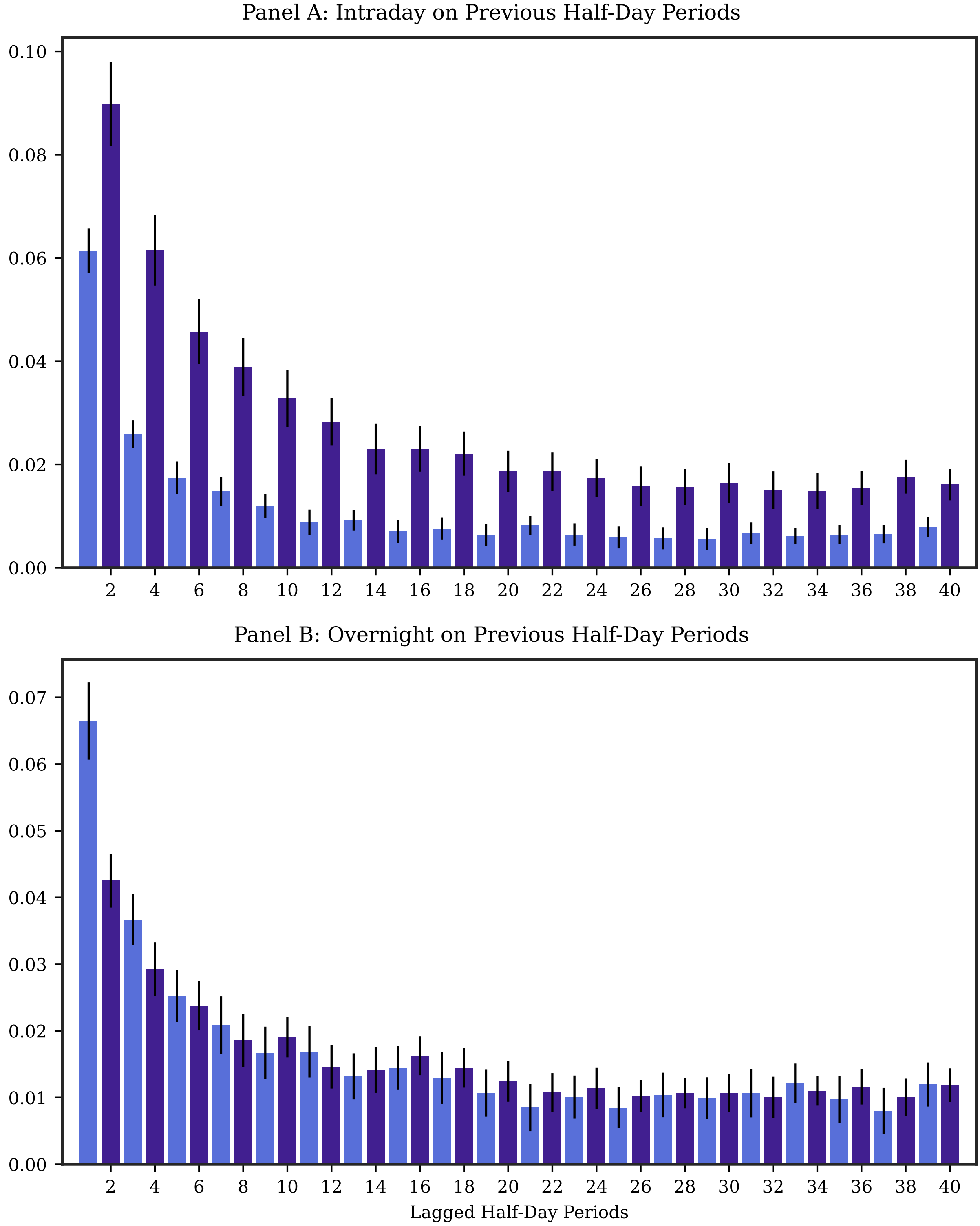

Figure 3: Cross-sectional regressions of intraday and overnight order imbalances on past same half-periods

The figure shows results for univariate Fama-MacBeth cross-sectional regressions of the form $oib_{i,t} = \alpha_{k,t} + \gamma_{k,t} oib_{i,t-k} + u_{i,t}$, where $oib_{i,t}$ denotes the option order imbalance of stock i during interval t. $oib_{i,t-k}$ is the option order imbalance of stock i in interval $t-k$. Panel A reports results for intraday periods, whereas Panel B reports results for overnight periods. We consider lags k 1 through 40. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

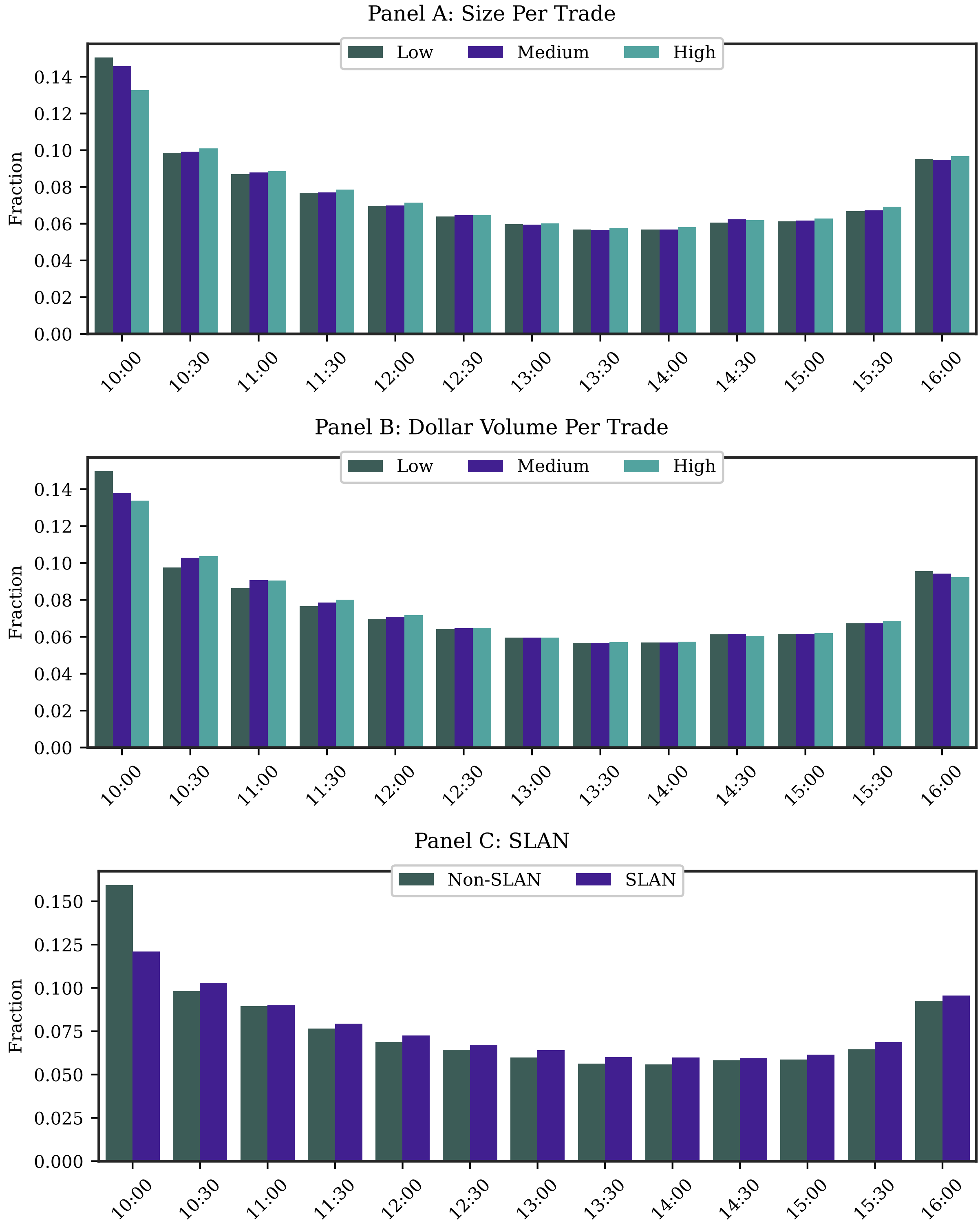

Figure 4: The distribution of trading volume for different market participants

The figure shows the distribution of trading volume over 30-minute intervals throughout the trading day. Panel A (B) shows results for different buckets of volume (dollar volume) per trade. Small volume is based on less than 2 contracts (USD 2000) per trade, large volume is based on more than 10 contracts (USD 10000) per trade in Panel A (B). Panel C shows the distribution of trades with payment for order flow vs. trades without payment for order flow according to Bryzgalova, Pavlova, and Sikorskaya (2023). The sample period for Panels A and B ranges from over the period from 2014 to 2021 whereas it starts in 2019 for Panel C.

Table 1: Summary statistics

	Mean	Sd	1p	Q1	Q2	Q3	99p
Panel A: Global							
Overnight	0.006	1.417	−2.873	−0.232	−0.050	0.124	3.995
Intraday	0.002	0.897	−2.289	−0.200	−0.019	0.172	2.499
Panel B: Cross-Sectional Average							
Overnight	0.002	1.250	−2.485	−0.238	−0.048	0.142	3.464
Intraday	0.002	0.779	−2.047	−0.202	−0.013	0.184	2.188

The table reports summary statistics for overnight and intraday option returns. Statistics are shown separately for the entire sample (Panel A) and as the time-series average of the cross-sectional statistics at each half-day period. The overnight period last from 16:00 at time t to 10:30 at time $t+1$, whereas the intraday period lasts from 10:00 to 16:00 at time $t+1$. The table shows the mean (Mean), standard deviation (Sd), 1^{st} percentile (1p), first quartile (Q1), median (Q2), third quartile (Q3), and 99^{th} percentile (99p). The sample period is from January 2004 to December 2021.

Table 2: Cross-Sectional Regressions of Option Returns on Past Option Returns

Lag	Intraday on Previous Half-Day Periods		Overnight on Previous Half-Day Periods	
	w/o Controls	w/ Controls	w/o Controls	w/ Controls
1	−0.152 (−30.48)	−0.170 (−49.42)	−0.229 (−40.70)	−0.211 (−49.02)
2	0.094 (11.78)	0.082 (15.31)	0.095 (13.77)	0.111 (22.82)
3	−0.019 (−11.23)	−0.017 (−12.77)	−0.025 (−8.40)	−0.022 (−8.26)
4	0.075 (10.53)	0.072 (13.87)	0.095 (14.31)	0.105 (24.22)
5	−0.013 (−8.79)	−0.011 (−8.84)	−0.023 (−9.64)	−0.020 (−8.29)
6	0.064 (9.44)	0.058 (12.08)	0.082 (14.58)	0.087 (21.37)
7	−0.010 (−7.38)	−0.008 (−6.21)	−0.016 (−6.01)	−0.014 (−5.83)
8	0.057 (9.58)	0.054 (12.68)	0.076 (14.04)	0.077 (20.90)
9	−0.010 (−7.45)	−0.008 (−7.77)	−0.017 (−5.77)	−0.016 (−6.87)
10	0.054 (9.08)	0.048 (11.07)	0.067 (13.84)	0.069 (18.62)
11	−0.009 (−7.15)	−0.007 (−6.01)	−0.013 (−4.90)	−0.012 (−5.68)
12	0.048 (8.72)	0.042 (10.53)	0.064 (13.86)	0.062 (17.13)
13	−0.007 (−5.83)	−0.007 (−6.16)	−0.015 (−6.56)	−0.010 (−4.68)
14	0.046 (8.27)	0.041 (10.29)	0.057 (12.48)	0.056 (15.65)
15	−0.007 (−7.24)	−0.006 (−5.93)	−0.011 (−4.94)	−0.008 (−4.11)
16	0.042 (7.37)	0.034 (8.79)	0.055 (12.43)	0.053 (16.10)
17	−0.006 (−4.40)	−0.004 (−3.35)	−0.012 (−6.14)	−0.008 (−3.52)
18	0.043 (7.66)	0.037 (10.01)	0.052 (12.51)	0.051 (16.22)
19	−0.005 (−5.36)	−0.003 (−2.88)	−0.013 (−6.36)	−0.012 (−5.51)
20	0.040 (8.28)	0.034 (9.27)	0.051 (13.14)	0.044 (15.73)
21	−0.004 (−4.04)	−0.004 (−3.96)	−0.007 (−3.40)	−0.009 (−4.38)
22	0.037 (7.35)	0.030 (8.36)	0.046 (12.71)	0.043 (14.23)
23	−0.005 (−5.43)	−0.005 (−4.63)	−0.010 (−4.95)	−0.009 (−4.15)
24	0.033 (6.42)	0.027 (7.51)	0.046 (13.26)	0.041 (14.19)
25	−0.005 (−4.43)	−0.005 (−4.40)	−0.010 (−4.61)	−0.007 (−3.52)
26	0.032 (6.96)	0.026 (7.07)	0.045 (11.50)	0.042 (13.94)
27	−0.005 (−5.18)	−0.004 (−3.87)	−0.008 (−4.16)	−0.007 (−3.42)
28	0.032 (6.76)	0.025 (6.66)	0.043 (12.16)	0.038 (13.61)
29	−0.004 (−4.13)	−0.005 (−4.49)	−0.004 (−2.37)	−0.001 (−0.68)
30	0.031 (6.56)	0.028 (7.73)	0.045 (14.14)	0.040 (14.54)
31	−0.003 (−3.28)	−0.003 (−3.39)	−0.007 (−3.65)	−0.006 (−3.15)
32	0.031 (6.78)	0.024 (6.92)	0.041 (11.79)	0.038 (14.13)
33	−0.004 (−4.13)	−0.004 (−3.91)	−0.008 (−3.46)	−0.007 (−3.48)
34	0.028 (6.07)	0.021 (6.37)	0.039 (11.89)	0.034 (13.94)
35	−0.004 (−3.76)	−0.004 (−3.70)	−0.009 (−4.65)	−0.006 (−2.91)
36	0.029 (6.27)	0.022 (6.90)	0.039 (12.16)	0.035 (13.39)
37	−0.003 (−3.80)	−0.003 (−3.49)	−0.008 (−4.22)	−0.005 (−2.29)
38	0.031 (7.15)	0.022 (7.24)	0.041 (13.15)	0.034 (12.83)
39	−0.004 (−4.21)	−0.003 (−3.24)	−0.005 (−2.57)	−0.002 (−1.21)
40	0.030 (6.99)	0.022 (7.75)	0.040 (12.63)	0.037 (13.12)

The table reports results for Fama-MacBeth cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + \Gamma'_{k,t} C_{i,t-k} + u_{i,t}$, where $r_{i,t}$ denotes the option return of stock i during interval t, the variable $r_{i,t-k}$ is the option return of stock i in interval $t-k$, and $C_{i,t-k}$ denotes a vector of controls. $C_{i,t-k}$ includes the trading volume, the return of the underlying stock, the absolute return of the underlying stock, and the relative bid-ask spread of the options as controls. The column "w/o Controls" ("w Controls") shows the slope coefficient $\gamma_{k,t}$ when excluding (including) $C_{i,t-k}$ in the regression. The regressions are done separately for intraday and overnight returns. We consider lags k 1 through 40. Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Table 3: Option Portfolios Based on Past Performances

Panel A: Intraday on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.11	−0.02	0.00	0.02	0.11	0.23 (19.85)	0.23 (19.87)	0.22 (21.08)	0.21 (18.42)
2, 4, ..., 20	−0.12	−0.02	0.00	0.02	0.12	0.23 (13.54)	0.23 (13.54)	0.22 (14.66)	0.20 (13.74)
2, 4, ..., 40	−0.11	−0.02	0.00	0.01	0.11	0.22 (9.43)	0.22 (9.41)	0.21 (10.27)	0.19 (9.76)
12, 14, 16, 18, 20	−0.07	−0.01	0.00	0.01	0.06	0.13 (11.38)	0.13 (11.39)	0.12 (12.05)	0.11 (9.42)
12, 14, ..., 40	−0.08	−0.01	0.00	0.01	0.08	0.15 (8.32)	0.15 (8.29)	0.14 (8.92)	0.13 (8.15)
22, 24, ..., 40	−0.06	−0.01	0.00	0.01	0.06	0.12 (7.99)	0.12 (7.94)	0.11 (8.57)	0.11 (7.47)
1, 3, 5, 7, 9	0.12	0.03	0.01	−0.01	−0.13	−0.25 (−29.32)	−0.25 (−29.52)	−0.25 (−32.36)	−0.22 (−14.49)
1, 3, ..., 19	0.09	0.02	0.01	−0.01	−0.10	−0.18 (−19.39)	−0.18 (−19.47)	−0.18 (−20.82)	−0.16 (−12.59)
1, 3, ..., 39	0.06	0.02	0.01	−0.01	−0.07	−0.13 (−12.58)	−0.13 (−12.63)	−0.13 (−13.02)	−0.13 (−9.56)
11, 13, 15, 17, 19	0.01	0.01	0.01	−0.00	−0.03	−0.05 (−9.41)	−0.05 (−9.63)	−0.05 (−10.13)	−0.05 (−8.92)
11, 13, ..., 39	0.01	0.01	0.01	−0.00	−0.03	−0.05 (−7.11)	−0.05 (−7.15)	−0.05 (−7.23)	−0.06 (−7.32)
21, 23, ..., 39	0.01	0.01	0.01	0.00	−0.03	−0.03 (−5.88)	−0.03 (−5.83)	−0.03 (−6.29)	−0.04 (−5.41)

Panel B: Overnight on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.17	−0.04	−0.02	−0.00	0.25	0.42 (19.34)	0.42 (20.74)	0.39 (17.91)	0.37 (18.90)
2, 4, ..., 20	−0.18	−0.04	−0.02	−0.00	0.27	0.45 (14.92)	0.45 (16.01)	0.42 (13.80)	0.39 (14.44)
2, 4, ..., 40	−0.19	−0.05	−0.02	−0.00	0.26	0.45 (11.18)	0.45 (12.07)	0.42 (10.49)	0.39 (11.07)
12, 14, 16, 18, 20	−0.11	−0.03	−0.02	−0.01	0.17	0.29 (14.09)	0.29 (14.89)	0.27 (13.14)	0.25 (13.48)
12, 14, ..., 40	−0.14	−0.04	−0.02	−0.01	0.20	0.34 (10.80)	0.34 (11.56)	0.32 (10.13)	0.30 (10.61)
22, 24, ..., 40	−0.12	−0.03	−0.02	−0.01	0.17	0.28 (10.71)	0.28 (11.40)	0.27 (10.01)	0.25 (10.60)
1, 3, 5, 7, 9	0.11	0.01	−0.01	−0.02	−0.17	−0.28 (−33.66)	−0.28 (−34.99)	−0.28 (−31.13)	−0.28 (−31.61)
1, 3, ..., 19	0.09	0.01	−0.01	−0.02	−0.13	−0.22 (−22.10)	−0.22 (−22.93)	−0.22 (−20.21)	−0.21 (−20.47)
1, 3, ..., 39	0.06	0.01	−0.01	−0.02	−0.11	−0.17 (−14.30)	−0.17 (−14.64)	−0.17 (−13.48)	−0.16 (−12.82)
11, 13, 15, 17, 19	0.01	−0.00	−0.01	−0.02	−0.06	−0.06 (−9.09)	−0.06 (−9.49)	−0.06 (−8.75)	−0.07 (−8.64)
11, 13, ..., 39	0.01	−0.00	−0.01	−0.02	−0.06	−0.06 (−6.88)	−0.06 (−7.11)	−0.06 (−6.66)	−0.06 (−5.99)
21, 23, ..., 39	−0.00	−0.00	−0.01	−0.02	−0.05	−0.04 (−5.90)	−0.04 (−6.22)	−0.04 (−5.77)	−0.05 (−5.58)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. Panel A reports intraday option returns, and Panel B shows results for overnight option returns. The table also shows the high-minus-low ("H−L") portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio. The table also shows alphas of the H−L controlling for an average option market return (CAPM), the factor model of Horenstein, Vasquez, and Xiao (2025) (HVX), and the factor model of Tian and Wu (2023) (TW). Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Table 4: Cross-Sectional versus Time-Series Reversal and Momentum

Formation Period	Intraday on Previous Half-Day Periods		Overnight on Previous Half-Day Periods	
	CS	TS	CS	TS
2, 4, 6, 8, 10	0.08 (18.59)	0.10 (15.90)	0.14 (14.51)	0.14 (16.81)
2, 4, ..., 20	0.08 (16.81)	0.10 (13.93)	0.15 (14.75)	0.15 (18.12)
2, 4, ..., 40	0.08 (15.58)	0.09 (12.59)	0.15 (15.00)	0.15 (19.01)
12, 14, 16, 18, 20	0.04 (14.02)	0.05 (10.97)	0.10 (14.10)	0.10 (20.24)
12, 14, ..., 40	0.05 (13.54)	0.06 (10.41)	0.12 (14.51)	0.12 (20.45)
22, 24, ..., 40	0.04 (12.70)	0.05 (9.71)	0.10 (14.55)	0.10 (21.48)
1, 3, 5, 7, 9	−0.09 (−19.53)	−0.08 (−17.85)	−0.10 (−22.73)	−0.09 (−20.30)
1, 3, ..., 19	−0.07 (−17.88)	−0.06 (−13.41)	−0.08 (−21.12)	−0.08 (−16.24)
1, 3, ..., 39	−0.05 (−16.41)	−0.05 (−11.24)	−0.07 (−18.72)	−0.06 (−12.13)
11, 13, 15, 17, 19	−0.02 (−12.63)	−0.02 (−5.77)	−0.03 (−9.90)	−0.02 (−5.39)
11, 13, ..., 39	−0.02 (−11.24)	−0.03 (−6.63)	−0.03 (−9.50)	−0.03 (−5.03)
21, 23, ..., 39	−0.02 (−10.60)	−0.02 (−7.07)	−0.02 (−9.07)	−0.02 (−5.79)

The table reports average option returns of decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Average option returns over the formation period are used as signals. "CS" shows returns to a cross-sectional strategy following Equation (6), whereas "TS" shows returns to a time-series strategy following Equation (5). Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Table 5: Spanning Long-Short Option Portfolios Based On Past Option Performances with Option Portfolios Based on Past Stock Performances

Formation Period	Intraday on Previous Half-Day Periods			Overnight on Previous Half-Day Periods		
	α	β^{Stock}	R^2	α	β^{Stock}	R^2
2, 4, 6, 8, 10	0.23 (26.07)	−0.03 (−0.54)	0.03%	0.42 (25.51)	−0.03 (−0.28)	0.02%
2, 4, ..., 20	0.23 (18.19)	0.02 (0.50)	0.02%	0.45 (20.28)	−0.20 (−2.94)	0.98%
2, 4, ..., 40	0.21 (12.71)	0.11 (1.73)	0.40%	0.45 (15.37)	−0.20 (−2.42)	0.84%
12, 14, 16, 18, 20	0.13 (15.31)	−0.06 (−1.02)	0.16%	0.29 (19.01)	−0.16 (−3.81)	0.82%
12, 14, ..., 40	0.15 (11.23)	0.03 (0.45)	0.04%	0.34 (14.86)	−0.18 (−2.03)	0.85%
22, 24, ..., 40	0.12 (10.88)	0.01 (0.14)	0.00%	0.28 (14.59)	−0.04 (−0.41)	0.05%
1, 3, 5, 7, 9	−0.25 (−31.21)	−0.09 (−1.32)	0.43%	−0.28 (−40.13)	0.02 (0.33)	0.03%
1, 3, ..., 19	−0.18 (−22.70)	−0.03 (−0.45)	0.07%	−0.22 (−28.35)	0.07 (1.50)	0.46%
1, 3, ..., 39	−0.13 (−15.07)	−0.03 (−0.27)	0.05%	−0.17 (−18.30)	0.05 (0.72)	0.20%
11, 13, 15, 17, 19	−0.05 (−10.92)	−0.06 (−2.00)	0.29%	−0.06 (−11.09)	0.09 (1.86)	0.68%
11, 13, ..., 39	−0.05 (−8.66)	−0.02 (−0.51)	0.04%	−0.06 (−8.59)	0.04 (0.81)	0.12%
21, 23, ..., 39	−0.03 (−6.89)	−0.06 (−1.13)	0.27%	−0.04 (−7.26)	0.05 (1.43)	0.21%

The table reports spanning regressions of long–short option portfolios constructed on past option performances on long–short option portfolios constructed on past stock performances. For each formation period, we compute past half-day returns of the underlying stock and of the option over the indicated set of previous half-day intervals. Based on these past-performance measures, we sort options into deciles and form long–short option portfolios that buy the highest-performance decile and short the lowest-performance decile. One long–short portfolio is formed using past option returns, and a second long–short portfolio is formed using past stock returns. For each formation period, we regress the long–short portfolio based on past option returns on the corresponding long–short portfolio based on past stock returns. The left block reports results for intraday test returns, labelled "Intraday on Previous Half-Day Periods", and the right block reports results for overnight test returns, labelled "Overnight on Previous Half-Day Periods". In each block, α denotes the regression intercept (in percent per half-day), β^{Stock} is the slope coefficient on the stock-based long–short option portfolio, and R^2 is the coefficient of determination. Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Table 6: Average Characteristics per Portfolio Decile for Option Portfolios Based on Past Performances

Characteristic	Formation Period 2, 4, 6, 8, 10					Formation Period 1, 3, 5, 7, 9				
	Low	3	5	7	High	Low	3	5	7	High
Day-Night-Vol-Ratio	0.508	0.499	0.497	0.497	0.507	0.508	0.499	0.497	0.497	0.507
Hedging Costs	0.726	0.492	0.377	0.384	0.672	0.726	0.493	0.378	0.384	0.671
Age	0.393	0.493	0.563	0.563	0.423	0.393	0.493	0.562	0.563	0.422
BM	0.514	0.497	0.489	0.494	0.515	0.513	0.497	0.489	0.494	0.515
Beta	0.562	0.509	0.464	0.462	0.539	0.563	0.508	0.463	0.461	0.541
Ivol	0.680	0.509	0.406	0.402	0.620	0.681	0.509	0.406	0.402	0.623
Size	0.282	0.508	0.620	0.612	0.335	0.282	0.507	0.619	0.612	0.337
Max5	0.628	0.506	0.431	0.429	0.591	0.628	0.506	0.431	0.428	0.592
Jump Risk	0.514	0.502	0.497	0.493	0.506	0.514	0.502	0.498	0.494	0.505
Illiq	0.620	0.506	0.417	0.424	0.606	0.622	0.506	0.418	0.423	0.606
Log Price	0.304	0.514	0.591	0.584	0.380	0.305	0.514	0.591	0.585	0.377
OI	0.369	0.514	0.582	0.568	0.384	0.370	0.513	0.581	0.568	0.387
Volume	0.390	0.505	0.567	0.556	0.421	0.389	0.502	0.565	0.558	0.425

The table reports average portfolio characteristics of select decile option portfolios based on past performances. We consider two different formation periods capturing momentum and reversal, respectively. For each characteristic, we first cross-sectional normalize it every half-day period into the interval $[0, 1]$. Subsequently, we compute the its mean for each decile and each half-day period. Finally, we time-series average for each decile. The table presents pooled results for intraday and overnight half-day periods. "Day-Night-Vol-Ratio" is the ratio of the 60-day standard deviation of intraday and overnight returns, "Hedging Costs" and "Jump Risk" are two of three primary risks of option market makers following Tian and Wu (2023), "Age" is the firm age of the underlying, "BM" denotes the book-to-market of the underlying, "Beta" is the stock beta of the underlying using monthly data over the last 5 years, "Ivol" is the idiosyncratic volatility of the underlying using daily returns over the last one year, "Size" denotes the market capitalization of the underlying, "'Max5" denotes the average of the five highest stock returns over the previous month, "Log Price" is the log of the underlying's stock price, "OI" denotes open-interest, "Volume" denotes option trading volume, and "Illiq" denotes an Amihud (2002)-type illiquidity measure based on 30-minute intervals and absolute changes in implied volatility scaled by trading volume. We use data from Jensen, Kelly, and Pedersen (2023). The sample period is January 2004 to December 2021.

Table 7: Bivariate Portfolio Sorts for Long-Short Option Portfolios Based on Past Performances

Panel A: Formation Period 2, 4, 6, 8, 10

Control	Intraday on Previous Half-Day Periods				Overnight on Previous Half-Day Periods			
	Low	Medium	High	Diff.	Low	Medium	High	Diff.
Size	0.25 (25.49)	0.13 (30.16)	0.05 (23.95)	−0.20 (−22.22)	0.46 (25.25)	0.21 (23.47)	0.06 (20.38)	−0.40 (−24.26)
Ivol	0.08 (29.36)	0.13 (25.98)	0.23 (25.20)	0.15 (19.68)	0.16 (22.47)	0.22 (23.75)	0.36 (23.81)	0.21 (18.24)
Max5	0.10 (28.38)	0.14 (27.03)	0.21 (26.39)	0.11 (18.32)	0.18 (23.65)	0.24 (24.20)	0.34 (23.97)	0.16 (16.18)
Arb	0.06 (26.49)	0.13 (23.69)	0.26 (18.40)	0.19 (14.69)	0.08 (17.09)	0.23 (18.93)	0.46 (19.16)	0.37 (18.32)
Illiq	0.06 (25.19)	0.09 (29.57)	0.20 (23.81)	0.15 (18.66)	0.08 (16.70)	0.11 (20.81)	0.27 (20.08)	0.20 (17.74)

Panel B: Formation Period 1, 3, 5, 7, 9

Control	Intraday on Previous Half-Day Periods				Overnight on Previous Half-Day Periods			
	Low	Medium	High	Diff.	Low	Medium	High	Diff.
Size	−0.31 (−39.16)	−0.14 (−34.99)	−0.05 (−18.78)	0.26 (38.77)	−0.32 (−38.83)	−0.15 (−36.92)	−0.06 (−21.07)	0.27 (34.73)
Ivol	−0.09 (−34.03)	−0.16 (−35.21)	−0.28 (−35.80)	−0.18 (−28.86)	−0.10 (−31.03)	−0.17 (−36.20)	−0.29 (−36.26)	−0.19 (−26.08)
Max5	−0.12 (−37.53)	−0.17 (−36.15)	−0.24 (−34.91)	−0.12 (−22.96)	−0.13 (−33.57)	−0.19 (−35.94)	−0.25 (−34.98)	−0.13 (−19.66)
Arb	−0.07 (−21.62)	−0.17 (−28.87)	−0.29 (−29.29)	−0.22 (−27.29)	−0.08 (−19.21)	−0.17 (−30.29)	−0.31 (−31.72)	−0.23 (−26.66)
Illiq	−0.07 (−22.39)	−0.10 (−25.17)	−0.22 (−30.70)	−0.15 (−25.72)	−0.07 (−22.63)	−0.11 (−22.22)	−0.23 (−30.27)	−0.16 (−24.26)

The table reports average returns of bivariate portfolio sorts of high-minus-low option portfolios based on past option performances conditional on characteristics of the underlying. As characteristics, we consider the market capitalization ("Size"), idiosyncratic volatility ("Ivol"), the average top five past daily stock returns ("Max5"), an arbitrage index ("Arb") constructed of the three primary risks of option market makers (delta-hedging costs, stochastic volatility risk, and jump risk Tian and Wu 2023), and an Amihud (2002)-type illiquidity measure ("Illiq") based on 30min-intervals and absolute changes in implied volatility scaled by trading volume, averaged over the last 5 business days. Dependent bivariate portfolios are constructed as follows. We first sort options into terciles based on one of the characteristics. Subsequently, we sort options based on past average returns over the formation period into quintiles within each conditioning tercile. Then, we construct long-minus-short portfolio returns going long the highest quintile portfolio and shorting the lowest quintile portfolio. For each tercile, we report the high-minus-low portfolio returns, as well as the difference-in-difference portfolio returns as the difference in the high-minus-low quintile portfolios across the highest and lowest conditioning tercile. Newey and West (1987) t-statistics are given in parentheses. The sample period is from January 2004 to December 2021.

Table 8: Long-Short Option Portfolios Based on Past Performances Conditional on Day-Night-Volatility-Ratio

Formation Period	Intraday on Previous Half-Day Periods				Overnight on Previous Half-Day Periods			
	Low	Mid	High	Diff.	Low	Mid	High	Diff.
2, 4, 6, 8, 10	0.15 (27.28)	0.15 (26.53)	0.16 (27.10)	0.01 (2.85)	0.26 (25.60)	0.25 (24.12)	0.27 (23.76)	0.01 (1.38)
2, 4, ..., 20	0.14 (19.52)	0.15 (19.00)	0.16 (19.46)	0.01 (2.78)	0.27 (20.52)	0.27 (18.97)	0.28 (19.01)	0.01 (1.28)
2, 4, ..., 40	0.13 (14.27)	0.14 (13.55)	0.15 (13.52)	0.02 (3.16)	0.28 (15.57)	0.27 (14.46)	0.28 (14.56)	0.01 (0.70)
12, 14, 16, 18, 20	0.08 (15.23)	0.08 (14.48)	0.09 (14.73)	0.01 (2.66)	0.18 (18.74)	0.17 (17.73)	0.18 (17.05)	0.01 (0.79)
12, 14, ..., 40	0.09 (11.68)	0.09 (11.76)	0.10 (11.40)	0.01 (2.70)	0.21 (14.80)	0.21 (14.14)	0.22 (13.54)	0.01 (0.75)
22, 24, ..., 40	0.07 (10.75)	0.08 (10.90)	0.08 (10.80)	0.01 (3.54)	0.18 (14.10)	0.17 (13.94)	0.18 (13.37)	0.01 (0.68)
1, 3, 5, 7, 9	−0.18 (−36.55)	−0.18 (−34.90)	−0.19 (−35.97)	−0.01 (−2.91)	−0.19 (−33.44)	−0.19 (−35.58)	−0.20 (−35.17)	−0.01 (−1.57)
1, 3, ..., 19	−0.13 (−25.25)	−0.13 (−23.79)	−0.14 (−24.79)	−0.01 (−1.51)	−0.16 (−24.44)	−0.15 (−24.98)	−0.15 (−25.73)	0.00 (0.34)
1, 3, ..., 39	−0.10 (−15.64)	−0.10 (−16.08)	−0.10 (−16.38)	−0.00 (−0.52)	−0.12 (−16.20)	−0.12 (−17.29)	−0.12 (−18.17)	0.00 (0.16)
11, 13, 15, 17, 19	−0.04 (−11.57)	−0.03 (−9.99)	−0.04 (−10.17)	0.00 (0.36)	−0.05 (−9.68)	−0.04 (−9.03)	−0.04 (−9.70)	0.00 (0.54)
11, 13, ..., 39	−0.03 (−7.92)	−0.04 (−8.91)	−0.04 (−8.81)	−0.00 (−0.48)	−0.05 (−8.25)	−0.04 (−7.69)	−0.05 (−8.02)	0.01 (1.36)
21, 23, ..., 39	−0.03 (−6.50)	−0.03 (−7.52)	−0.03 (−7.74)	−0.00 (−0.23)	−0.03 (−6.24)	−0.03 (−6.85)	−0.04 (−7.11)	−0.00 (−0.29)

The table reports average returns of bivariate portfolio sorts of high-minus-low option portfolios based on past option performances conditional on the day-night-volatility-ratio. The day-night-volatility ratio is computed as the ratio between the 60-day standard deviation of intraday and overnight stock returns. Dependent bivariate portfolios are constructed as follows. We first sort options into terciles based on the day-night-volatility ratio. Subsequently, we sort options based on past average returns over the formation period into quintiles within each conditioning tercile. Then, we construct long-minus-short portfolio returns going long the highest quintile portfolio and shorting the lowest quintile portfolio. For each tercile of the day-night-volatility ratio, we report the high-minus-low portfolio returns, as well as the difference in the high-minus-low quintile portfolios across the highest and lowest conditioning tercile. Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Table 9: Option Portfolios Based on Past Performance for Low-Volume Options

Panel A: Intraday on Previous Half-Day Periods

Formation Period	1	2	3	4	5	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.11	−0.02	0.00	0.03	0.15	0.26 (17.62)	0.26 (17.67)	0.26 (18.74)	0.24 (16.15)
2, 4, ..., 20	−0.12	−0.03	0.00	0.03	0.16	0.28 (13.02)	0.27 (13.12)	0.27 (14.03)	0.23 (13.13)
2, 4, ..., 40	−0.11	−0.02	−0.00	0.03	0.15	0.26 (9.06)	0.26 (9.14)	0.26 (9.81)	0.22 (9.50)
12, 14, 16, 18, 20	−0.07	−0.01	0.00	0.03	0.10	0.17 (11.51)	0.17 (11.64)	0.16 (12.13)	0.13 (10.91)
12, 14, ..., 40	−0.07	−0.02	0.00	0.02	0.12	0.19 (7.81)	0.19 (7.86)	0.19 (8.42)	0.16 (8.13)
22, 24, ..., 40	−0.06	−0.01	0.00	0.02	0.09	0.15 (7.79)	0.15 (7.85)	0.15 (8.17)	0.13 (7.90)
1, 3, 5, 7, 9	0.16	0.06	0.01	−0.05	−0.14	−0.30 (−29.76)	−0.30 (−29.81)	−0.30 (−30.68)	−0.26 (−23.01)
1, 3, ..., 19	0.11	0.05	0.00	−0.04	−0.09	−0.21 (−18.98)	−0.21 (−19.07)	−0.20 (−19.65)	−0.18 (−15.50)
1, 3, ..., 39	0.09	0.03	−0.00	−0.03	−0.06	−0.15 (−11.19)	−0.15 (−11.22)	−0.15 (−11.55)	−0.14 (−11.63)
11, 13, 15, 17, 19	0.03	0.02	0.01	−0.01	−0.02	−0.04 (−6.07)	−0.04 (−6.05)	−0.04 (−6.40)	−0.06 (−6.44)
11, 13, ..., 39	0.03	0.02	0.01	−0.01	−0.02	−0.05 (−4.81)	−0.05 (−4.80)	−0.05 (−4.98)	−0.05 (−4.13)
21, 23, ..., 39	0.02	0.02	0.01	−0.01	−0.01	−0.04 (−4.34)	−0.04 (−4.35)	−0.04 (−4.85)	−0.04 (−3.86)

Panel B: Overnight on Previous Half-Day Periods

Formation Period	1	2	3	4	5	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.15	−0.03	0.02	0.07	0.42	0.57 (18.78)	0.57 (20.10)	0.52 (18.23)	0.50 (18.94)
2, 4, ..., 20	−0.17	−0.03	0.01	0.07	0.45	0.63 (14.88)	0.62 (15.84)	0.57 (14.04)	0.55 (14.45)
2, 4, ..., 40	−0.18	−0.05	0.01	0.06	0.46	0.64 (11.50)	0.64 (12.27)	0.59 (11.03)	0.56 (11.51)
12, 14, 16, 18, 20	−0.09	−0.01	0.03	0.06	0.33	0.42 (13.43)	0.42 (14.01)	0.38 (12.75)	0.36 (12.66)
12, 14, ..., 40	−0.13	−0.03	0.02	0.06	0.38	0.51 (10.87)	0.51 (11.42)	0.47 (10.43)	0.44 (10.69)
22, 24, ..., 40	−0.10	−0.01	0.02	0.06	0.34	0.44 (10.64)	0.43 (11.27)	0.40 (10.24)	0.37 (10.68)
1, 3, 5, 7, 9	0.17	0.09	0.05	−0.00	−0.15	−0.32 (−29.72)	−0.32 (−30.23)	−0.31 (−26.73)	−0.31 (−27.00)
1, 3, ..., 19	0.14	0.08	0.05	0.01	−0.09	−0.24 (−20.22)	−0.24 (−20.48)	−0.23 (−18.76)	−0.23 (−18.01)
1, 3, ..., 39	0.10	0.07	0.05	0.01	−0.06	−0.17 (−12.25)	−0.17 (−12.38)	−0.17 (−11.81)	−0.17 (−10.59)
11, 13, 15, 17, 19	0.05	0.05	0.05	0.04	−0.01	−0.06 (−6.76)	−0.06 (−6.86)	−0.06 (−6.37)	−0.06 (−5.74)
11, 13, ..., 39	0.05	0.05	0.04	0.03	−0.01	−0.06 (−4.08)	−0.06 (−4.16)	−0.06 (−4.02)	−0.06 (−3.63)
21, 23, ..., 39	0.04	0.05	0.06	0.04	0.00	−0.04 (−3.27)	−0.04 (−3.31)	−0.04 (−3.30)	−0.04 (−3.19)

The table reports average option returns of quintile portfolios based on past option performances restricting the sample to options with less than 10 traded contracts per day over the last six months. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low ("H−L") portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio. The table also shows alphas of the high-minus-low portfolio controlling for an average option market return (CAPM), the factor model of Horenstein, Vasquez, and Xiao (2025) (HVX), and the factor model of Tian and Wu (2023) (TW). Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Table 10: Long-Short Option Portfolios Based on Past Performances Conditional on Volatility of the Relative Bid-Ask Spread

Formation Period	Intraday on Previous Half-Day Periods				Overnight on Previous Half-Day Periods			
	Low	Mid	High	Diff.	Low	Mid	High	Diff.
2, 4, 6, 8, 10	0.06 (23.51)	0.13 (28.00)	0.25 (25.56)	0.19 (21.07)	0.07 (15.43)	0.19 (20.46)	0.47 (27.16)	0.40 (25.79)
2, 4, ..., 20	0.05 (16.02)	0.13 (19.59)	0.25 (18.58)	0.20 (16.68)	0.07 (12.09)	0.20 (16.24)	0.50 (21.89)	0.42 (21.14)
2, 4, ..., 40	0.05 (11.19)	0.12 (14.11)	0.24 (12.99)	0.19 (11.96)	0.07 (9.15)	0.20 (11.91)	0.50 (17.03)	0.42 (16.53)
12, 14, 16, 18, 20	0.02 (10.67)	0.07 (13.18)	0.15 (15.58)	0.12 (14.23)	0.05 (12.14)	0.13 (14.58)	0.31 (20.62)	0.26 (18.95)
12, 14, ..., 40	0.03 (8.62)	0.08 (11.15)	0.17 (11.50)	0.14 (10.73)	0.06 (9.52)	0.16 (11.43)	0.38 (16.26)	0.32 (15.42)
22, 24, ..., 40	0.02 (8.16)	0.06 (10.76)	0.13 (10.94)	0.11 (10.09)	0.05 (9.63)	0.13 (11.23)	0.31 (15.98)	0.26 (14.93)
1, 3, 5, 7, 9	−0.03 (−11.47)	−0.17 (−32.95)	−0.29 (−42.61)	−0.26 (−43.93)	−0.05 (−16.02)	−0.17 (−34.03)	−0.31 (−42.88)	−0.26 (−37.53)
1, 3, ..., 19	−0.03 (−9.34)	−0.12 (−22.10)	−0.20 (−28.66)	−0.18 (−28.99)	−0.05 (−12.95)	−0.13 (−22.96)	−0.24 (−29.77)	−0.19 (−25.35)
1, 3, ..., 39	−0.02 (−7.80)	−0.09 (−14.94)	−0.14 (−17.80)	−0.12 (−17.70)	−0.04 (−11.08)	−0.11 (−16.21)	−0.17 (−18.81)	−0.13 (−16.35)
11, 13, 15, 17, 19	−0.01 (−7.25)	−0.04 (−10.35)	−0.05 (−10.21)	−0.03 (−6.96)	−0.02 (−6.37)	−0.04 (−8.58)	−0.07 (−10.47)	−0.05 (−8.20)
11, 13, ..., 39	−0.02 (−7.70)	−0.04 (−9.06)	−0.04 (−7.17)	−0.03 (−4.91)	−0.02 (−5.55)	−0.04 (−8.51)	−0.06 (−7.37)	−0.04 (−5.83)
21, 23, ..., 39	−0.01 (−5.66)	−0.03 (−8.46)	−0.03 (−5.90)	−0.02 (−3.71)	−0.01 (−3.50)	−0.03 (−8.41)	−0.04 (−5.72)	−0.03 (−4.35)

The table reports average returns of bivariate portfolio sorts of high-minus-low option portfolios based on past option performances conditional on the volatility of changes in the option bid-ask spread. The volatility of the option bid-ask spread is calculated using the last 42 half-day observations. Dependent bivariate portfolios are constructed as follows. We first sort options into terciles based on the volatility of the bid-ask spread. Subsequently, we sort options based on past average returns over the formation period into quintiles within each conditioning tercile. Then, we construct long-minus-short portfolio returns going long the highest quintile portfolio and shorting the lowest quintile portfolio. For each tercile of the volatility in the bid-ask spreads, we report the high-minus-low portfolio returns, as well as the difference in the high-minus-low quintile portfolios across the highest and lowest conditioning tercile. Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Table 11: Long-Short Option Portfolios Based on Past Performances Conditional on Exchange Volume Concentration

Formation Period	Intraday on Previous Half-Day Periods				Overnight on Previous Half-Day Periods			
	Low	Mid	High	Diff.	Low	Mid	High	Diff.
2, 4, 6, 8, 10	0.11 (22.72)	0.19 (25.19)	0.27 (22.34)	0.16 (16.60)	0.15 (16.99)	0.30 (26.42)	0.63 (29.14)	0.49 (25.85)
2, 4, ..., 20	0.10 (16.08)	0.19 (18.59)	0.27 (16.31)	0.17 (13.06)	0.16 (14.38)	0.32 (22.39)	0.67 (24.91)	0.51 (23.18)
2, 4, ..., 40	0.10 (11.97)	0.18 (13.66)	0.26 (11.71)	0.15 (9.58)	0.16 (11.17)	0.32 (18.03)	0.64 (18.12)	0.48 (17.38)
12, 14, 16, 18, 20	0.06 (12.23)	0.10 (12.69)	0.16 (13.64)	0.09 (9.79)	0.11 (15.24)	0.20 (20.17)	0.44 (22.17)	0.33 (19.95)
12, 14, ..., 40	0.07 (10.36)	0.12 (11.18)	0.18 (10.54)	0.11 (8.57)	0.13 (11.99)	0.24 (17.35)	0.50 (17.12)	0.37 (16.30)
22, 24, ..., 40	0.06 (9.17)	0.10 (11.26)	0.15 (9.93)	0.09 (8.04)	0.10 (11.68)	0.20 (17.10)	0.42 (16.23)	0.31 (15.33)
1, 3, 5, 7, 9	−0.11 (−21.04)	−0.23 (−38.30)	−0.33 (−39.94)	−0.22 (−35.06)	−0.12 (−19.61)	−0.24 (−28.08)	−0.33 (−36.66)	−0.21 (−24.90)
1, 3, ..., 19	−0.08 (−15.30)	−0.17 (−26.45)	−0.24 (−25.41)	−0.16 (−20.18)	−0.10 (−15.20)	−0.20 (−23.00)	−0.25 (−25.83)	−0.15 (−16.57)
1, 3, ..., 39	−0.06 (−10.69)	−0.12 (−16.63)	−0.18 (−14.66)	−0.12 (−11.73)	−0.08 (−10.48)	−0.15 (−16.61)	−0.20 (−15.29)	−0.11 (−9.98)
11, 13, 15, 17, 19	−0.03 (−7.61)	−0.04 (−8.47)	−0.07 (−11.29)	−0.04 (−6.90)	−0.03 (−6.42)	−0.06 (−8.76)	−0.09 (−10.59)	−0.05 (−6.48)
11, 13, ..., 39	−0.03 (−6.40)	−0.04 (−6.24)	−0.07 (−7.96)	−0.04 (−5.29)	−0.04 (−5.73)	−0.07 (−7.65)	−0.09 (−7.78)	−0.05 (−4.67)
21, 23, ..., 39	−0.02 (−5.05)	−0.03 (−6.74)	−0.05 (−6.63)	−0.03 (−4.27)	−0.03 (−4.56)	−0.06 (−8.22)	−0.07 (−6.44)	−0.04 (−4.04)

The table reports average returns of bivariate portfolio sorts of high-minus-low option portfolios based on past option performances conditional on the exchange-level concentration of option trading, measured as the HHI orthogonalized with respect to total trading volume. For each full trading day and each optionable stock, we obtain the option trading volume on every exchange. Using these volumes, we compute for each stock-day the concentration of trading activity across exchanges using a Herfindahl–Hirschman–type index. To account for demand effects, we orthogonalize this raw HHI in the cross-section with respect to total option trading volume, and use the resulting residual as our concentration measure. Dependent bivariate portfolios are constructed as follows. Options are first sorted into terciles based on the orthogonalized HHI measure. Within each tercile, options are subsequently sorted into quintiles according to their past average returns over the formation period. Long-minus-short portfolio returns are formed by going long the highest-return quintile and short the lowest-return quintile within each conditioning tercile. For each tercile of the orthogonalized HHI, the table reports the corresponding high-minus-low portfolio returns, as well as the difference between the high-minus-low portfolios of the highest and lowest conditioning terciles. Newey and West (1987) t-statistics are reported in parentheses. The sample period is January 2012 to December 2019.

Internet Appendix

(Not for publication)

In Search of Seasonality in Intraday and Overnight Option Returns

Table of Contents:

- **Internet Appendix A** shows the intraday and overnight auto-correlation of bid-ask spreads.
- **Internet Appendix B** shows additional summary statistics of the sample:
  - The rolling average cross-sectional median over time (B.1),
  - Cross-sectional size of the sample over time (B.2).
- **Internet Appendix C** shows results for measuring returns either from bid-to-bid or ask-to-ask quotes.
- **Internet Appendix D** shows results for different return measures
  - Using open-interest weighted returns (D.1)
  - Using initially delta-hedged returns (D.2),
  - Using all option returns written on an underlying (D.3).
- **Internet Appendix E** shows results for various subsample analyses:
  - Across months with low and high VIX values (E.1),
  - Across months where stock market momentum experienced "crashes" (E.2),
  - Across weekdays (E.3),
  - Controlling for earnings announcements (E.4),
- **Internet Appendix F** shows additional results.

Internet Appendix A Persistence of Intraday Bid-Ask Spreads

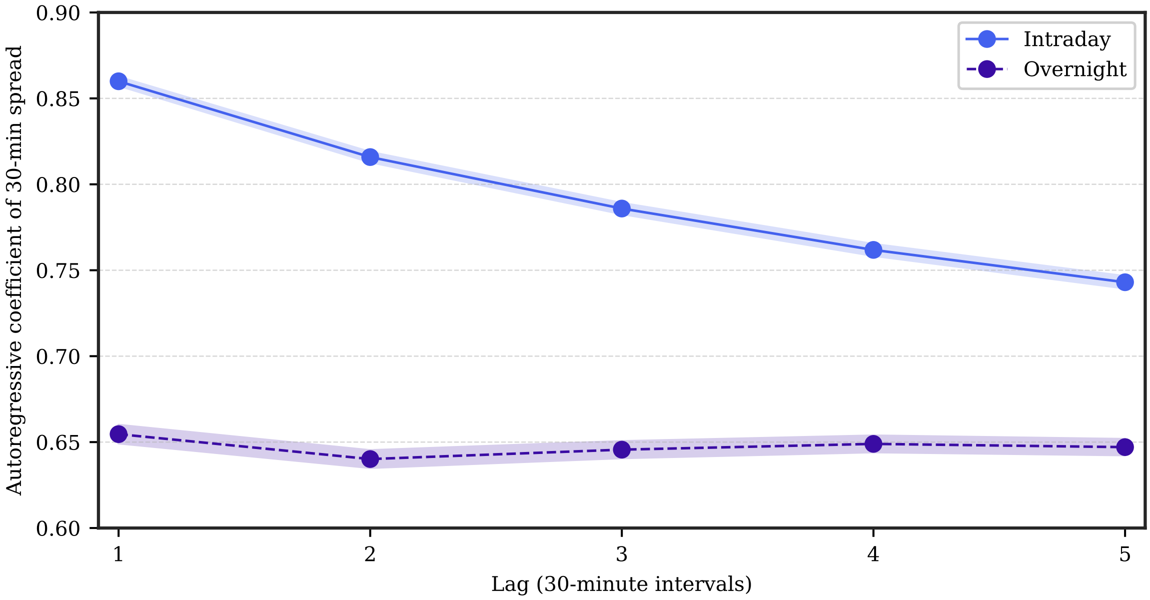

Figure A.1: Intraday vs. Overnight Persistence of 30-Minute Bid-Ask Spreads
The figure plots average autoregressive coefficients of 30-minute bid–ask spreads within the trading day and including the overnight transition, respectively. d indexes trading days and τ indexes 30-minute intervals within day d. For each stock and lag $L = 1, \ldots, 5$, we estimate $s_{d,\tau} = \alpha + \beta\, s_{d',\tau-L} + \varepsilon_{d,\tau}$, where $(d', \tau - L)$ denotes the timestamp L intervals prior to (d, τ). Observations with $d' = d$ enter the "Intraday" sample, and observations with $d' \neq d$ enter the "Overnight" sample. We then average the resulting coefficient estimates across stocks. This stock-by-stock estimation follows Ni, Pearson, Poteshman, and White (2021) preventing imposing homogeneous liquidity dynamics across stocks. The shaded bands denote 95% confidence intervals of the cross-sectional means using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

Internet Appendix B Additional Summary Statistics

B.1 Rolling Cross-Section Return

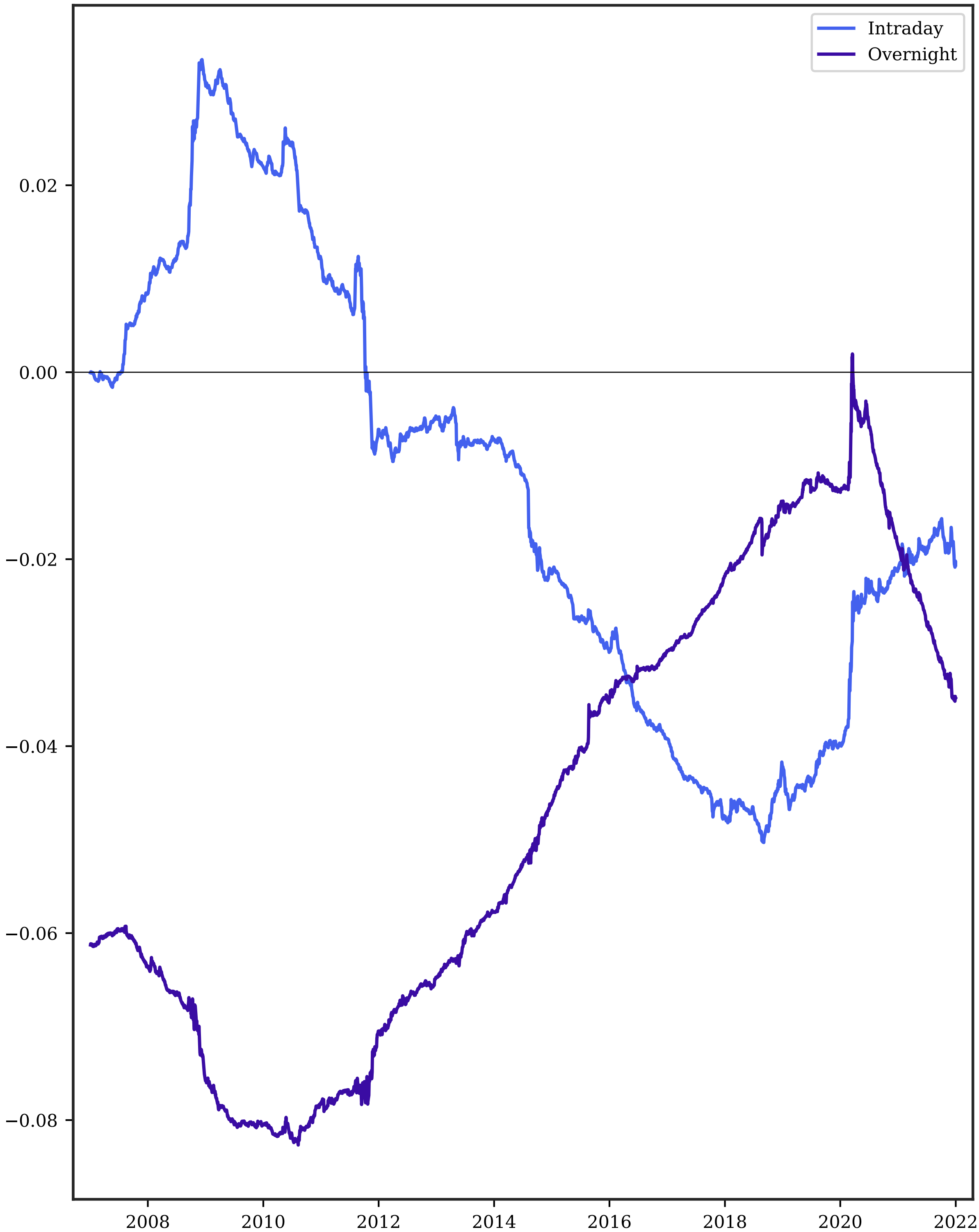

Figure B.1: Cross-sectional regressions of intraday and overnight returns using ask quotes

The figure shows the three-year average of the cross-sectional median of intraday and overnight returns, respectively. The entire sample period is from January 2004 to December 2021.

B.2 Cross-Sectional Size of the Sample over Time

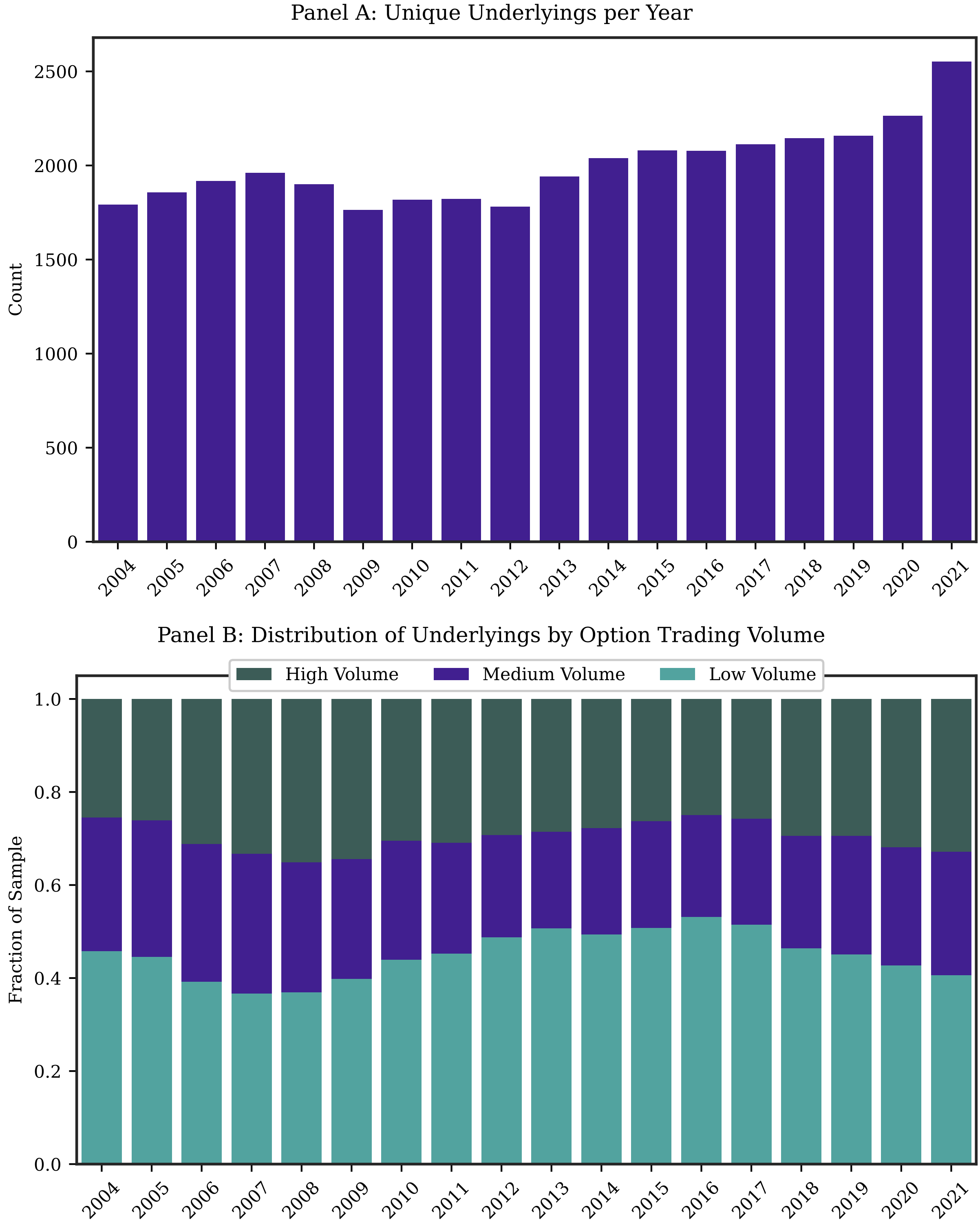

Figure B.2: Cross-sectional regressions of intraday and overnight returns using ask quotes
The figure shows the composition of the sample for each year in the sample period. Panel A shows the number of unique underlyings per year, whereas Panel B shows the composition of the sample with respect to underlyings with low, medium, and high option volume, respectively. Stocks are classified as having a low (high) option volume if the average daily volume is below 20 (above 200) per month. We compute first the fraction of low, medium, and high volume stocks at the monthly level. Subsequently, we average these fractions each year. The entire sample period is from January 2004 to December 2021.

Internet Appendix C Bid and Ask Return Measures

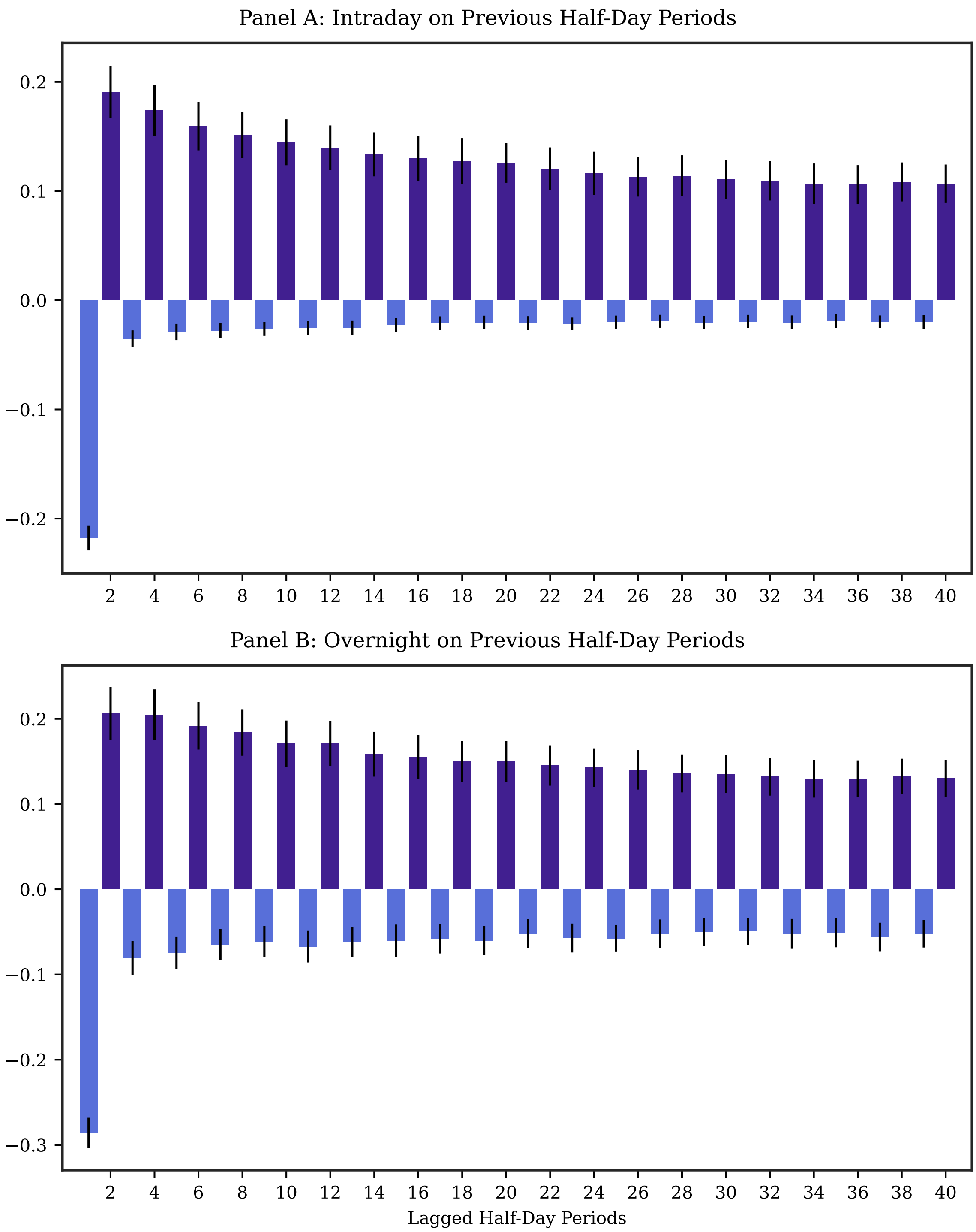

Figure C.1: Cross-sectional regressions of intraday and overnight returns using ask quotes
The figure shows results for univariate Fama-MacBeth cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ denotes the option return of stock i during interval t and $r_{i,t-k}$ is return in interval $t-k$. Option returns are computed using ask instead of mid quotes. The slope coefficients are estimated starting from intraday (Panel A) and overnight (Panel B) periods. We consider lags k 1 through 40. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

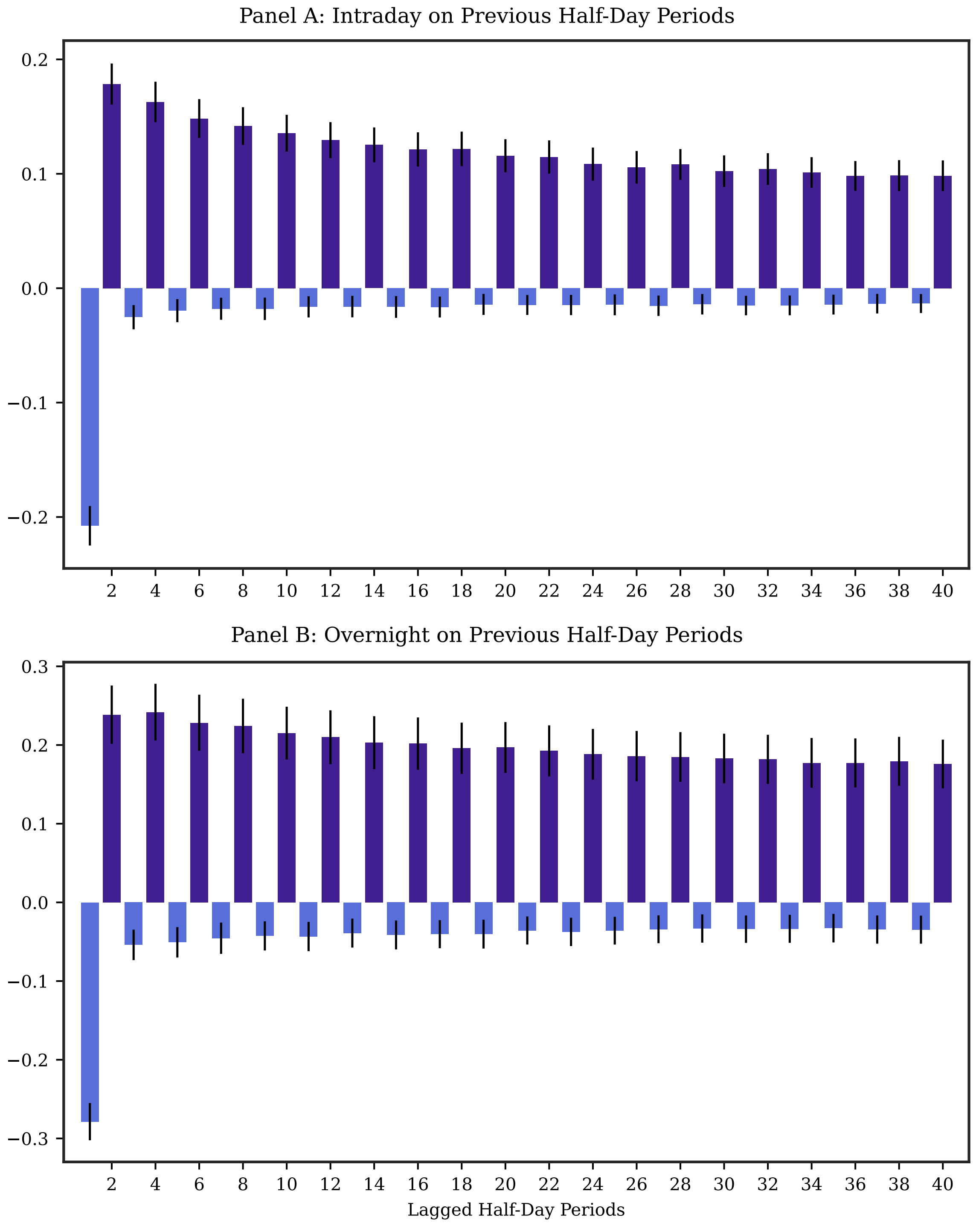

Figure C.2: Cross-sectional regressions of intraday and overnight returns using bid quotes
The figure shows results for univariate Fama-MacBeth cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ denotes the option return of stock i during interval t and $r_{i,t-k}$ is return in interval $t-k$. Option returns are computed using bid instead of mid quotes. The slope coefficients are estimated starting from intraday (Panel A) and overnight (Panel B) periods. We consider lags k 1 through 40. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

Internet Appendix D Different Return Measures

D.1 Open-Interest Weighted Option Returns

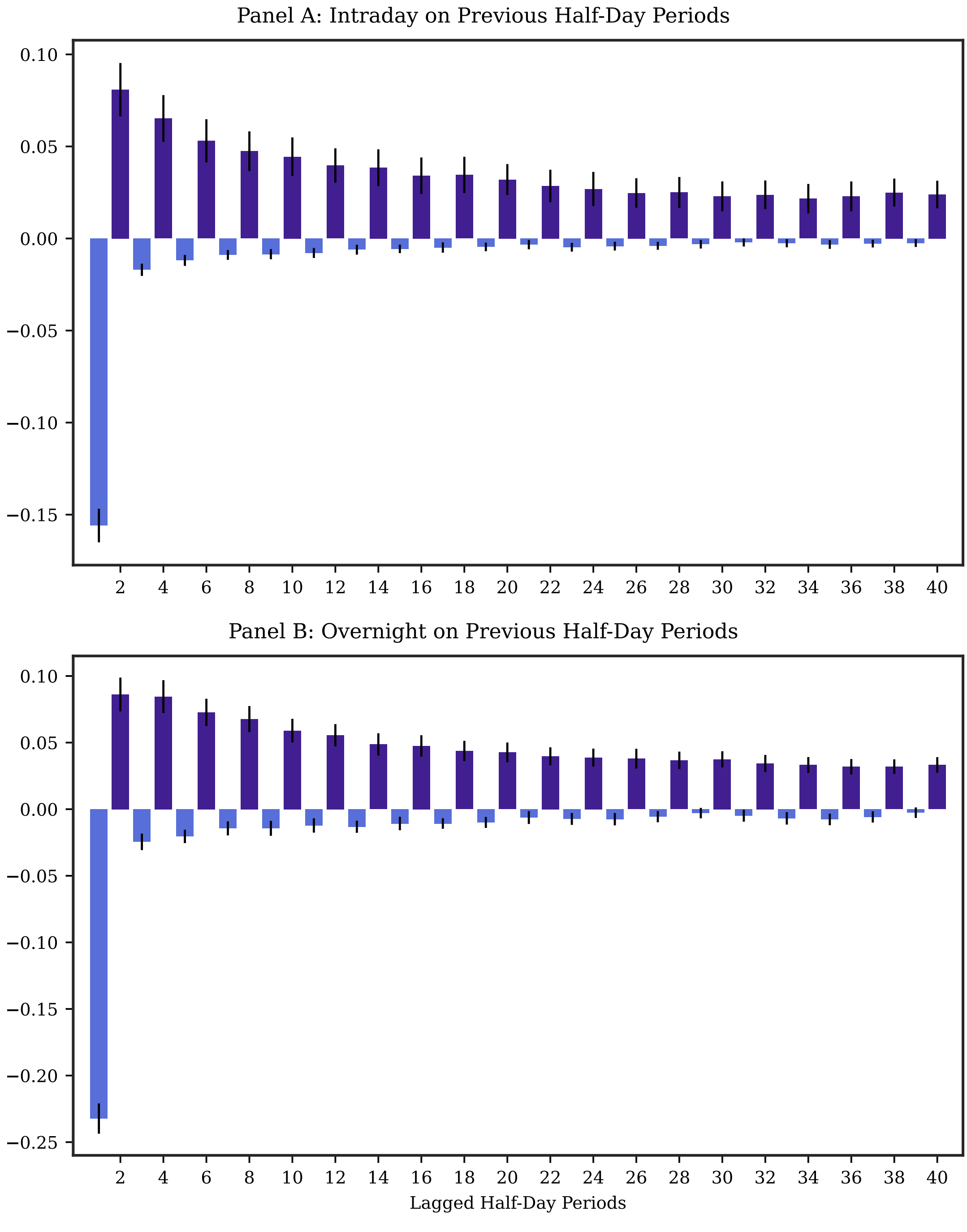

Figure D.1: Cross-sectional regressions of intraday and overnight returns using open-interest weighted returns

The figure shows results for univariate Fama-MacBeth cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ denotes the option return of stock i during interval t and $r_{i,t-k}$ is return in interval $t-k$. Option returns at the stock level are aggregated according to open-interest. The slope coefficients are estimated starting from intraday (Panel A) and overnight (Panel B) periods. We consider lags k 1 through 40. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

Table D.1: Option Portfolios Based on Past Performance using OI-Weighted Returns

Panel A: Intraday on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.11	−0.02	0.00	0.02	0.11	0.22 (20.67)	0.22 (20.64)	0.21 (21.98)	0.20 (19.40)
2, 4, ..., 20	−0.11	−0.02	0.00	0.02	0.11	0.22 (14.26)	0.22 (14.24)	0.21 (15.51)	0.19 (14.46)
2, 4, ..., 40	−0.10	−0.02	0.00	0.02	0.10	0.20 (10.04)	0.20 (9.99)	0.20 (10.97)	0.18 (10.43)
12, 14, 16, 18, 20	−0.07	−0.01	0.00	0.01	0.06	0.12 (11.89)	0.12 (11.88)	0.12 (12.56)	0.11 (10.80)
12, 14, ..., 40	−0.07	−0.01	0.00	0.01	0.07	0.14 (8.76)	0.14 (8.73)	0.13 (9.39)	0.12 (8.76)
22, 24, ..., 40	−0.06	−0.01	0.00	0.01	0.05	0.11 (8.38)	0.11 (8.31)	0.10 (8.94)	0.10 (7.57)
1, 3, 5, 7, 9	0.12	0.03	0.01	−0.01	−0.13	−0.25 (−31.63)	−0.25 (−31.88)	−0.25 (−34.69)	−0.22 (−16.46)
1, 3, ..., 19	0.09	0.02	0.01	−0.01	−0.10	−0.18 (−20.95)	−0.18 (−21.06)	−0.18 (−22.45)	−0.16 (−14.14)
1, 3, ..., 39	0.06	0.02	0.01	−0.01	−0.07	−0.13 (−13.61)	−0.13 (−13.69)	−0.13 (−14.08)	−0.13 (−10.15)
11, 13, 15, 17, 19	0.01	0.01	0.01	0.00	−0.03	−0.04 (−9.83)	−0.04 (−10.10)	−0.05 (−10.37)	−0.05 (−9.18)
11, 13, ..., 39	0.01	0.01	0.01	0.00	−0.03	−0.05 (−7.48)	−0.05 (−7.48)	−0.05 (−7.55)	−0.06 (−6.43)
21, 23, ..., 39	0.00	0.01	0.01	0.00	−0.03	−0.03 (−6.35)	−0.03 (−6.20)	−0.03 (−6.86)	−0.05 (−4.47)

Panel B: Overnight on Previous Half-Day Periods									
Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.17	−0.04	−0.02	−0.00	0.24	0.41 (20.04)	0.41 (21.33)	0.38 (18.66)	0.36 (19.56)
2, 4, ..., 20	−0.18	−0.04	−0.02	−0.00	0.26	0.44 (15.49)	0.44 (16.50)	0.41 (14.42)	0.38 (14.94)
2, 4, ..., 40	−0.18	−0.04	−0.02	−0.00	0.25	0.44 (11.63)	0.44 (12.49)	0.41 (10.99)	0.38 (11.56)
12, 14, 16, 18, 20	−0.11	−0.03	−0.02	−0.01	0.17	0.28 (14.46)	0.28 (15.27)	0.26 (13.62)	0.25 (13.98)
12, 14, ..., 40	−0.14	−0.04	−0.02	−0.01	0.19	0.34 (11.24)	0.33 (12.05)	0.31 (10.64)	0.29 (11.17)
22, 24, ..., 40	−0.11	−0.03	−0.02	−0.01	0.16	0.28 (11.08)	0.28 (11.79)	0.26 (10.43)	0.24 (11.03)
1, 3, 5, 7, 9	0.11	0.02	−0.01	−0.02	−0.18	−0.29 (−36.89)	−0.29 (−38.11)	−0.29 (−34.21)	−0.28 (−34.21)
1, 3, ..., 19	0.09	0.01	−0.01	−0.02	−0.14	−0.23 (−24.20)	−0.23 (−25.15)	−0.23 (−22.25)	−0.21 (−21.89)
1, 3, ..., 39	0.06	0.01	−0.01	−0.02	−0.11	−0.17 (−15.84)	−0.17 (−16.10)	−0.17 (−14.92)	−0.16 (−14.11)
11, 13, 15, 17, 19	0.00	−0.00	−0.01	−0.02	−0.06	−0.06 (−9.55)	−0.06 (−10.13)	−0.06 (−9.12)	−0.06 (−8.80)
11, 13, ..., 39	0.00	−0.00	−0.01	−0.01	−0.06	−0.06 (−7.09)	−0.06 (−7.27)	−0.06 (−6.92)	−0.06 (−5.95)
21, 23, ..., 39	−0.01	−0.00	−0.01	−0.01	−0.05	−0.04 (−5.66)	−0.04 (−5.89)	−0.04 (−5.62)	−0.04 (−5.39)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. All options are weighted by open-interest to yield an underlying-half-day period observation. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low (“H−-L”) portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio. The table also shows alphas of the high-minus-low portfolio controlling for an average option market return (CAPM), the factor model of Horenstein, Vasquez, and Xiao (2025) (HVX), and the factor model of Tian and Wu (2023) (TW). Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

D.2 Initial Delta-Hedged Option Returns

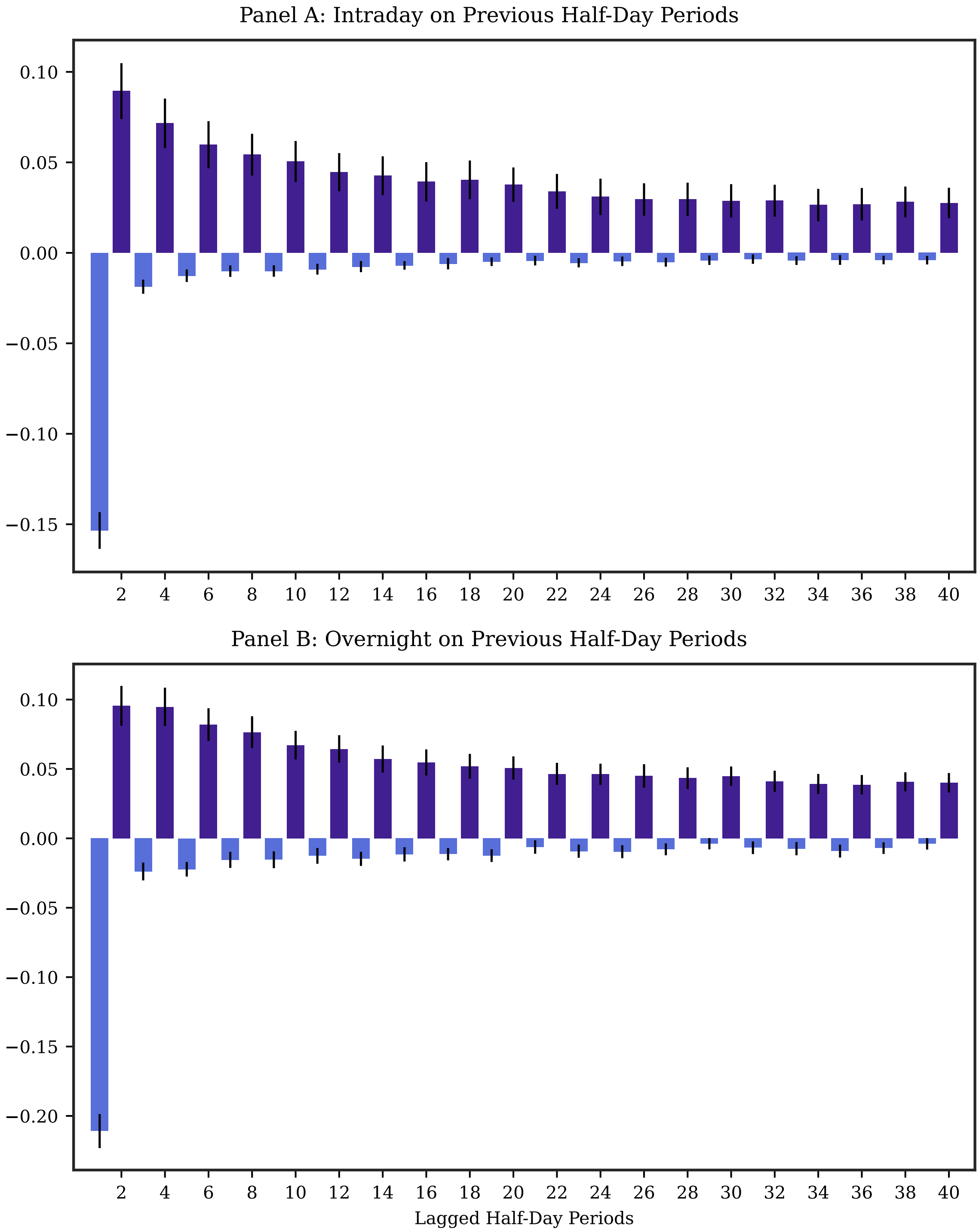

Figure D.2: Cross-sectional regressions of intraday and overnight returns using initial-delta hedging

The figure shows results for univariate Fama-MacBeth cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ denotes the option return of stock i during interval t and $r_{i,t-k}$ is return in interval $t-k$. Option returns are computed using initial delta-hedges. The slope coefficients are estimated starting from intraday (Panel A) and overnight (Panel B) periods. We consider lags k 1 through 40. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

Table D.2: Option Portfolios Based on Past Performance using Initially Delta-Hedged Returns

Panel A: Intraday on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.12	−0.02	−0.00	0.01	0.11	0.23 (20.31)	0.23 (20.28)	0.22 (21.50)	0.21 (17.26)
2, 4, ..., 20	−0.12	−0.02	−0.00	0.01	0.11	0.23 (13.73)	0.23 (13.70)	0.22 (14.77)	0.20 (13.51)
2, 4, ..., 40	−0.11	−0.02	−0.00	0.01	0.10	0.21 (9.49)	0.21 (9.46)	0.21 (10.32)	0.19 (9.68)
12, 14, 16, 18, 20	−0.07	−0.01	−0.00	0.01	0.06	0.13 (11.48)	0.13 (11.47)	0.12 (12.05)	0.11 (10.78)
12, 14, ..., 40	−0.08	−0.01	−0.00	0.01	0.07	0.15 (8.22)	0.15 (8.19)	0.14 (8.80)	0.13 (8.03)
22, 24, ..., 40	−0.06	−0.01	0.00	0.00	0.05	0.12 (7.86)	0.12 (7.82)	0.11 (8.54)	0.10 (7.47)
1, 3, 5, 7, 9	0.12	0.03	0.00	−0.01	−0.14	−0.25 (−29.97)	−0.25 (−30.23)	−0.25 (−32.68)	−0.22 (−21.19)
1, 3, ..., 19	0.08	0.02	0.00	−0.01	−0.10	−0.19 (−19.69)	−0.19 (−19.79)	−0.18 (−21.06)	−0.16 (−14.85)
1, 3, ..., 39	0.06	0.01	0.00	−0.01	−0.07	−0.13 (−12.70)	−0.13 (−12.80)	−0.13 (−13.17)	−0.12 (−11.11)
11, 13, 15, 17, 19	0.01	0.01	0.00	−0.00	−0.04	−0.05 (−9.72)	−0.05 (−9.99)	−0.05 (−10.35)	−0.05 (−8.61)
11, 13, ..., 39	0.01	0.01	0.00	−0.00	−0.04	−0.05 (−7.37)	−0.05 (−7.50)	−0.05 (−7.45)	−0.06 (−7.35)
21, 23, ..., 39	0.00	0.01	0.00	−0.00	−0.03	−0.03 (−6.01)	−0.03 (−6.04)	−0.03 (−6.37)	−0.04 (−6.28)

Panel B: Overnight on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.17	−0.04	−0.02	−0.00	0.25	0.42 (19.34)	0.42 (20.74)	0.39 (17.91)	0.37 (18.90)
2, 4, ..., 20	−0.18	−0.04	−0.02	−0.00	0.27	0.45 (14.92)	0.45 (16.01)	0.42 (13.80)	0.39 (14.44)
2, 4, ..., 40	−0.19	−0.05	−0.02	−0.00	0.26	0.45 (11.18)	0.45 (12.07)	0.42 (10.49)	0.39 (11.07)
12, 14, 16, 18, 20	−0.11	−0.03	−0.02	−0.01	0.17	0.29 (14.09)	0.29 (14.89)	0.27 (13.14)	0.25 (13.48)
12, 14, ..., 40	−0.14	−0.04	−0.02	−0.01	0.20	0.34 (10.80)	0.34 (11.56)	0.32 (10.13)	0.30 (10.61)
22, 24, ..., 40	−0.12	−0.03	−0.02	−0.01	0.17	0.28 (10.71)	0.28 (11.40)	0.27 (10.01)	0.25 (10.60)
1, 3, 5, 7, 9	0.11	0.02	−0.01	−0.03	−0.16	−0.27 (−32.55)	−0.27 (−34.04)	−0.27 (−29.90)	−0.27 (−30.83)
1, 3, ..., 19	0.09	0.01	−0.01	−0.02	−0.13	−0.22 (−22.16)	−0.22 (−22.95)	−0.22 (−20.29)	−0.21 (−20.43)
1, 3, ..., 39	0.06	0.01	−0.01	−0.02	−0.10	−0.16 (−14.07)	−0.16 (−14.38)	−0.16 (−13.26)	−0.16 (−11.81)
11, 13, 15, 17, 19	0.00	−0.01	−0.01	−0.01	−0.05	−0.06 (−8.93)	−0.06 (−9.25)	−0.06 (−8.53)	−0.06 (−8.26)
11, 13, ..., 39	0.00	−0.00	−0.01	−0.02	−0.05	−0.06 (−6.56)	−0.06 (−6.75)	−0.06 (−6.36)	−0.06 (−5.66)
21, 23, ..., 39	−0.00	−0.01	−0.01	−0.01	−0.04	−0.04 (−5.33)	−0.04 (−5.54)	−0.04 (−5.15)	−0.04 (−4.64)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. Options are initially delta-hedged. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low ("H−L") portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio. The table also shows alphas of the high-minus-low portfolio controlling for an average option market return ("CAPM), the factor model of Horenstein, Vasquez, and Xiao (2025) (HVX), and the factor model of Tian and Wu (2023) (TW). Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

D.3 All Options Written on Underlying

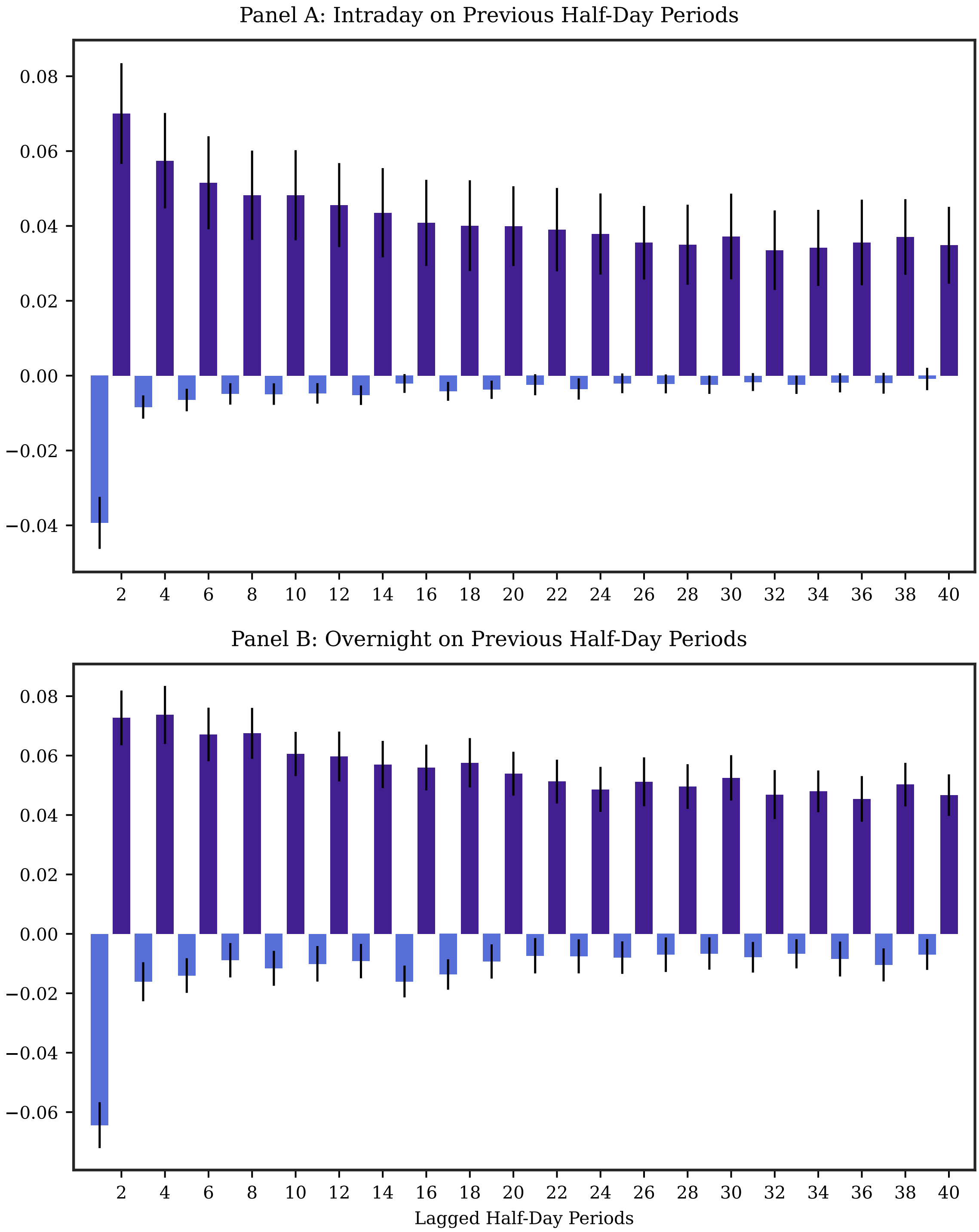

Figure D.3: Cross-sectional regressions of intraday and overnight returns using initial-delta hedging

The figure shows results for univariate Fama-MacBeth cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ denotes the option return of stock i during interval t and $r_{i,t-k}$ is return in interval $t-k$. All options after filters are used at the stock-level. The slope coefficients are estimated starting from intraday (Panel A) and overnight (Panel B) periods. We consider lags k 1 through 40. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

Table D.3: Option Portfolios Based on Past Performance using All Option Returns

Panel A: Intraday on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.35	−0.08	−0.03	−0.00	0.18	0.54 (16.95)	0.54 (16.92)	0.52 (17.88)	0.47 (13.67)
2, 4, ..., 20	−0.37	−0.07	−0.03	−0.00	0.20	0.57 (12.24)	0.57 (12.22)	0.55 (12.97)	0.49 (11.74)
2, 4, ..., 40	−0.38	−0.07	−0.03	−0.00	0.20	0.57 (8.95)	0.57 (8.93)	0.55 (9.55)	0.50 (9.17)
12, 14, 16, 18, 20	−0.29	−0.06	−0.03	−0.01	0.11	0.41 (11.30)	0.41 (11.29)	0.39 (11.94)	0.34 (11.43)
12, 14, ..., 40	−0.33	−0.06	−0.03	−0.01	0.14	0.47 (8.45)	0.47 (8.43)	0.46 (8.99)	0.41 (8.63)
22, 24, ..., 40	−0.29	−0.06	−0.03	−0.01	0.11	0.40 (8.05)	0.40 (8.03)	0.39 (8.51)	0.34 (8.07)
1, 3, 5, 7, 9	0.04	0.00	−0.01	−0.04	−0.25	−0.29 (−25.47)	−0.29 (−25.55)	−0.28 (−26.22)	−0.26 (−11.54)
1, 3, ..., 19	−0.01	−0.01	−0.02	−0.04	−0.19	−0.18 (−16.86)	−0.18 (−16.87)	−0.18 (−16.94)	−0.17 (−8.72)
1, 3, ..., 39	−0.05	−0.02	−0.02	−0.03	−0.15	−0.10 (−8.76)	−0.10 (−8.78)	−0.10 (−8.66)	−0.10 (−6.39)
11, 13, 15, 17, 19	−0.09	−0.03	−0.02	−0.03	−0.12	−0.04 (−4.77)	−0.04 (−4.78)	−0.04 (−5.21)	−0.03 (−1.91)
11, 13, ..., 39	−0.10	−0.03	−0.02	−0.02	−0.11	−0.01 (−0.85)	−0.01 (−0.84)	−0.01 (−1.14)	−0.02 (−1.70)
21, 23, ..., 39	−0.11	−0.03	−0.02	−0.02	−0.10	0.01 (0.81)	0.01 (0.84)	0.00 (0.47)	−0.02 (−1.57)

Panel B: Overnight on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.51	−0.12	−0.05	−0.02	0.50	1.01 (23.18)	1.01 (24.23)	0.98 (20.66)	0.91 (21.97)
2, 4, ..., 20	−0.55	−0.13	−0.06	−0.02	0.55	1.11 (18.24)	1.10 (19.15)	1.06 (16.72)	0.99 (17.69)
2, 4, ..., 40	−0.56	−0.13	−0.06	−0.02	0.56	1.12 (13.98)	1.12 (14.74)	1.08 (13.08)	1.01 (13.77)
12, 14, 16, 18, 20	−0.43	−0.11	−0.05	−0.03	0.40	0.83 (17.72)	0.83 (18.55)	0.79 (16.68)	0.76 (17.13)
12, 14, ..., 40	−0.49	−0.11	−0.06	−0.03	0.48	0.97 (14.02)	0.97 (14.71)	0.92 (13.33)	0.88 (13.68)
22, 24, ..., 40	−0.43	−0.11	−0.06	−0.03	0.41	0.84 (13.93)	0.84 (14.64)	0.80 (13.25)	0.77 (13.58)
1, 3, 5, 7, 9	0.06	−0.01	−0.03	−0.06	−0.28	−0.34 (−25.13)	−0.34 (−25.35)	−0.33 (−24.73)	−0.29 (−14.40)
1, 3, ..., 19	0.01	−0.01	−0.03	−0.05	−0.21	−0.22 (−14.09)	−0.22 (−14.12)	−0.22 (−13.97)	−0.18 (−7.23)
1, 3, ..., 39	−0.04	−0.02	−0.03	−0.05	−0.16	−0.12 (−6.61)	−0.12 (−6.63)	−0.12 (−6.63)	−0.08 (−2.60)
11, 13, 15, 17, 19	−0.08	−0.04	−0.04	−0.05	−0.12	−0.03 (−2.98)	−0.03 (−3.03)	−0.03 (−2.89)	−0.03 (−2.21)
11, 13, ..., 39	−0.10	−0.04	−0.04	−0.04	−0.10	−0.00 (−0.16)	−0.00 (−0.13)	−0.00 (−0.08)	−0.01 (−0.66)
21, 23, ..., 39	−0.10	−0.04	−0.04	−0.05	−0.09	0.01 (0.66)	0.01 (0.72)	0.01 (0.79)	−0.01 (−0.36)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. All options of an underlying (after filter) are used to construct an underlying-half-day period observation. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low ("H−-L") portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio. The table also shows alphas of the high-minus-low portfolio controlling for an average option market return (CAPM), the factor model of Horenstein, Vasquez, and Xiao (2025) (HVX), and the factor model of Tian and Wu (2023) (TW). Newey and West (1987) *t*-statistics are given in parentheses. The sample period is January 2004 to December 2021.

D.4 Closest ATM Option

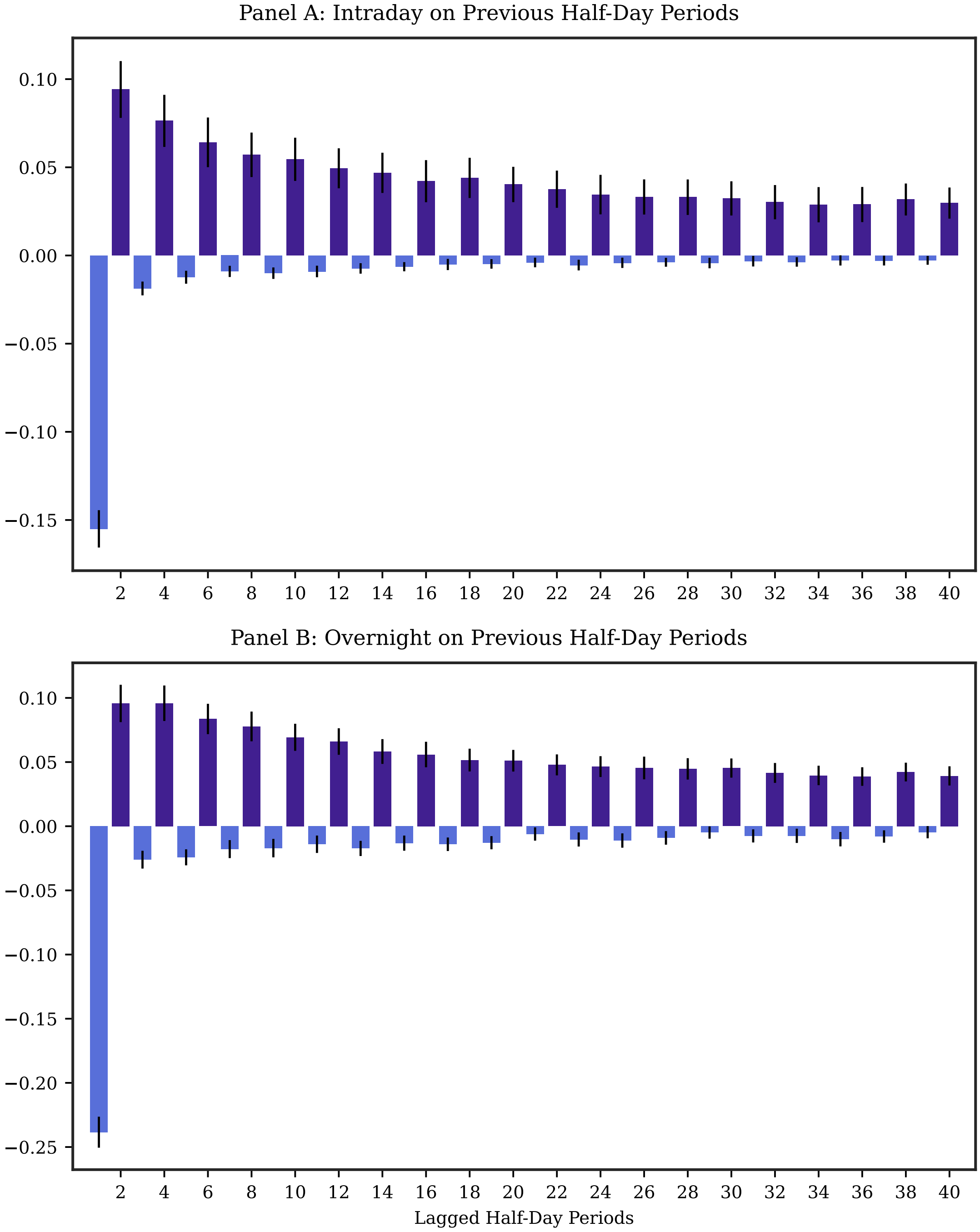

Figure D.4: Cross-sectional regressions of intraday and overnight returns for options being closest to ATM

The figure shows results for univariate Fama-MacBeth cross-sectional regressions of the form $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + u_{i,t}$, where $r_{i,t}$ denotes the option return of stock i during interval t and $r_{i,t-k}$ is return in interval $t-k$. The option closest to being ATM is taken at the stock-half-day level. The slope coefficients are estimated starting from intraday (Panel A) and overnight (Panel B) periods. We consider lags k 1 through 40. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

Table D.4: Option Portfolios Based on Past Performance using the Closest ATM Option Returns

Panel A: Intraday on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.11	−0.01	0.00	0.02	0.10	0.22 (21.32)	0.22 (21.24)	0.21 (22.54)	0.20 (19.14)
2, 4, ..., 20	−0.11	−0.02	0.00	0.02	0.11	0.22 (14.76)	0.22 (14.78)	0.22 (15.84)	0.19 (12.31)
2, 4, ..., 40	−0.11	−0.01	0.00	0.01	0.10	0.21 (10.20)	0.21 (10.16)	0.20 (10.96)	0.19 (9.81)
12, 14, 16, 18, 20	−0.06	−0.01	0.01	0.01	0.05	0.12 (11.81)	0.12 (11.83)	0.11 (12.58)	0.10 (8.61)
12, 14, ..., 40	−0.07	−0.01	0.00	0.01	0.07	0.14 (8.50)	0.14 (8.49)	0.14 (9.13)	0.12 (7.84)
22, 24, ..., 40	−0.06	−0.01	0.01	0.01	0.05	0.11 (8.31)	0.10 (8.25)	0.10 (8.71)	0.10 (6.98)
1, 3, 5, 7, 9	0.15	0.05	0.01	−0.02	−0.17	−0.32 (−33.91)	−0.32 (−34.17)	−0.31 (−35.09)	−0.28 (−30.40)
1, 3, ..., 19	0.10	0.03	0.01	−0.01	−0.12	−0.22 (−22.88)	−0.22 (−23.00)	−0.22 (−23.09)	−0.20 (−20.71)
1, 3, ..., 39	0.07	0.02	0.01	−0.01	−0.09	−0.16 (−14.63)	−0.16 (−14.69)	−0.16 (−15.06)	−0.15 (−13.58)
11, 13, 15, 17, 19	0.00	0.01	0.01	0.00	−0.04	−0.04 (−7.35)	−0.04 (−7.53)	−0.04 (−8.31)	−0.04 (−8.11)
11, 13, ..., 39	0.00	0.01	0.01	0.00	−0.03	−0.04 (−5.65)	−0.04 (−5.68)	−0.04 (−6.25)	−0.04 (−4.81)
21, 23, ..., 39	−0.00	0.01	0.01	0.00	−0.03	−0.02 (−4.08)	−0.02 (−4.08)	−0.02 (−4.33)	−0.02 (−4.11)

Panel B: Overnight on Previous Half-Day Periods

Formation Period	1	3	5	7	10	H−L	CAPM	HVX	TW
2, 4, 6, 8, 10	−0.17	−0.04	−0.02	−0.01	0.22	0.39 (19.66)	0.39 (21.40)	0.37 (17.75)	0.35 (19.62)
2, 4, ..., 20	−0.18	−0.04	−0.02	−0.01	0.24	0.42 (15.29)	0.42 (16.80)	0.39 (14.16)	0.37 (15.12)
2, 4, ..., 40	−0.18	−0.04	−0.02	−0.01	0.23	0.42 (11.38)	0.42 (12.56)	0.39 (10.72)	0.37 (11.43)
12, 14, 16, 18, 20	−0.11	−0.03	−0.02	−0.01	0.14	0.25 (14.63)	0.25 (15.59)	0.23 (13.68)	0.22 (13.98)
12, 14, ..., 40	−0.14	−0.04	−0.02	−0.01	0.17	0.31 (11.01)	0.30 (11.91)	0.29 (10.34)	0.27 (10.79)
22, 24, ..., 40	−0.11	−0.03	−0.02	−0.01	0.14	0.24 (10.82)	0.24 (11.58)	0.23 (10.03)	0.21 (10.49)
1, 3, 5, 7, 9	0.12	0.03	−0.01	−0.03	−0.22	−0.35 (−36.31)	−0.35 (−36.57)	−0.35 (−31.67)	−0.33 (−32.76)
1, 3, ..., 19	0.09	0.02	−0.01	−0.03	−0.17	−0.26 (−25.72)	−0.26 (−25.95)	−0.26 (−23.20)	−0.25 (−23.32)
1, 3, ..., 39	0.06	0.01	−0.01	−0.03	−0.14	−0.19 (−16.42)	−0.19 (−16.71)	−0.20 (−15.77)	−0.19 (−15.70)
11, 13, 15, 17, 19	−0.01	−0.01	−0.01	−0.02	−0.07	−0.05 (−8.96)	−0.05 (−9.11)	−0.05 (−8.32)	−0.06 (−8.72)
11, 13, ..., 39	−0.01	−0.00	−0.01	−0.02	−0.07	−0.06 (−6.27)	−0.06 (−6.44)	−0.06 (−6.54)	−0.07 (−6.87)
21, 23, ..., 39	−0.02	−0.01	−0.01	−0.02	−0.06	−0.04 (−4.84)	−0.04 (−5.01)	−0.04 (−4.96)	−0.05 (−5.64)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. Only the option being closest to ATM is used to construct an underlying-half-day period observation. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low ("H−L") portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio. The table also shows alphas of the H−L portfolio controlling for an average option market return (CAPM), the factor model of Horenstein, Vasquez, and Xiao (2025) (HVX), and the factor model of Tian and Wu (2023) (TW). Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Internet Appendix E Subsample Analyses

E.1 Across Periods of High and Low VIX Levels

Table E.1: Option Portfolios Based on Past Performance Conditional on the Level of the VIX Index

Formation Period	Intraday on Previous Half-Day Periods		Overnight on Previous Half-Day Periods	
	Low VIX	High VIX	Low VIX	High VIX
2, 4, 6, 8, 10	0.20 (15.79)	0.26 (13.92)	0.38 (14.74)	0.47 (13.57)
2, 4, ..., 20	0.20 (11.19)	0.27 (9.39)	0.40 (10.97)	0.50 (10.70)
2, 4, ..., 40	0.18 (8.29)	0.25 (6.48)	0.39 (7.97)	0.51 (8.34)
12, 14, 16, 18, 20	0.11 (9.06)	0.15 (7.97)	0.26 (10.64)	0.31 (9.83)
12, 14, ..., 40	0.13 (7.54)	0.17 (5.61)	0.30 (7.84)	0.39 (7.94)
22, 24, ..., 40	0.10 (7.24)	0.14 (5.34)	0.25 (7.73)	0.32 (7.86)
1, 3, 5, 7, 9	−0.23 (−20.85)	−0.28 (−21.69)	−0.25 (−21.91)	−0.32 (−27.48)
1, 3, ..., 19	−0.16 (−13.90)	−0.20 (−14.33)	−0.20 (−14.29)	−0.24 (−17.80)
1, 3, ..., 39	−0.12 (−9.20)	−0.15 (−9.38)	−0.16 (−9.22)	−0.18 (−11.63)
11, 13, 15, 17, 19	−0.05 (−7.40)	−0.05 (−6.18)	−0.06 (−6.87)	−0.06 (−6.11)
11, 13, ..., 39	−0.04 (−5.62)	−0.05 (−4.80)	−0.07 (−5.60)	−0.06 (−4.49)
21, 23, ..., 39	−0.03 (−4.86)	−0.03 (−3.77)	−0.05 (−4.66)	−0.04 (−4.05)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio across for months with average VIX level above and below its median. Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

E.2 Across Periods of Stock Market Momentum Crashes

Table E.2: Option Portfolios Based on Past Performance Conditional on Stock Market Momentum Crash

Formation Period	Intraday on Previous Half-Day Periods		Overnight on Previous Half-Day Periods	
	No MOM Crash	MOM Crash	No MOM Crash	MOM Crash
2, 4, 6, 8, 10	0.23 (18.84)	0.25 (6.72)	0.42 (18.43)	0.47 (6.22)
2, 4, ..., 20	0.23 (12.89)	0.26 (4.72)	0.44 (14.19)	0.52 (5.14)
2, 4, ..., 40	0.21 (8.96)	0.24 (3.46)	0.44 (10.55)	0.52 (4.56)
12, 14, 16, 18, 20	0.13 (10.69)	0.14 (4.23)	0.28 (13.39)	0.33 (4.91)
12, 14, ..., 40	0.15 (7.84)	0.16 (3.18)	0.34 (10.27)	0.41 (4.24)
22, 24, ..., 40	0.12 (7.58)	0.13 (2.90)	0.28 (10.27)	0.32 (3.91)
1, 3, 5, 7, 9	−0.25 (−27.42)	−0.27 (−11.78)	−0.28 (−31.69)	−0.32 (−12.76)
1, 3, ..., 19	−0.18 (−18.23)	−0.20 (−8.24)	−0.22 (−21.27)	−0.23 (−7.13)
1, 3, ..., 39	−0.13 (−11.95)	−0.16 (−5.29)	−0.17 (−13.61)	−0.16 (−5.85)
11, 13, 15, 17, 19	−0.04 (−8.50)	−0.05 (−3.95)	−0.06 (−9.28)	−0.04 (−1.87)
11, 13, ..., 39	−0.04 (−6.82)	−0.06 (−2.82)	−0.07 (−7.09)	−0.03 (−1.22)
21, 23, ..., 39	−0.03 (−5.74)	−0.04 (−2.76)	−0.05 (−5.73)	−0.03 (−1.85)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio for months with ("MOM Crash") and without ("No MOM Crash") stock market momentum crashes. A month is classified as stock market momentum crash month if the value-weighted stock market momentum performance is among the bottom 20 months across our entire sample period. Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

E.3 Across Weekdays

Table E.3: Option Portfolios Based on Past Performances Across Weekdays

Panel A: Intraday on Previous Half-Day Periods					
Formation Period	Mon	Tue	Wed	Thu	Fri
2, 4, 6, 8, 10	0.22 (9.31)	0.23 (8.69)	0.23 (9.04)	0.24 (9.71)	0.23 (9.47)
2, 4, ..., 20	0.22 (6.30)	0.23 (5.86)	0.23 (6.38)	0.24 (6.74)	0.24 (6.71)
2, 4, ..., 40	0.20 (4.49)	0.22 (4.37)	0.22 (4.50)	0.23 (4.85)	0.22 (4.76)
12, 14, 16, 18, 20	0.12 (5.08)	0.13 (4.81)	0.13 (5.76)	0.13 (5.82)	0.14 (5.88)
12, 14, ..., 40	0.14 (3.87)	0.15 (4.06)	0.16 (3.99)	0.15 (4.31)	0.15 (4.25)
22, 24, ..., 40	0.11 (3.80)	0.13 (4.14)	0.12 (3.69)	0.12 (4.24)	0.11 (3.79)
1, 3, 5, 7, 9	−0.24 (−13.14)	−0.26 (−14.42)	−0.25 (−14.62)	−0.26 (−12.97)	−0.25 (−13.03)
1, 3, ..., 19	−0.18 (−9.81)	−0.19 (−10.24)	−0.18 (−9.13)	−0.18 (−8.86)	−0.19 (−8.55)
1, 3, ..., 39	−0.12 (−6.55)	−0.14 (−6.67)	−0.13 (−5.77)	−0.13 (−6.07)	−0.14 (−6.03)
11, 13, 15, 17, 19	−0.04 (−4.84)	−0.05 (−5.31)	−0.05 (−4.42)	−0.04 (−4.81)	−0.05 (−5.53)
11, 13, ..., 39	−0.04 (−4.29)	−0.05 (−4.58)	−0.05 (−3.60)	−0.03 (−3.27)	−0.05 (−4.18)
21, 23, ..., 39	−0.03 (−3.27)	−0.04 (−3.60)	−0.04 (−3.87)	−0.02 (−2.74)	−0.04 (−3.96)
Panel B: Overnight on Previous Half-Day Periods					
Formation Period	Mon	Tue	Wed	Thu	Fri
2, 4, 6, 8, 10	0.40 (8.75)	0.42 (9.02)	0.42 (9.82)	0.43 (9.21)	0.43 (8.37)
2, 4, ..., 20	0.43 (7.22)	0.45 (7.20)	0.46 (7.33)	0.44 (7.20)	0.47 (6.38)
2, 4, ..., 40	0.43 (5.86)	0.44 (5.32)	0.45 (5.82)	0.44 (5.35)	0.47 (4.88)
12, 14, 16, 18, 20	0.27 (7.36)	0.27 (6.97)	0.30 (6.83)	0.27 (6.71)	0.32 (5.88)
12, 14, ..., 40	0.34 (5.89)	0.34 (5.24)	0.34 (5.56)	0.33 (5.09)	0.37 (4.65)
22, 24, ..., 40	0.28 (5.79)	0.29 (4.83)	0.28 (5.50)	0.28 (5.03)	0.30 (4.75)
1, 3, 5, 7, 9	−0.28 (−14.24)	−0.29 (−15.83)	−0.29 (−16.42)	−0.30 (−17.50)	−0.26 (−15.31)
1, 3, ..., 19	−0.23 (−9.74)	−0.23 (−11.33)	−0.23 (−11.05)	−0.23 (−11.15)	−0.21 (−10.76)
1, 3, ..., 39	−0.16 (−7.03)	−0.17 (−8.12)	−0.17 (−7.44)	−0.17 (−7.62)	−0.16 (−6.20)
11, 13, 15, 17, 19	−0.05 (−4.68)	−0.06 (−4.66)	−0.07 (−5.07)	−0.06 (−5.26)	−0.07 (−4.37)
11, 13, ..., 39	−0.06 (−3.58)	−0.06 (−3.82)	−0.07 (−3.85)	−0.07 (−3.49)	−0.06 (−3.15)
21, 23, ..., 39	−0.04 (−3.20)	−0.04 (−3.66)	−0.04 (−3.07)	−0.05 (−3.03)	−0.05 (−3.37)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low ("H−-L") portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio across weekdays. Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

E.4 Earnings Announcements

Table E.4: Option Portfolios Based on Past Performance Conditional on Earnings Announcements

Formation Period	Intraday on Previous Half-Day Periods		Overnight on Previous Half-Day Periods	
	w/o EA	w/ EA	w/o EA	w/ EA
2, 4, 6, 8, 10	0.16 (22.88)	0.10 (10.88)	0.27 (19.94)	0.14 (9.12)
2, 4, ..., 20	0.16 (15.45)	0.11 (12.24)	0.29 (15.14)	0.19 (12.66)
2, 4, ..., 40	0.15 (10.89)	0.11 (9.66)	0.29 (11.21)	0.21 (11.81)
12, 14, 16, 18, 20	0.08 (12.46)	0.08 (8.98)	0.18 (14.46)	0.10 (8.02)
12, 14, ..., 40	0.10 (9.02)	0.08 (8.25)	0.22 (10.80)	0.16 (11.27)
22, 24, ..., 40	0.08 (8.67)	0.06 (7.34)	0.18 (10.81)	0.12 (9.06)
1, 3, 5, 7, 9	−0.19 (−30.36)	−0.11 (−12.41)	−0.19 (−32.78)	−0.12 (−11.35)
1, 3, ..., 19	−0.14 (−20.84)	−0.09 (−11.68)	−0.16 (−22.55)	−0.11 (−13.22)
1, 3, ..., 39	−0.11 (−13.64)	−0.07 (−10.27)	−0.12 (−14.72)	−0.10 (−12.14)
11, 13, 15, 17, 19	−0.04 (−11.33)	−0.02 (−3.68)	−0.04 (−9.55)	−0.01 (−1.13)
11, 13, ..., 39	−0.04 (−8.22)	−0.02 (−4.57)	−0.05 (−7.38)	−0.04 (−4.45)
21, 23, ..., 39	−0.03 (−7.20)	−0.01 (−2.63)	−0.03 (−6.76)	−0.03 (−3.05)

The table reports average option returns of select decile portfolios based on past option performances. The formation period spans multiple past half-day periods. Options are sorted into decile portfolios based on their average option return over the formation period. Panel A reports intraday option returns whereas Panel B shows results for overnight option returns. The table shows the high-minus-low ("H−L") portfolio which goes long in the decile ten portfolio and shorts the first decile portfolio. The table differentiates if there has been ("w/ EA") or there was no ("w/o EA") earnings announcement throughout the formation period. Newey and West (1987) t-statistics are given in parentheses. The sample period is January 2004 to December 2021.

Internet Appendix F Additional Results

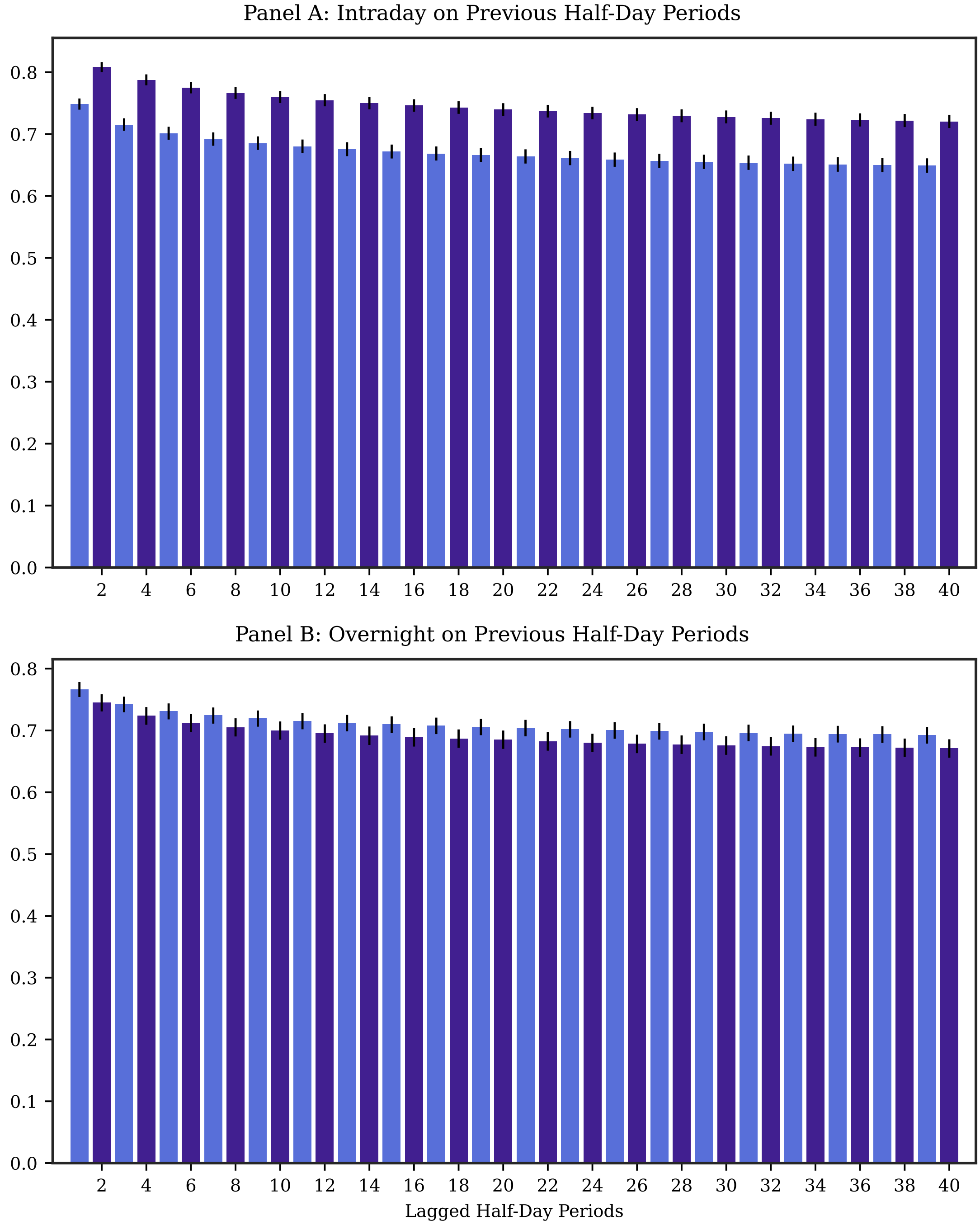

Figure F.1: Cross-sectional regressions of intraday and overnight standardized log trading volume on past same half-periods

The figure shows results for univariate Fama-MacBeth cross-sectional regressions of the form $v_{i,t} = \alpha_{k,t} + \gamma_{k,t} v_{i,t-k} + u_{i,t}$, where $v_{i,t}$ denotes cross-sectionally standardized log option trading volume of stock i during interval t. The variable $v_{i,t-k}$ is the cross-sectionally standardized log option trading volume of stock i in interval $t-k$. We consider lags k 1 through 40. The figure shows pooled results across intraday and overnight half-day periods. The vertical lines at each bar denote the bounds of the 95% confidence interval using Newey and West (1987) standard errors. The sample period is from January 2004 to December 2021.

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