Do S&P 500 Options Increase Market Volatility?
Evidence from 0DTEs

Greg Adams
The Wharton School

Chukwuma Dim
George Washington University

Bjørn Eraker
University of Wisconsin-Madison

Jean-Sébastien Fontaine
Bank of Canada

Chay Ornthanalai
Rotman School of Management & CDI

Grigory Vilkov
Frankfurt School of Finance & Management

July 15, 2026

Abstract

The recent surge in trading of S&P 500 zero-days-to-expiration options (0DTEs) raises concerns that market makers' hedging can spill over from option markets and destabilize the stock market. We show instead that the presence of expiring 0DTE contracts dampens intraday market volatility, on average, by shifting market makers' hedging needs. This shift arises not from same-day 0DTE trading but from positions accumulated earlier in longer-dated options that become 0DTEs on the expiration day. Consistent with this mechanism, intraday variation in market makers' hedging needs predicts stronger order-flow reversals, lower momentum returns, and lower intraday volatility.

This draft subsumes two working papers "0DTEs: Trading, Gamma Risk and Volatility Propagation" and "The Market for 0DTE options: The Role of Liquidity Providers in Volatility Attenuation." For helpful comments, we thank Caio Almeida (discussant), Svetlana Bryzgalova, Claire Célérier, Ing-Haw Cheng, Jefferson Duarte, Evan Dudley, Amit Goyal, Piotr Orlowski (discussant), Neil Pearson (discussant), George Skiadopoulos, Karamfil Todorov (discussant), Marliese Uhrig-Homburg (discussant), Chris Miller (discussant), and Christian Wagner (discussant), as well as participants at the Annual Hedge Fund Conference on Quantitative Investing, EFA, FIRS, WFA, SoFIE, Canadian Derivatives Institute, SAFE Microstructure Conference, Virtual Derivatives Workshop, Derivatives and Asset Pricing Conference in Cancun, Liverpool Workshop in Option Markets, Cboe Academic Roundtable, the University of Toronto, Federal Reserve Board, Frankfurt School, University of Porto, Collegio Carlo Alberto, Manchester University, University of Houston, Erasmus School of Economics, and seminars at Arrowstreet Capital, Deutsche Bank Quant Summit, and BlackRock Global Trading. We thank the Bank of Canada, CDI, Rotman-FinHub, Rotman-TDMDAL, and the Social Sciences and Humanities Research Council (SSHRC) for financial support. Views expressed in this paper are those of the authors and do not represent those of the Bank of Canada. All remaining errors are our own. E-mail addresses of the authors: Greg Adams adams99@wharton.upenn.edu, Chukwuma Dim cdim@gwu.edu, Bjørn Eraker bjorn.eraker@wisc.edu, Jean-Sébastien Fontaine jsfontaine@bank-banque-canada.ca, Chay Ornthanalai chay.ornthanalai@rotman.utoronto.ca, Grigory Vilkov vilkov@vilkov.net.

1. Introduction

In the last five years, the trading volume in SPX options linked to the S&P 500 index has more than doubled, largely due to trading in zero-days-to-expiration options (0DTEs).[1] 0DTE trading volume continues to grow and now accounts for more than half of total SPX trading volume.[2] 0DTE prices are far more sensitive than those of longer-dated options to changes in the S&P 500 index. As a result, investors and regulators have raised concerns about potential spillovers and feedback effects between the S&P 500 option and equity markets. A central question in this debate is whether option market makers generate large order flows in the S&P 500 market when they hedge their 0DTE positions, thereby amplifying volatility or even destabilizing the index.

We provide evidence that the presence of 0DTEs dampens S&P 500 intraday volatility, on average, and that market makers' hedging needs underpin this effect. The results highlight the importance of specialized intermediaries in the integration of option and equity markets (Arrow, 1964). It is remarkable that this role can lead to a reduction in *aggregate* volatility in today's S&P 500 market despite potential limits to intermediary capacity (Grossman and Miller, 1988) or the presence of noise traders (Stein, 1987).

We offer causal evidence linking 0DTEs to market makers' hedging needs and underlying market volatility. Because 0DTE market makers hedge within the day, we focus on the intraday realized volatility as the natural object of interest. We find that on days when 0DTE contracts expire, the 10-minute realized volatility of S&P 500 index returns is lower by 61 annualized basis points (bps) on average—which is about 7% of the average realized volatility in our sample.[3] We identify this effect using exogenous variation in the presence of 0DTEs on Tuesdays and Thursdays during our baseline sample period. We also find that the

[1] 0DTEs are S&P 500 options with symbol root SPXW that expire at the end of the trading day and settle using the index closing price. Other SPX contracts settle in the morning using the index opening price.

[2] See Cboe, "Volatility Insights," May 2025.

[3] The average 10-minute realized volatility over the baseline sample is 9.10% annualized (Table 3), so the 61 bps reduction equals $0.61/9.10 \approx 7\%$ of the mean.

difference in volatility across weekdays disappears once 0DTE options expire every business day after our baseline sample period, narrowing the room for potential confounding effects.[4]

Second, we show that the presence of 0DTEs shifts market makers' intraday hedging needs in the direction that attenuates market volatility. Building on the logic of the hedging mechanism outlined in Ni, Pearson, Poteshman, and White (2021), we measure the fraction of S&P 500 shares that option market makers would need to buy to hedge their option portfolio against a one-percent decline in the index, and vice versa. We find that market makers as a group have hedging needs of about one percent of S&P 500 shares on average in our sample, and that the presence of 0DTEs on a given day increases those hedging needs by 0.15 percentage points on average. Therefore, intraday hedging activity in the underlying market offers a plausible causal mechanism linking the presence of 0DTEs to lower S&P 500 high-frequency volatility. Using a two-stage regression, we estimate a multiplier of close to -4 from aggregate market makers' hedging needs to volatility: a 1 bp increase in the amount market makers need to trade against the direction of S&P 500 returns within the day to hedge option positions is associated with a 4 bps decrease in realized volatility.

Third, we show that 0DTE trading *per se* does not explain our results. Instead, positions established *before* the expiration day drive the shift in market makers' hedging needs that we observe when 0DTEs are present. To show this, we split market makers' hedging needs into: (i) a component due to new 0DTE positions accumulated during the expiration day and (ii) a component due to pre-existing positions. We find that the increase in hedging needs when 0DTEs are present stems from pre-existing positions established in longer-dated options that subsequently become 0DTEs. These pre-existing positions raise hedging needs by 25 bps during the expiration day on average. By contrast, new 0DTE positions contribute 3 bps, while non-0DTE hedging needs decrease when 0DTEs are present.

[4]Since 2016, 0DTE contracts have expired regularly on all Mondays, Wednesdays, and Fridays. From around May 2022, they also expired regularly on all Tuesdays and Thursdays. Between these two dates, 0DTE contracts occasionally expired on Tuesdays and Thursdays, either because of end-of-quarter or end-of-month SPXW expiration, or when a Monday, Wednesday, or Friday fell on a holiday.

The second part of the paper leverages rich intraday data for S&P 500 E-mini futures, which are the main instrument for hedging S&P 500 options. This evidence is not causal. Instead, the results reveal a set of intraday predictive relationships that are telling signs of the hedging mechanism. We first confirm that intraday market makers' net gamma is a robust predictor of S&P 500 intraday realized volatility. Shifting 0DTE net gamma in a 10-minute interval by one standard deviation reduces predicted S&P 500 realized volatility by about 23 basis points (annualized) in the next 10-minute interval. The effect on volatility persists for the next hour, and the implied cumulative reduction in volatility is close in scale to the treatment effect estimated using the exogenous variation in 0DTE expirations. This suggests that market makers quickly act to hedge their positions.

We also show that market makers' net gamma predicts stronger order-flow reversals in the E-mini futures market. Similar to existing results, we find that a negative 10-minute return is followed by positive net order flow during the next interval, on average. We also find, consistent with the hedging mechanism, that this relationship strengthens significantly when market makers have elevated total net gamma. This predictability remains statistically significant for about 30 minutes and decays toward zero within the hour, much as we find for volatility.

Finally, we document that market makers' hedging needs predict weaker intraday return momentum. Specifically, intraday momentum returns from one hour to the next tend to be positive when market makers' hedging needs are low, but these returns tend to be negative—reversal returns tend to be positive—when hedging needs are elevated. To be clear, we cannot directly link E-mini order flow with specific option market makers, and we cannot attribute the weaker momentum returns solely to their hedging activity. Nonetheless, the direction, strength, and timing of the intraday predictive relationships are consistent with market makers' hedging their outstanding option positions in the futures market and, in this way, strengthening order-flow reversal, dampening momentum returns, and compressing S&P 500 volatility.

Jarrow (1994) and Frey (1998) show that market makers' hedging activity can affect volatility if the underlying market is imperfectly elastic. Empirically, Ni, Pearson, Poteshman, and White (2021) (NPPW, henceforth) find that higher market makers' net gamma due to holding long-dated individual stock options predicts lower underlying daily volatility. O'Donovan, Yu, and Zhang (2024) show that market makers with positive portfolio gamma supply liquidity and stabilize markets for individual stocks. Lipson, Tomio, and Zhang (2023) find that demand for long-dated options on a retail platform induces options market makers' short positions and raises the underlying stocks' volatility.[5]

We expand the evidence showing that market makers shape conditions in the S&P 500 stock market, where trading volume and market depth in futures and derivatives dwarf those of individual equities. 0DTEs are pivotal to this impact. Because an option's gamma is greatest at expiration, 0DTE contracts have far larger hedging needs than longer-dated options. This makes them the single most potent source of intraday variation in market makers' hedging needs, warranting special investigation of their market.[6] We find that market makers' intraday hedging needs lower aggregate S&P 500 volatility and predict significant subsequent intraday E-mini order flow, realized volatility, and momentum returns.

Our analysis extends previous work on the effects that the introduction of new option contracts can have on the underlying asset market. In our setting, adding 0DTE expiration days to an already active SPXW market lowers aggregate volatility on average. We cannot directly extend this result to other markets or to all market conditions. The effect arises because expiring 0DTE positions make an economically meaningful contribution to market makers' net gamma and therefore to their intraday hedging needs. Whether introducing 0DTEs in other markets, such as individual stocks, affects intraday volatility depends on the resulting trading activity relative to the underlying market, and how market makers manage

[5]Hu, Kirilova, Muravyev, and Ryu (2024) provide an alternative view of how market makers seldom delta-hedge long-dated Kospi 200 index options that trade on the Korea Exchange.

[6]Some analysts have argued that 0DTE imbalances raise the risk of a flash crash in the stock market; see Xu (2023) and Saksena, Welty, Serur, and Bowler (2023).

the inventories. We leave this question for future research.

In related work, Amaya, Garcia-Ares, Pearson, and Vasquez (2025) look beyond the average effect and assess variation in the impact of hedging activity by option market makers on volatility. Their results confirm that the average effect dampens volatility. By contrast, Brogaard, Han, and Won (2025) suggest that market volatility increases when a larger share of SPX trading volume consists of 0DTE transactions. Our work differs from theirs in significant ways. They identify the result using the staggered introduction dates of SPXW contracts to instrument for the 0DTE volume share; this identification relies on the assumption that the introduction decision is unrelated to market volatility. In contrast, we exploit exogenous variations in the presence of 0DTE contracts on Tuesdays and Thursdays because of business holidays or end-of-month and end-of-quarter days *after* these contracts were introduced. Our identification relies on the restriction that these calendar variations are unrelated to volatility. Finally, whereas they emphasize the share of 0DTE trading in total volume, the lower market volatility we document is not related to the trading of 0DTEs but to the accumulation of positions in longer-dated options that subsequently turn into 0DTEs and raise hedging needs on the expiration day.

Other work investigates the growing demand for trading 0DTE options. In particular, Beckmeyer, Branger, and Gayda (2023) find that retail and institutional investors are driving the shift toward trading 0DTE contracts. Finally, an emerging and important asset pricing literature also focuses on 0DTE options. Bandi, Fusari, and Reno (2023) develop a pricing model for ultra-short-term options; Almeida, Freire, and Hizmeri (2024) examine risk premia in 0DTE prices and conclude that 0DTE options are mispriced.

The remainder of this paper is organized as follows. Section 2 documents the impact of 0DTE contracts on stock market volatility. Section 3 describes our measures of market makers' hedging needs and estimates their responses to 0DTEs. Section 4 turns to high-frequency evidence that market makers' hedging predicts index volatility, order-flow reversal, and momentum returns within the day and also examines the end-user 0DTE positions that drive these hedging needs. Section 5 concludes. Appendix A1 summarizes our data sources, and the Internet Appendix IA1 contains additional empirical results and derivations.

2. The Impact of 0DTEs on Index Volatility

This section establishes the treatment effect that the presence of 0DTE contracts on a given day has on the S&P 500 index volatility within that day. We discuss the expiration schedule of SPX options, explain the identification strategy, define intraday realized volatility measures, and then provide the key empirical tests and robustness checks.

2.1. Introduction of 0DTEs

SPX options are plain Cboe European contracts that reference the S&P 500 index. The 0DTEs belong to the subset of SPX options that are settled when the market closes (PM settlement). The options in this group are listed using weekly, end-of-month, or end-of-quarter maturity schedules, but they all turn into 0DTEs on the expiration day. By contrast, other SPX options are settled when the market opens (AM settlement) and cannot become 0DTEs. We use the non-0DTE label for all SPX options that are not 0DTEs.

0DTE options became available in 2005 when the Cboe introduced weekly contracts expiring on Friday with PM settlement. This allowed investors to trade index options during the expiration day, thus leading to the emergence of 0DTE options trading. Other SPX options with PM settlement were subsequently introduced in a staggered way over time. Contracts that expire on the last business day of each quarter (SPX Quarterly) and on the last business day of each month (SPX end-of-month) were introduced in 2006 and 2014, respectively. Contracts that expire every week on Mondays and Wednesdays were introduced in 2016. Lastly, contracts that expire every week at the end of the day on Tuesdays and Thursdays were introduced in April and May 2022, respectively. The Cboe symbol root SPXW now represents all the index contracts with PM settlement.

Figure 1 illustrates the surge in demand for 0DTE trading between 2012 and 2024. We report the average daily trading volume for each year separately for three groups of contracts:

(i) SPXW 0DTE options, (ii) SPXW non-0DTE options, and (iii) all other SPX options. The data come from the intraday trades and quotes across all exchanges as reported by the Options Price Reporting Authority (OPRA). These results show that 0DTE trading volume is rapidly growing and attracts an increasing share of the S&P 500 index options volume. In 2015, roughly one million contracts were traded every day, but the 0DTE trading volume then accounted for less than one-fifth of the total. In 2024, more than 3 million contracts were traded every day. The trading volume has tripled mostly due to the weekly SPXW options, and the 0DTEs accounted for nearly half of the total trading volume in 2024.

2.2. Identification Strategy

Our identification strategy rests on the fact that, between 2016 and April 2022, 0DTE options regularly expired on Mondays, Wednesdays, and Fridays, but also sometimes expired on specific Tuesdays or Thursdays. These latter exceptions occurred when the end-of-month and end-of-quarter contracts expired on one of these two weekdays, or when a business holiday occurred on a Monday, Wednesday, or Friday, in which case the Cboe moved the expiration date to the neighboring business day.[7]

These calendar-based rules generated plausibly exogenous variation in the presence of expiring 0DTE contracts on Tuesdays and Thursdays. The identification strategy requires that these rules affect S&P 500 volatility only through the presence of 0DTEs and isolate changes in market conditions that are orthogonal to other unobserved drivers of intraday index volatility. The key challenge would come from confounding effects that drive volatility and are somehow correlated with holidays or end-of-month days—for example, information revelation effects or shifts in market participation that are associated with those days. We provide additional evidence supporting the exclusion restriction in Section 2.5 by showing that any such channel would also need to vanish precisely when regular Tuesday and Thurs-

[7] During the 2021 calendar year, as an example, there were eleven days when 0DTE contracts traded on a Tuesday or a Thursday, and four of these cases occurred when end-of-month SPX options expired. See the Cboe 2021 calendar.

day expirations were introduced in 2022.

Figure 2 shows the growth in 0DTE trading volumes over time between January 2018 and December 2024, separately for each weekday. In the upper panel, we report 0DTE volumes on Mondays, Wednesdays, and Fridays. 0DTE contracts were available on these days throughout our sample. In the lower panel, we report the 0DTE volumes on Tuesdays and Thursdays. Two vertical red lines indicate the dates in 2022 when SPXW weekly contracts with Tuesday and Thursday expirations were introduced.[8]

In the upper panel, we see that the daily trading volumes for the Monday, Wednesday, and Friday contracts share a common growing trend throughout the sample. This trend is consistent with Figure 1. In the lower panel, we see that the 0DTE trading volume is typically zero before the vertical red lines but with a few exceptions when 0DTE contracts sometimes expired on Tuesdays and Thursdays between 2018 and early 2022. The 0DTE trading volume on these exception Tuesdays and Thursdays is similar to the trading volume on other weekdays for the same week in the upper panel. Finally, 0DTE contracts expire every Tuesday and Thursday after 2022. By then, the trading volumes are similar and share a consistent trend across all weekdays. For completeness, Figure IA1 in the Internet Appendix reports the volumes across weekdays during the period between 2012 and 2018.

2.3. Intraday Volatility Measures

We calculate the S&P 500 realized volatility for every 10-minute interval between 9:30 am and 4:00 pm. Using 10-minute intervals matches the highest frequency at which we can compute the intraday market makers' hedging needs in our data. To compute the realized volatility, we sample 1-minute S&P 500 returns using the close prices for the cash index, or the mid-quote for the SPY ETF and the E-mini futures from *DTN IQFeed*. The SPX contracts settle using the cash index level, but the index itself is not a traded security. By contrast, the S&P 500 E-mini contract is highly liquid and commonly used for hedging SPX

[8]SPXW contracts expiring on Tuesdays were introduced on April 18, 2022, with first expiration on April 26, and contracts expiring on Thursdays were introduced on May 11, 2022, with first expiration on May 19.

options. For brevity, we rely on E-mini futures data throughout most of the paper.

We use the E-mini future contract with the shortest maturity but switch to the next contract when the first contract reaches eight days to expiration. We construct the *Realized Vol* measure as the square root of the sum of squared one-minute log returns in an intraday 10-minute interval. We scale this 10-minute volatility measure to annualized terms by assuming 252 trading days per year and 39 intervals per trading day.

2.4. 0DTEs and Intraday Volatility

We estimate the change in intraday volatility of the S&P 500 index when 0DTEs are present. The baseline panel regression is given by:

$$\sigma_{d,t} = a + b \times \mathit{0DTE}_d + \text{Controls} + \text{FE} + \epsilon_{d,t}, \tag{1}$$

where each observation corresponds to one of the 39 10-minute intervals t in a trading day d. We study 10-minute realized volatility because market makers hedge their gamma exposure within the day. Section 4 provides several sources of evidence for this. The intraday interval is therefore the economically appropriate unit of analysis. The independent variable of interest is *0DTE*, an indicator equal to 1 if 0DTE contracts expire at the end of the trading day and 0 otherwise. Its coefficient measures the average difference between realized volatility in 10-minute intervals across days with and without 0DTEs. We estimate Equation (1) with ordinary least squares (OLS) for the period from January 1, 2018, until May 19, 2022, when SPXW options begin expiring on every weekday (i.e., *0DTE* is always 1 after this date). Table 1 reports the results, with Newey-West standard errors to account for residual autocorrelation up to five lags within a trading day.[9]

In Column (1), the regression includes *Year* × *Week* × *Time* fixed effects, where *Year* is the calendar year, *Week* is the calendar week of the year, and *Time* is a 10-minute interval

[9]The recommended number of lags is 3 based on a conventional rule of $4(T/100)^{(2/9)}$ with $T = 39$.

within the day. These fixed effects control for predictable intraday seasonality patterns separately for each week. The coefficient estimate for *0DTE* is negative and significant. Next, in Column (2) the regression includes *Day-of-Week* fixed effects to sharpen the identification: the point estimate is identified by variations in *0DTE* on Tuesdays and Thursdays. The coefficient estimate is larger and statistically significant.

Column (3), our baseline regression, includes *Day-of-Week* $\times$ *Year* instead of *Day-of-Week* fixed effects. We find that the intraday volatility of the S&P 500 declines by 61 annualized basis points on average when 0DTEs are present, after controlling for the average volatility during the same year, the same week, and the same 10-minute interval within a day. This is about 7% of the average 10-minute realized volatility over the baseline sample (0.61/9.10, using the sample mean of 9.10% in Table 3). Because the variation in the presence of 0DTEs on Tuesdays and Thursdays is plausibly exogenous, we interpret this estimate as the treatment effect of expiring 0DTE contracts.

The Internet Appendix offers the following robustness checks. First, Table IA1 repeats the regression in Table 1 but for a sample starting in 2012. The coefficient estimates are again negative and statistically significant, but smaller. We focus on the period after 2018 throughout the paper due to the availability of high-frequency information about the positions of option market makers. Second, Table IA2 makes the SPY and cash-index robustness explicit: the effect is similar when realized volatility is computed with the SPDR S&P 500 ETF or the S&P 500 cash index rather than E-mini futures. Finally, Table IA3 confirms the robustness of our findings to different fixed-effects specifications and inference strategies.

2.5. The Introduction of SPXW with Tuesday and Thursday Expiration

Overall, we find that the treatment effect of 0DTE availability on the S&P 500 10-minute volatility is negative, on average, and economically significant. The introduction in 2022 of regular weekly SPXW contracts that expire on Tuesdays and Thursdays offers the opportunity for a complementary test supporting the exclusion restriction in our main results. If the presence of 0DTEs is the mechanism behind the lower intraday volatility documented in

Table 1, then we expect this difference to disappear once 0DTE contracts start to expire regularly on every business day. In that case, any confounding effect would need to be correlated with the exception rules before 2022 *and* this correlation would need to vanish precisely when regular Tuesday and Thursday expirations were introduced—a coincidence that is difficult to reconcile if potential end-of-month or holiday-driven confounds are independent from the presence of expiring 0DTE contracts.

This idea can be implemented in a difference-in-differences regression that we estimate for the sample period from January 2018 to December 2024, where we include the following indicator variables. First, the indicator *Introduction* is equal to one starting on April 26, 2022, and zero otherwise. Its coefficient measures any change in intraday volatility that is common across all weekdays after the introduction of the new contracts in 2022. Next, the indicator variable *Tuesday/Thursday* is equal to 1 on Tuesdays or Thursdays and 0 otherwise. Its coefficient measures whether intraday realized volatility is different on these weekdays relative to other weekdays. Finally, the variable of interest is the interaction of the two indicator variables *Tuesday/Thursday*×*Introduction*. Its coefficient measures the difference in differences in intraday volatility between weekdays before and after 2022, when 0DTE contracts that regularly trade on Tuesdays and Thursdays were introduced.

Table 2 reports the results. Note that we exclude exception Tuesdays and Thursdays when 0DTEs were present before April 26, 2022, because we want to measure the effect of the presence of 0DTEs after this date relative to a baseline when no 0DTE contracts expire. The regression includes *Year* × *Week* × *Time* fixed effects to absorb intraday seasonalities. We introduce the indicator variables one by one across Columns (1)–(3), for completeness. Column (3) presents the main result.

First, the coefficient estimates of *Tuesday/Thursday* are positive and significant, meaning that the S&P 500 10-minute volatility is higher on average on Tuesday and Thursday relative to the other business days in the same week. The magnitude is consistent with the estimates reported in Column (1) of Table 1 based on regressions with the same fixed effects. Second, the coefficient estimate on *Introduction* is negative but not statistically significant: we find no evidence that the introduction of SPXW contracts that expire weekly on Tuesdays and Thursdays affects intraday volatility during the other weekdays as well.

Finally, the coefficient estimate of interest on *Tuesday/Thursday*×*Introduction* is negative and statistically significant, and its magnitude is similar to the coefficient estimate on *Tuesday/Thursday*. In other words, the higher intraday volatility on Tuesdays and Thursdays relative to the other weekdays disappeared after the Cboe filled the gaps in the availability of 0DTE contracts across weekdays. The results in Table 2 are consistent with our interpretation that the presence of 0DTEs lowers 10-minute volatility on average in a day.

The rest of this paper investigates the mechanism behind the documented net reduction in the S&P 500 index intraday volatility. Ni, Pearson, Poteshman, and White (2021) show that market makers' hedging needs due to holdings of non-0DTE options linked to individual stocks can affect stock volatility the following day. Building on their results, we provide causal evidence that market makers accumulate contracts that become 0DTE, but this inventory is built up before the expiration day. This inventory then generates hedging needs during the expiration day that are consistent with a dampening of intraday volatility. Therefore, 0DTE trading *per se* is not the main force reducing index intraday volatility.

3. The Impact of 0DTEs on Market Makers' Hedging

This section uses a simple framework that summarizes the mechanics of delta hedging by market makers and, based on this framework, we develop two measures of their hedging needs. Empirically, we use the Cboe Open-Close Volume Summary data to identify positions held by market makers and compute these measures of hedging needs intraday at 10-minute intervals. We find that the exogenous variation in the presence of 0DTEs is associated with substantial changes in market makers' hedging needs. In addition, this shift is in the direction that can explain the lower index volatility on expiration days documented in the previous section.

3.1. Market Makers' Hedging Needs

Start at time $t-1$. Consider a market maker holding $w_{i,t-1}$ option contracts i and $-w_{i,t-1}\Delta_{i,t-1}$ shares in the underlying security as a hedge, where $\Delta_{i,t-1}$ is the option's delta. We build on the following two key assumptions. First, we assume that market makers use the Black-Scholes option pricing model and the observed implied volatility of the option to compute $\Delta_{i,t-1}$, as a practical approximation. Second, we assume that market makers re-balance their hedge positions in the underlying market at the start of the next discrete interval t. We ignore tracking errors, which are small in practice for short intervals.

The following two quantities change at time t: (i) the price of the underlying shares changes from S_{t-1} to S_t, and as a result, the option delta changes from $\Delta_{i,t-1}$ to $\Delta_{i,t}$ and (ii) the market maker's inventory of option contracts changes from $w_{i,t-1}$ to $w_{i,t}$. After rebalancing, in our framework, the change in the market maker's holdings of underlying shares is given by:

$$-w_{i,t}\Delta_{i,t} - \big(-w_{i,t-1}\Delta_{i,t-1}\big) = \underbrace{-w_{i,t-1}\big(\Delta_{i,t} - \Delta_{i,t-1}\big)}_{\text{hedge earlier position}} + \underbrace{-\big(w_{i,t} - w_{i,t-1}\big)\Delta_{i,t}}_{\text{hedge new position}}, \tag{2}$$

where we added and subtracted $w_{i,t-1}\Delta_{i,t}$. This accounting decomposition isolates two components of the hedging needs. The first component, given by:

$$n_{i,t} = -(w_{i,t} - w_{i,t-1})\,\Delta_{i,t}, \tag{3}$$

sets the hedge for the new option position due to the change in the market maker's inventory during this interval. The second component is given by

$$q_{i,t} = -w_{i,t-1}\,(\Delta_{i,t} - \Delta_{i,t-1}) = -w_{i,t-1}\left(\Gamma_{i,t}\,\Delta S_t + O\big(\Delta S_t^2\big)\right) \approx -w_{i,t-1}\Gamma_{i,t}\,\Delta S_t, \tag{4}$$

where we used a Taylor expansion of $\Delta_{i,t}$ for small changes in the underlying price ΔS_t, and

$\Gamma_{i,t} \equiv \partial \Delta_{i,t} / \partial S_t$ is the option's gamma, which can be computed from Black-Scholes results.[10] This rebalancing component $q_{i,t}$ resets the hedge for the preexisting position $w_{i,t-1}$.

3.2. Net Gamma

We aggregate the hedging needs component $q_{i,t}$ due to the pre-existing positions in Equation (4) across all related option contracts i and define the market makers' $Net\Gamma_t$ as an elasticity measure: the percentage of underlying shares that the market maker needs to sell to hedge a one-percent *increase* in the underlying share price:

$$\mathrm{Net}\Gamma_t \equiv \left(\frac{-100 \cdot \sum_i q_{i,t}}{M} \right) / \left(\frac{\Delta S_t}{S_t} \right) \approx \frac{100 \cdot S_t}{M} \cdot \sum_i w_{i,t-1} \cdot \Gamma_{i,t} \tag{5}$$

where M is the number of outstanding shares and we use Equation (4) to substitute for $q_{i,t}$ to arrive at Equation (5). We multiply $q_{i,t}$ by -100 because each option contract represents 100 underlying shares, and the negative sign sets the hedging needs direction opposite to the change in the price of the underlying security. The sign of $Net\Gamma_t$ depends on the sign of the pre-existing weights $w_{i,t-1}$ because $\Gamma_{i,t}$ is always positive (the option payoff is convex). If short positions dominate, then $Net\Gamma_t$ is negative and the market maker would buy more of the underlying security as its price increases, exacerbating the underlying asset's volatility. Conversely, if long positions dominate, then $Net\Gamma_t$ is positive and the market maker would rebalance in the direction that dampens volatility.

3.3. Net Delta

We aggregate the hedging needs component $n_{i,t}$ due to the new positions in Equation (3) across all related option contracts and define the market makers' $Net\Delta_t$ as an elasticity measure: the percentage of underlying shares that the market maker needs to sell to hedge

[10] Appendix Section IA1.2 discusses the impact on the market makers' hedging needs of including higher-order terms in the Taylor expansion.

a one-percent increase in the underlying share price:

$$\text{Net}\Delta_t \equiv \left(\frac{-100 \cdot \sum_i n_{i,t}}{M}\right) / \left(\frac{\Delta S_t}{S_t}\right)$$
$$\approx \frac{100}{M \cdot R_t} \sum_i (w_{i,t} - w_{i,t-1}) \cdot \Delta_{i,t}, \tag{6}$$

where $R_t \approx \Delta S_t / S_{t-1}$ is the log asset return. Note that a market maker with new option positions $w_{i,t} - w_{i,t-1}$ would trade a finite number of shares to hedge its inventory even when the index does not move over the interval. The numerator $\frac{100}{M} \sum_i (w_{i,t} - w_{i,t-1}) \, \Delta_{i,t}$ in Equation (6) is the finite quantity of shares as a percentage of outstanding shares. We divide by R_t only to obtain an elasticity concept and construct $Net\Gamma_t$ and $Net\Delta_t$ measures that are directly comparable. However, this comparability has a cost. One drawback is that, in contrast with the case of $Net\Gamma_t$, the term ΔS_t does not cancel out and the $Net\Delta_t$ measure is not well defined when the share price does not change and $R_t = 0$ in the interval. We use a regularization technique to protect against this.[11]

The sign of $Net\Delta_t$ determines whether the market maker would buy or sell the underlying security to hedge new positions when the hedge is implemented in the next interval. The sign depends on: (i) whether the contracts are put or call options ($\Delta_{i,t}$ is positive for calls and negative for puts) and (ii) the sign of $\frac{w_{i,t} - w_{i,t-1}}{R_t}$. For example, an increase in a call position when the underlying return is positive indicates that the market maker must sell some of the underlying securities since $\Delta_{i,t} > 0$ and $\frac{w_{i,t} - w_{i,t-1}}{R_t}$ are positive. A positive value for $Net\Delta_t$ indicates that market maker activity creates hedging needs in the opposite direction of the underlying price change, which would *dampen* the asset volatility. A negative value would imply the opposite effect.

[11] If $|R_t|$ is less than the threshold 0.001% then we sum the return over a trailing window until it crosses the threshold, looking back up to five 10-minute intervals. These cases arise in less than 1% of the observations. If the cumulative return does not cross the threshold, then we set $Net\Delta_t$ to missing for that interval.

3.4. Measuring Market Makers' Hedging Needs

This section details the empirical implementation of the $Net\Gamma_t$ and $Net\Delta_t$ measures given in Equations (5) and (6), respectively. First, the number M of shares is the ratio of the S&P 500 market value divided by the index level, calculated using information at the end of the previous trading day. Then, we compute the market makers' positions using the Cboe's intraday Option Quotes and Open-Close Volume Summary data. This data set provides snapshots of cumulative volume and trade direction on Cboe's C1 primary exchange for SPX options at 10-minute intervals for each option contract, categorized by market participant type. This intraday data set is essential for studying trading activity in 0DTE contracts throughout their expiration day. Our sample period ranges from January 2018 to December 2024.

Intraday volume for each option contract is identified as originating from one of four market participant types: *Customers*, *Professional Customers*, *Firm Proprietary*, and *Broker-Dealers*. *Customers* are public investors who represent the primary end-users of options, including both retail and institutional investors. *Professional Customers* are public accounts with high levels of intraday trading activity. *Firm Proprietary* trades originate from proprietary accounts of banks or trading firms that are clearing members of the Options Clearing Corporation (OCC), the central clearing party for all exchange-traded options. *Broker-Dealers* are trades originating from brokerage houses.

The direction of the trade is reported under four categories: (1) Open-buy volume represents the number of contracts purchased to open new positions; (2) Open-sell volume represents the number of contracts sold to open positions; (3) Close-buy volume represents the number of contracts purchased to close existing positions; (4) Close-sell volume represents the number of contracts sold to close existing positions. The Cboe data report the cumulative volumes for each category from the start of the day up to each 10-minute interval. Therefore, the trading volume for each 10-minute interval is the difference between the reported cumulative volumes in two successive intervals. The gross trading volume of each option contract in a given interval is the sum of buy and sell volumes within that interval.

The order imbalance (OIB) is the net of buy and sell volumes for each option contract within an interval. We calculate the OIB every 10-minute interval, separately for each option contract i and investor group j as follows:

$$\text{OIB}_{i,j,t} = \text{Open-Buy}_{i,j,t} + \text{Close-Buy}_{i,j,t} - \text{Open-Sell}_{i,j,t} - \text{Close-Sell}_{i,j,t}. \tag{7}$$

Next, the net open interest (NOI) captures the net position held by each investor group at the end of each interval. We calculate the NOI by summing the OIB since the inception of the option contract until the end of the current 10-minute interval t, as follows:

$$\text{NOI}_{i,j,t} = \sum_{s=0}^{t-1} \text{OIB}_{i,j,t-s}. \tag{8}$$

Each option contract is traded in zero net supply, and market makers clear the market and offset the OIB netted across all other investor types. Therefore, we estimate the OIB and the NOI of option market makers as the negative values of the sums across all other investor groups j, as follows:

$$\text{OIB}_{i,t} = -\sum_{j} \text{OIB}_{i,j,t} \quad ; \quad \text{NOI}_{i,t} = -\sum_{j} \text{NOI}_{i,j,t}. \tag{9}$$

We calculate the market makers' NetΔ_t and NetΓ_t using Equations (5)-(6) with $\text{NOI}_{i,t-1}$ as the pre-existing market makers' position $w_{i,t-1}$ and $\text{OIB}_{i,t}$ as the change in that position $w_{i,t} - w_{i,t-1}$, respectively, and using the delta $\Delta_{i,t}$ and gamma $\Gamma_{i,t}$ available from the Cboe data set. The aggregation of NetΔ_t and NetΓ_t in these equations can be done for all options or for 0DTEs and non-0DTEs separately.

3.5. Summary Statistics

Table 3 reports summary statistics for the S&P 500 realized volatility and measures of market makers' hedging needs. We report these statistics separately for the periods before and after

May 19, 2022, when 0DTEs began expiring every weekday. Recall that both measures are expressed as the percentage of the S&P 500 that market makers would need to sell to hedge a one-percent rise in the index, and buy to hedge a one-percent decline. The average market makers' $Net\Gamma_t$ rises from 0.88 percent before May 2022 to 1.42 percent afterward. The $Net\Delta_t$ is smaller, averaging 0.08 and 0.28 percent in the same two sub-periods, respectively. Therefore, in any 10-minute interval in our sample, most of the market makers' hedging needs arise from positions that existed before this interval rather than from new positions. Overall, the magnitudes suggest that market makers would need to make large transactions in the underlying market to hedge these exposures and, as a result, that the attenuating effect on volatility could be empirically significant.

The 0DTEs contribute a large fraction of the overall net gamma: the $Net\Gamma_t$ due to 0DTE exposures is 0.23 percent before 2022 and 0.54 percent afterward. This means that since 2022, contracts with just several hours until expiry have generated roughly one-third of the market makers' SPX $Net\Gamma_t$ hedging needs and most of the $Net\Delta_t$ hedging needs. Nonetheless, the non-0DTE positions contribute to the increase in $Net\Gamma_t$ after 2022: their contribution to the market makers' $Net\Gamma_t$ rises from 0.64 to 0.87 percent across these two periods.

The market makers' net gamma is positive on average and throughout most of our sample. Figure IA2 shows that $Net\Gamma_t$ is positive for 88 percent of all 10-minute trading intervals. Figure IA3 reports only a handful of small negative values in the time series of monthly averages of 0DTE net gamma. Figure IA4 shows the same result for non-0DTE exposures. Summing 0DTE and non-0DTE exposures, we find that the monthly average is always positive.

Panel (a) of Figure IA5 shows that 0DTE contracts are the single most important source of variation in market makers' net gamma during the day. This larger intraday volatility is expected because short-dated options are more sensitive to variations in the underlying S&P 500 level, and this sensitivity increases rapidly as the contract approaches maturity.

Panel (b) of Figure IA5 shows that this gap has also increased in our sample as 0DTEs make a growing share of the market makers' inventory. Overall, the evidence shows that 0DTEs drive the most potent source of intraday variations in market makers' hedging needs.

3.6. Market Makers' Stale and New 0DTE Positions

All non-0DTE options with PM settlement eventually become 0DTEs. This means that the market for any non-0DTE SPXW option today is related to a future 0DTE market some later day. This link arises when market makers build positions in longer-dated SPXW options over the course of several days or weeks and carry them until these options become 0DTEs on the expiration date. Therefore, on any 0DTE expiration day, the market makers' 0DTE hedging needs combine exposures due to the following groups of positions. First, the market makers hold "Stale" 0DTE positions accumulated prior to the expiration day. Second, they build up "New" 0DTE positions due to contracts accumulated throughout the expiration day itself. Finally, they hold non-0DTE contracts that will expire at a later date, but we do not distinguish between Stale and New positions for these contracts.

We track the intraday composition of market makers' $Net\Gamma_t$. For every day in our sample, we zoom in on the market makers' SPXW positions at 4 pm and identify positions in options that are scheduled to expire the following business day. Holding these positions fixed, we track the implied net gamma throughout the following day and label the results as Stale 0DTE $Net\Gamma_t$. Separately, we track the net gamma for all new 0DTE positions accumulated by market makers after the 4 pm point and label these as New 0DTE $Net\Gamma_t$. The net gamma for all other option positions is the non-0DTE $Net\Gamma_t$.

Table 3 shows that Stale 0DTE positions account for the larger share of market makers' total 0DTE net gamma. The daily average Stale 0DTE $Net\Gamma_t$ on expiration days was 0.29 and 0.39 percent before and after May 2022, respectively, but 0.08 and 0.16 percent for new 0DTE $Net\Gamma_t$. How far in advance are these Stale 0DTE positions established? Figure 3 traces the market makers' Stale 0DTE net gamma back to the trading day on which each position was opened. We find that, on average, about half of the Stale positions were opened one day before the expiration date, close to 90 percent were opened during the week before expiration, and very few were opened more than two weeks before.

Looking within the day, Figure 4 reports the median and interquartile range of New and Stale 0DTE $Net\Gamma_t$ for each hour of the trading day after 2022. The New 0DTE $Net\Gamma_t$ is zero by construction at 4 pm the previous trading day. The median New 0DTE $Net\Gamma_t$ is still close to zero at the start of the trading day and remains near zero throughout most of the expiration day. In contrast, the median Stale 0DTE $Net\Gamma_t$ starts the day near 0.3 percent and remains largely unchanged until the market closes. Therefore, Stale 0DTE $Net\Gamma_t$ is typically responsible for most of market makers' 0DTE hedging needs throughout the day. This finding highlights that market makers start the day with pre-existing inventories of 0DTE contracts accumulated in the days before the expiration date.

Note that the volatility of the 0DTE $Net\Gamma_t$ naturally increases steadily during the day because of time decay.[12] The effect tends to be larger on the volatility of New 0DTE $Net\Gamma_t$ if their strike prices tend to be closer to at-the-money toward the end of the day than those of the Stale 0DTE positions. In that case, the net gamma of New 0DTE positions is more susceptible to exhibiting exponential growth toward the end of the expiration day, adding to the intraday volatility of the New 0DTE $Net\Gamma_t$.

3.7. Customers' 0DTE Positions

The market makers offset the net positions aggregated across *Customers*, *Professional Customers*, *Firm Proprietary*, and *Broker-Dealers*, according to the Cboe classification. This section provides a brief description of the positions held by *Customers*, which captures the larger share of market makers' overall positions (Figures IA3-IA4).

Panel A of Figure 5 shows *Customers*' net open interest by put and call contracts, by moneyness buckets, at 2-hour intervals within the day, on average between May 19, 2022

[12] The intraday volatilities of the New and Stale 0DTE $Net\Gamma_t$ do not sum to the intraday volatility of overall 0DTE $Net\Gamma_t$ because they are negatively correlated and can offset each other during the day.

and the end of our sample.[13] We find that *Customers* begin the day with significant short 0DTE positions in at-the-money (ATM) or slightly out-of-the-money (OTM) options but long positions in far-OTM options. Thus, as a group, their holdings appear to follow an "iron butterfly" or "iron condor" strategy. Within the day, we find that *Customers* increase long OTM positions but keep the short positions relatively stable on average.

Panel B of Figure 5 reports the net gamma that results from these holdings. We find that the *Customers'* portfolio net gamma is very negative throughout the day, despite the fact that their long positions in OTM options are larger than their short positions in ATM options. The reason for this is that the gamma of ATM options starts growing exponentially as we near the expiration time, while the gamma of OTM options decays toward zero. Overall, the *Customers*' aggregate short ATM straddle position explains the large positive 0DTE net gamma of market makers.

3.8. Market Makers' Netting of New 0DTE Positions

This section addresses the apparent tension between the observations that (i) 0DTE trading accounts for the largest share of trading volume and, yet, that (ii) most of the market makers' 0DTE net gamma appears due to Stale positions. What explains this is that market makers net out the trading volumes across 0DTEs during the day in a way that mitigates the effect on the hedging needs.

To show this, Figure 6 disaggregates *Customers*' intraday 0DTE trading volume (Panel A) and order imbalance (Panel B), by put and call contracts, by moneyness, and for 2-hour intervals throughout the day, on average between May 19, 2022, and the end of our sample.

The results show that the large 0DTE trading volume is concentrated in put and call at-the-money options and builds up gradually during the day. However, despite 0DTE daily trading volume averaging close to 1 million contracts, the *Customers*' cumulative order

[13] Moneyness is the strike price divided by the end-of-day closing index level. This maintains the moneyness buckets unchanged throughout each trading day and aligns all positions with their cash-settlement values at expiration. Our conclusions are unchanged if we define moneyness using the current index level.

imbalance for at-the-money 0DTEs—which the market makers absorb—is less than 5,000 contracts toward the end of the day. The order imbalance is larger for other 0DTE contracts further away from the index price, but these out-of-the-money 0DTEs have a small contribution to the market makers' net gamma. Overall, the results show that the market makers are able to manage their 0DTE inventory during the expiration day and control the contribution of New 0DTE positions to their median intraday net gamma exposures (in Figure 4).

3.9. 0DTE Contracts and Market Makers' Hedging Needs

In this section, we estimate the impact that the presence of 0DTEs has on the market makers' hedging needs. As before, we use variations in the presence of 0DTEs on Tuesdays and Thursdays to identify the effect (see details in Section 2). Since the presence of 0DTE contracts on a given day is known in advance to market makers, they can choose to change their positions ahead of time to target their net gamma exposures at the beginning of the expiration day. We find that much of the effect of 0DTEs on the market makers' $Net\Gamma_t$ works through an increase in the Stale 0DTE $Net\Gamma_t$.

Table 4 reports results from panel regressions where the dependent variable is one measure of market makers' 10-minute hedging needs and the independent variable of interest is the *0DTE* expiration dummy. Column (1) reports the effect on the 0DTE net gamma. Columns (2)-(3) distinguish between the effects on the Stale and New 0DTE net gamma exposures, respectively. Column (4) reports the effect aggregated across non-0DTE exposures, and Column (5) reports the estimated effect on net gamma aggregated across all market makers' SPX positions. The fixed effects specification is the same as in Column (3) of Table 1.

We find that market makers' 0DTE $Net\Gamma_t$ is 27.5 bps on average across 10-minute intervals, after controlling for fixed effects (Column 1). This estimate is comparable to the average 0DTE net gamma for this subsample before May 2022 (see the summary statistics in Table 3). We also find that this increase in market makers' $Net\Gamma_t$ is essentially due to Stale 0DTE positions, which increases by 25 bps (Column 2). In contrast, the change in New 0DTE $Net\Gamma_t$ plays a much smaller role (Column 3).

The change in the market makers' 10-minute non-0DTE hedging needs goes in the opposite direction (Column 4). We observe that non-0DTE $Net\Gamma_t$ decreases by 14 bps on average across 10-minute intervals on days with 0DTE expiration. Hence, there is some evidence that introducing 0DTE contracts leads to substitution before the expiration day. Yet, the net effect across all SPX options is positive and statistically significant. The total market makers' $Net\Gamma_t$ increases by 15 bps on average across 10-minute intervals when 0DTEs are present. Additional analysis reported in Internet Appendix Table IA5 shows no evidence that the market makers' net delta changes due to the presence of 0DTEs. The stability of net delta is consistent with the evidence in Section 3.8 that market makers are able to balance end-users' buying and selling. The evidence also argues against the possibility that directional 0DTE trading by end users could drive the intraday changes in both the market makers' hedging needs and future realized volatility.

Finally, we estimate the effect of market makers' $Net\Gamma_t$ on S&P 500 realized volatility using a two-stage least squares regression (2SLS). The first stage of the estimation isolates the change in $Net\Gamma_t$ due to 0DTEs (Column 5). The second stage then measures its impact on volatility. We report the results of the second stage in Column (6) of Table 4. The coefficient estimate is -4.04, implying that a 1 bp increase in net gamma is associated with a 4 bps decrease in intraday volatility (annualized). Together, this estimate essentially combines the increase of 15 bps in total market makers' $Net\Gamma_t$ with the estimated decline in realized volatility of 61 bps in Table 1.

If we add the assumption that the presence of 0DTEs acts on realized volatility solely through the market makers' net gamma, then the 2SLS regression can be interpreted as estimating a causal relationship: a 1 bp increase in market makers' net gamma would reduce realized volatility by about 4 bps. The channel for this connection would run through market makers hedging their net gamma exposures during the course of each day in the underlying S&P 500 market. We present intraday evidence for this channel in Section 4.

3.10. Hedging Needs across Hours of the Day

We ask whether the impact on the 0DTE net gammas is similar across different hours of the day. For this purpose, we repeat the regression in Table 4, but now interact *0DTE* with a dummy variable for each hour of the trading day, separately. We report the coefficient estimates in Figure 7 along with their confidence intervals.

The coefficient estimates for the Stale 0DTE $Net\Gamma_t$ are stable throughout the day, around a level consistent with Table 4, slightly above 20 bps, except during the last hour of the day when the estimate reaches almost 40 bps. However, the confidence interval also widens during this hour and mostly spans the estimates from the earlier hours. In contrast, the estimate for New 0DTE $Net\Gamma_t$ is small throughout the day and statistically insignificant in most cases. Again, the confidence interval increases towards the end of the day.[14]

3.11. Discussion

Summarizing the evidence so far, we document three causal facts. On average, in a 10-minute interval on days when 0DTEs are present (i) S&P 500 realized volatility is lower, (ii) market makers have a positive portfolio net gamma throughout the day that is larger when 0DTEs are present, and, crucially, (iii) this larger exposure comes from pre-existing option positions accumulated before the expiration day. These facts indicate that the presence of 0DTEs does not amplify volatility or destabilize the index on average; instead, the associated rise in market makers' hedging needs helps explain the reduction in volatility.

We cannot connect the hedging needs of option market makers with transactions on the S&P 500 futures exchange. To address this gap, Section 4 provides indirect evidence linking the intraday market makers' hedging needs to the intraday index volatility, order flow reversals, and momentum returns in the E-mini futures market.

---

[14] This decrease in precision toward the end of the day may be due to the fact that $Net\Gamma_t$ increases exponentially near the end of the day, adding noise to the estimate.

4. Market Makers' Hedging—High-Frequency Evidence

This section provides high-frequency evidence that hedging by market makers can explain the attenuation of S&P 500 intraday volatility. This evidence goes beyond the single-stock setting in Ni, Pearson, Poteshman, and White (2021): we study the aggregate S&P 500 index market, measure market makers' hedging needs intraday from their positions, and link gamma to volatility, E-mini order-flow reversals, and momentum within the trading day. Overall, the results highlight that market makers' hedging needs have strong predictive content for intraday returns, order flow, and realized volatility of the S&P 500. First, variations in market makers' net gamma predict lower S&P 500 volatility in the next 10 minutes, and this effect dissipates after about one hour. Second, a higher net gamma predicts a stronger reversal pattern in E-mini order flow during the next interval. The direction is consistent with the observed damping effect on volatility, and the effect dissipates after one hour. Third, a higher net gamma predicts weaker momentum in high-frequency returns, which is consistent with both the effects on order flows and volatility. The pattern in these predictive relationships consistently points to market makers' hedging activity as a central mechanism that dampens index volatility. In addition, the pattern implies that high-frequency hedging of market makers' portfolio with positive net gamma can be profitable, on average, when transaction costs are low.[15]

4.1. Intraday Hedging Needs and Volatility

We examine the impact of market makers' hedging needs on the intraday realized volatility of the S&P 500 index during the next interval.[16] The analysis relies on a panel regression in which each cross section groups all 10-minute intervals within that day. The baseline panel

[15] Practitioners call this strategy gamma scalping, and it can likely be implemented by market makers with efficient execution systems.

[16] Table IA4 in the Internet Appendix reports the time-series averages of the intraday contemporaneous correlations between key variables. There is a negative correlation between the volatility measures and the net gamma for both the 0DTE and non-0DTE contracts.

regression is given by:

$$\sigma_{t+1} = a + b_1 \cdot Net\Gamma_t + b_2 \cdot \text{Net}\Delta_t + \text{Controls} + \text{Lags} + \text{FE} + \epsilon_t, \tag{10}$$

where we drop the date subscript d for simplicity, t is one 10-minute interval between market open at 9:30 am and market close at 4:00 pm, and σ_{t+1} is the intraday volatility of the E-mini futures during the interval $t+1$. The predictive variables of interest are the market makers' $Net\Gamma_t$ and $Net\Delta_t$ calculated using information available up to time t. They represent the fraction of underlying shares that market makers need to sell in the next interval to hedge their pre-existing and new option positions, respectively, against a one-percent increase in the S&P 500 in the current 10-minute interval, and vice versa. We expect the coefficients b_1 and b_2 to be negative if the hedging mechanism is present. We include two lags of the dependent variable in every specification. We also include *Date* fixed effects to control for the average level of volatility on each day and *Year* × *Week* × *Time* fixed effects to control for the seasonality across 10-minute intervals within a day. This rich set of fixed effects focuses on identifying whether intraday variations in market makers' hedging needs can predict the intraday index volatility.

Table 5 reports the panel regression results. Results for the baseline regression that uses total $Net\Gamma_t$ are reported in Column (1). The point estimate is negative and economically significant, consistent with the dampening effect of market makers' hedging on intraday volatility. Multiplying the coefficient estimate −0.40 by the intraday standard deviation of overall $Net\Gamma_t$ after May 2022 (0.54 percent according to Table 3) predicts that S&P 500 volatility will decrease by around 22 basis points (annualized) in the next interval. Applying the same calculation to the 0DTE $Net\Gamma_t$ alone (using the coefficient in Column (2) and the corresponding intraday standard deviation) yields a comparable magnitude, close to the 23 basis points reported in the Introduction.

For completeness, we also report the predictive content of the net gamma due to 0DTE and non-0DTE positions, separately in Columns (2) and (3). The coefficient estimate for 0DTE $Net\Gamma_t$ is significant and close to the value found in Column (1) for overall $Net\Gamma_t$. The coefficient estimate for non-0DTE $Net\Gamma_t$ is also negative and statistically significant, but the magnitude of the estimate is larger than for 0DTE $Net\Gamma_t$ (-0.96 vs. -0.44). In Column (4) we combine the hedging needs for 0DTE and non-0DTE contracts in the same regression. The coefficient estimates are similar to the results in Columns (2)–(3), and the *within* R^2 is essentially unchanged. In Column (5), we distinguish between non-0DTE positions for contracts with maturities between 1 and 5 days and maturities greater than 5 days, respectively. The coefficient estimate for shorter maturities is significant and close to the coefficient for the 0DTE $Net\Gamma_t$ in Column (2). By contrast, the coefficient for longer maturities is only marginally significant.

Table 5 shows a consistent predictive relationship between measures of market makers' hedging needs and realized volatility in the next interval. These are reduced-form regressions. Per unit of net gamma, the point estimates are statistically indistinguishable across option maturities: the non-0DTE coefficient is estimated less precisely, and its confidence interval covers the 0DTE estimate. This is consistent with one unit of gamma generating the same hedging pressure regardless of when the position was established. Scaled by the typical intraday fluctuation of each measure, the predicted effects are of the same order of magnitude—about 23 bps for the 0DTE $Net\Gamma_t$ and 12 bps for the non-0DTE $Net\Gamma_t$ per one intraday standard deviation after May 2022 (Table 3)—with the larger 0DTE effect reflecting that the intraday variation in 0DTE net gamma is about four times larger.

The Internet Appendix offers the following robustness checks of the results in Table 5. First, Table IA6 shows that the relationship between market makers' hedging needs and realized volatility in the next interval is pervasive throughout the day and appears to be stronger at the beginning of the day. Next, we show in Table IA7 that the results are robust when computing the hedging needs measures without relying on the $\Delta_{i,t}$ and $\Gamma_{i,t}$ measures provided in the Cboe data set. Last, we show in Table IA8 that the results are robust when we control for the second-order approximation (speed) and time decay (charm) components of the hedging needs.

4.2. Intraday Hedging Needs and Volatility at Longer Horizons

This section examines the intraday predictive power of the market makers' net gamma for S&P 500 volatility up to two hours ahead. These results illustrate both the speed and the persistence of market makers' intraday hedging activity. We estimate Equation (10) but with the volatility σ_{t+n} in future 10-minute intervals over the next two hours as the dependent variable. The independent variable of interest is the market makers' $Net\Gamma_t$; we include two lags of the dependent variable and control for a rich set of fixed effects, as before.

Figure 8 reports the predicted change in intraday volatility across the horizons, following an increase in the current $Net\Gamma_t$ by one intraday standard deviation. We report results separately for the 0DTE and non-0DTE $Net\Gamma_t$.[17] We find that the predicted change in volatility decays smoothly, flattens toward zero, and becomes statistically insignificant after about an hour. Figure 8 can be viewed as an impulse response function of the index volatility to the market makers' hedging needs. This response suggests that variations in market makers' hedging needs, as measured by net gamma exposures, persist and affect realized volatility for the next hour or so. In addition, the responses for 0DTE and non-0DTE exposures display the same decay pattern and are of the same order of magnitude, with the confidence intervals overlapping at most horizons.

Quantitatively, the sum of the coefficient estimates for 0DTE net gamma is -2.0 in the first hour (and -2.5 over the first two hours). We can compare this estimate with the evidence in Section 3. Specifically, if we interpret this sum of -2.0 as the cumulative effect of an intraday increase in 0DTE net gamma on realized volatility and multiply it by the increase in 0DTE net gamma of 27.5 basis points on days when 0DTE contracts expire (from Table 4), we get a reduction in realized volatility of 55 basis points. This magnitude is

[17] Tables IA9-IA10 in the Internet Appendix report the regression results.

similar to that of the expiring-0DTE treatment effect of 61 basis points that we documented in Column (3) of Table 1. These two estimates draw on different sources of variation. One draws on intra-day variations in realized volatility and market makers' $Net\Gamma_t$, while the other draws on exogenous variation across days in the presence of expiring 0DTE contracts. Although rough, the similarity between these estimates of the cumulative intraday effect and of the average treatment effect adds to the evidence that market makers' hedging activity is a central mechanism dampening the 10-minute index volatility on 0DTE expiration days.

4.3. Intraday Hedging and Order Flow in the E-mini Futures

This section leverages data about intraday order flows in the E-mini futures market. The E-mini contract is extremely liquid and one of the primary instruments that market makers can use to hedge SPX options. We document that higher market makers' net gamma in a 10-minute interval predicts a stronger reversal relationship between returns and subsequent order flow in following intervals. The evidence supports our hypothesis that the market makers' hedging activity dampens the index volatility.

We measure the order flow within each 10-minute interval to match the frequency of the option open-close volume data. We obtain intraday trades and top-of-book quotes from the Chicago Mercantile Exchange. Since trades are executed at the bid or ask price, we can identify each trade as a buy or a sell order. We can then cumulate the buy orders minus the sell orders within each 10-minute interval, which we use to construct two measures of order flows.

The first measure *Order Flow* has in the numerator the number of contracts that traded due to buy orders minus the number that traded due to sell orders, multiplied by 50, the number of shares represented by one futures contract. The denominator M is the number of S&P 500 shares. As a result, the *Order Flow* ratio measure is expressed relative to the size of the S&P 500. The second measure *Order Imbalance* also has in the numerator the difference between buy and sell orders in a given interval, but the denominator is the total E-mini trading volume during that interval. Therefore, the *Order Imbalance* ratio measures the net order flow as a share of the gross trading volume.

We combine information about the S&P 500 returns and the market makers' hedging needs to predict the order flows in the next 10-minute interval:

$$y_{t+1} = \alpha + b_0\Gamma_t + b_1 R_t + b_2(R_t \times \Gamma_t) + \text{Controls} + \text{Lags} + \text{FE} + \epsilon_{t+1}, \tag{11}$$

where we drop the date subscript d for simplicity, t is one 10-minute interval between market open at 9:30 am and market close at 4:00 pm, and y_{t+1} is either the *Order Imbalance* or the *Order Flow* measure over the next interval. We estimate Equation (11) in a panel regression where we again control for a rich set of fixed effects and two lags of the dependent variable.

Consider the partial effect of varying the current returns R_t on the future order flow, given by:

$$\frac{dE\left[y_{t+1}|\Gamma_t\right]}{dR_t} = b_1 + b_2\Gamma_t. \tag{12}$$

This shows that Equation (11) captures two important features. First, we expect the coefficient b_1 to be negative if there is a reversal relationship between returns and subsequent order flow. That is, if the net order flow in a given interval tends to move in the direction opposite to the index returns during the previous interval (a negative cross-autocorrelation between returns and order flow). Second, and this is our focus, we expect b_2 to be negative. In our framework, a positive net gamma indicates that market makers would need to sell S&P 500 shares to hedge positions when the index level rises and buy shares when it decreases. Furthermore, the magnitude of net gamma indicates how much of the underlying shares the market makers would need to buy or sell. Hence, a negative coefficient b_2 implies that this negative return–order-flow cross-autocorrelation is stronger at higher levels of net gamma (or a weaker momentum pattern if b_1 is positive).

Columns (1)–(2) of Table 6 report the estimation results for *Order Flow* and *Order Imbalance*, respectively. The estimated coefficients $\hat{b}_1$ for the current returns R_t are negative and statistically significant in both cases. The estimates are also economically significant.

Consider a 14 bps negative index return in a given interval, which amounts to one standard deviation in our sample. For *Order Flow*, the point estimate for b_1 in Column (1) predicts that buy orders will exceed the sell orders during the next 10 minutes by $0.0026 \times 0.0014 = 0.00036$ percent, relative to the size of the S&P 500. For the *Order Imbalance* measure, the point estimate for b_1 in Column (2) predicts that buy orders will exceed sell orders by 0.8 percent as a share of the gross trading volume.

The point estimate for the interaction term coefficient b_2 is negative, as predicted by the analysis of hedging needs. The estimate is also statistically significant and economically meaningful when using either order flow measure. We can compare it with the magnitudes obtained using only the coefficient b_1. Consider moving the value of market makers' net gamma from zero to 55 bps, close to the intraday standard deviation after May 2022 in Table 3. In the case of the *Order Flow* measure, the point estimate b_2 in Column (1) adds a term $0.0014 \times 0.0055 \times 0.17$ to the response, so that the total predicted gap between buy orders and sell orders over the next 10 minutes rises to about 0.00049 percent of the S&P 500 capitalization, an increase of about 36% over the b_1-only prediction of 0.00036 percent. In the case of the *Order Imbalance* measure, the point estimate in Column (2) implies that the total predicted gap rises to nearly 1.2 percent as a share of the gross trading volume over the next 10 minutes, about a 40% increase over the b_1-only prediction of 0.8 percent.

The order flow response persists beyond the next interval. To show this, we use the same model from Equation (12) but with order flow for each future 10-minute interval over the next hour as the dependent variable. Figure 9 shows the predicted response to a positive S&P 500 return across all horizons when $Net\Gamma_t$ increases by one intraday standard deviation. This shift in the order flow response is larger in the next 10-minute interval, and the estimates decay smoothly toward zero over the next hour. The estimates are statistically significant over the next 30 minutes. Looking back to earlier results, we see that this pattern is similar to the smooth decay in the predicted response of future volatility that we documented in Figure 8. This similarity is telling because the negative response of the E-mini order flow to the market return is a key step in the mechanism by which the market makers' hedging needs can dampen volatility.

We acknowledge that we cannot identify the originator of E-mini futures market orders. However, it is reasonable to assume that option market makers actively trade in the E-mini futures market to hedge some of their net gamma exposures. If that is the case, the patterns in intraday order flows add to the overall evidence that the market makers' hedging needs play a central role in dampening S&P 500 volatility. Nonetheless, other investors and intermediaries may also participate in inducing the reversal pattern in the E-mini order flows, and we do not attribute the predicted response exclusively to option market makers.

4.4. Momentum Returns

In this section, we analyze how S&P 500 momentum returns change across levels of market makers' net gamma. Because higher hedging needs are linked to a stronger reversal pattern in the intraday order flow, we should expect a compression effect in intraday momentum returns, unless the E-mini market is perfectly elastic.

We compute the simple returns $R_{t,t+n} = (\frac{ES_{t+n}}{ES_t} - 1) \times 10,000$ in bps units for a buy-and-hold investment across horizons between ten minutes and two hours, where ES_t is the E-mini futures price at time t. The momentum return for the horizon n is defined as the first difference $R_{t,t+n} - R_{t-n-1,t-1}$. Note that we omit the 10-minute returns $R_{t-1,t}$ to remain conservative: this reduces the overlap between the computation of the momentum returns and the computation of the $Net\Gamma_t$ measure.

We estimate panel regressions that include a set of dummy variables indicating the quartile of market makers' $Net\Gamma_t$. We use the same *Date* and *Year* × *Week* × *Time* fixed effects as before to isolate intraday variations, and we do not include a constant. The point estimates measure the average momentum returns across quartiles of the market makers' net gamma, after absorbing intraday seasonality with the fixed effects.

Table 7 reports the estimates across quartiles of net gamma in Columns (1) to (4) and across investment horizons across rows. In Column (1), for the low net gamma quartile, the average return estimates are positive across all investment horizons, and they increase monotonically from almost zero in the next 10-minute interval to around 0.7 bps at the 1- and 2-hour horizons.

We find that the average momentum returns consistently decrease across higher net gamma quartiles. The estimates turn negative once net gamma reaches the third quartile. This fourth-quartile effect is statistically significant at the 1- and 2-hour horizons. Overall, we observe small positive momentum returns for lower levels of market makers' net gamma, but negative momentum returns (or positive reversal returns) of around $1-2$ bps across the investment horizons for the higher level of net gamma. The difference between the first and fourth quartile ranges between -1 and -3 bps across investment horizons between 30 minutes and 2 hours, and it is statistically significant.

The pattern is consistent with the hedging mechanism compressing momentum returns, and consistent with the persistence that we documented for the predicted response of order flow and intraday volatility. The effect is also economically meaningful. For instance, Savor and Wilson (2013) finds that the average daily S&P 500 excess return is 2.24 bps between 1958 and 2009. Knox, Londono, Samadi, and Vissing-Jorgensen (2026) find an average daily implied equity premium of 3.68 bps.[18] However, this result does not translate into a feasible trading strategy since the market makers' net gamma is not observable to other investors.

5. Conclusion

The introduction of SPXW contracts expiring every weekday has led to a significant surge in 0DTE trading. It has also raised concerns that trading these ultra-short-maturity options leads market makers to accumulate large exposures that are highly sensitive to S&P 500 variations, which they may hedge in a way that destabilizes the stock market. Contrary to these concerns, we show that the availability of 0DTEs reduces intraday index volatility. We document the economic mechanism behind such volatility attenuation: days

[18] Both Savor and Wilson (2013) and Knox, Londono, Samadi, and Vissing-Jorgensen (2026) emphasize that the daily equity premium is much higher on days with macro announcements.

with expiring 0DTE contracts significantly increase the hedging needs of market makers in the direction that requires them to trade against index price movements, thereby acting as liquidity providers and dampening underlying index volatility. The evidence provides a baseline and contributes to the active debate among investors, regulators, and the Cboe exchange around the potential spillover from the options market to the S&P 500 due to the growth in 0DTE trading.

Our results also raise important questions for future research. We find that the market makers' net gamma increases on 0DTE expiration days because of transactions in non-0DTE options in earlier days. This points toward dynamic management of hedging needs over multiple days, beyond a traditional view of static or passive inventory management by intermediaries. We also conclude that intermediaries acting in the option market have a substantial price impact on the aggregate stock market. While the dampening effect on volatility appears beneficial to investors on average, variation in hedging needs may introduce a distinct source of aggregate risk with further asset pricing implications for the stock and option markets.

References

Almeida, C., G. Freire, and R. Hizmeri, 2024, "0DTE Asset Pricing," *Working paper, Princeton University.*

Amaya, D., P. A. Garcia-Ares, N. Pearson, and A. Vasquez, 2025, "0DTE Index Options and Market Volatility: How Large is Their Impact?," *Working paper, ITAM.*

Arrow, K. J., 1964, "The Role of Securities in the Optimal Allocation of Risk-Bearing," *Review of Economic Studies*, 31(2), 91–96.

Bandi, F. M., N. Fusari, and R. Reno, 2023, "0DTE Option Pricing," *Working paper, Johns Hopkins University.*

Beckmeyer, H., N. Branger, and L. Gayda, 2023, "Retail Traders Love 0DTE Options... But Should They?," *Working paper, University of Munster.*

Brogaard, J., J. Han, and P. Y. Won, 2025, "How Does Zero-Day-To-Expiry Options Trading Affect the Volatility of Underlying Assets?," *Working paper, University of Utah.*

Frey, R., 1998, "Perfect option hedging for a large trader," *Finance and Stochastics*, 2(2), 115–141.

Grossman, S. J., and M. H. Miller, 1988, "Liquidity and Market Structure," *The Journal of Finance*, 43(3), 617–633.

Hu, J., A. Kirilova, D. Muravyev, and D. Ryu, 2024, "Options Market Makers," *Working paper, Singapore Management University.*

Jarrow, R. A., 1994, "Derivative Security Markets, Market Manipulation, and Option Pricing Theory," *Journal of Financial and Quantitative Analysis*, 29(2), 241–261.

Knox, B., J. M. Londono, M. Samadi, and A. Vissing-Jorgensen, 2026, "Equity Premium Events," working paper, Federal Reserve Board and Rutgers Business School, Working Paper. New version, April 2026.

Lipson, M. L., D. Tomio, and J. Zhang, 2023, "A Real Cost of Free Trades: Retail Option Trading Increases the Volatility of Underlying Securities," *Working paper, Darden School of Business.*

Ni, S. X., N. D. Pearson, A. M. Poteshman, and J. White, 2021, "Does Option Trading Have a Pervasive Impact on Underlying Stock Prices?," *The Review of Financial Studies*, 34(4), 1952–1986.

O'Donovan, J., G. Y. Yu, and J. Zhang, 2024, "Option Market Maker Hedging and Stock Market Liquidity," Working Paper City University of Hong Kong.

Saksena, N., M. Welty, J. A. Serur, and B. Bowler, 2023, "The truth on 0DTE intraday gamma imbalances," *Bank of America Global Research Paper.*

Savor, P., and M. Wilson, 2013, "How Much Do Investors Care about Macroeconomic Risk? Evidence from Scheduled Economic Announcements," *Journal of Financial and Quantitative Analysis*, 48(2), 343–375.

Stein, J. C., 1987, "Informational Externalities and Welfare-Reducing Speculation," *Journal of Political Economy*, 95(6), 1123–1145.

Xu, M., 2023, "Much Ado About 0DTEs: Separating Fact from Friction," working paper, Chicago Board of Options Exchange.

Figures

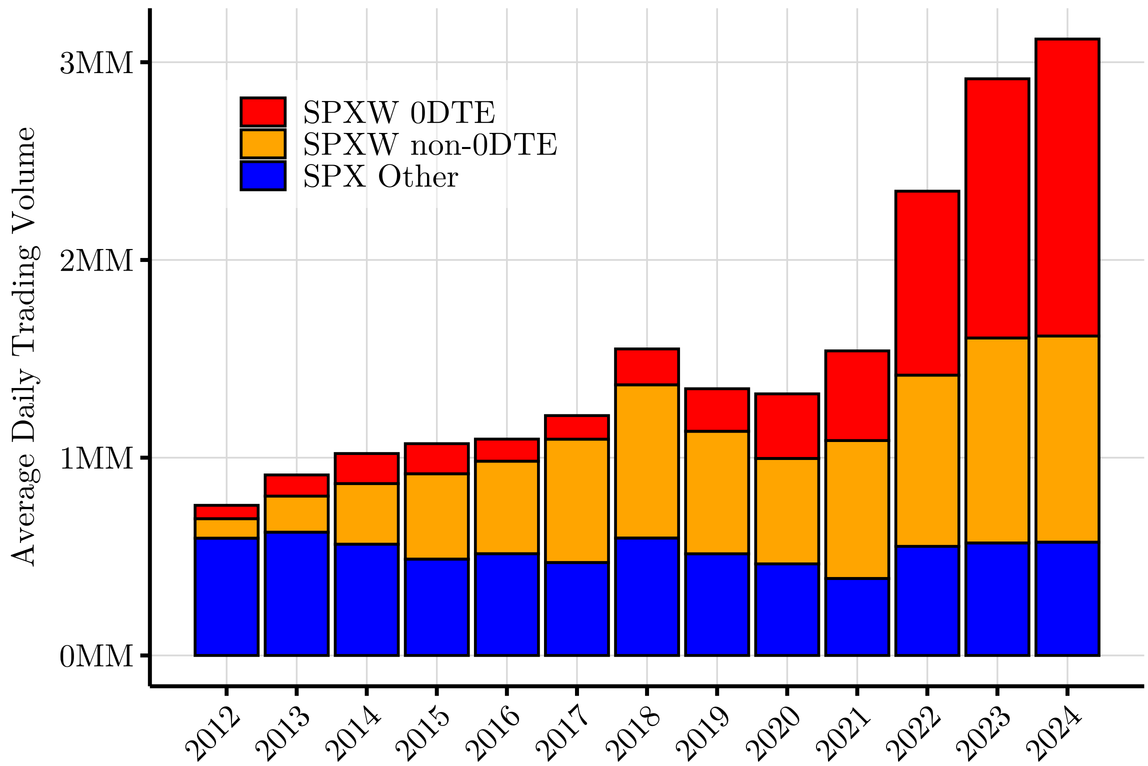


Figure 1: Growth in Trading Demand for SPXW Contracts. Average daily number of contracts traded across S&P 500 index options (SPX). The daily sum is the number of contracts traded by all investors other than market makers. We plot the results separately for weekly expiring contracts (SPXW) that have zero-days-to-expiration (SPXW 0DTE) or that have longer maturities (SPXW non-0DTE). We also plot the results for all other longer-dated SPX options (e.g., SPX, SPXQ, and SPXPM). Data come from the intraday trades and quotes across all exchanges as reported by the Options Price Reporting Authority (OPRA).

Alternative text: Annual SPXW 0DTE trading volume rises sharply after 2022, while SPXW non-0DTE and other SPX option volumes grow more gradually.

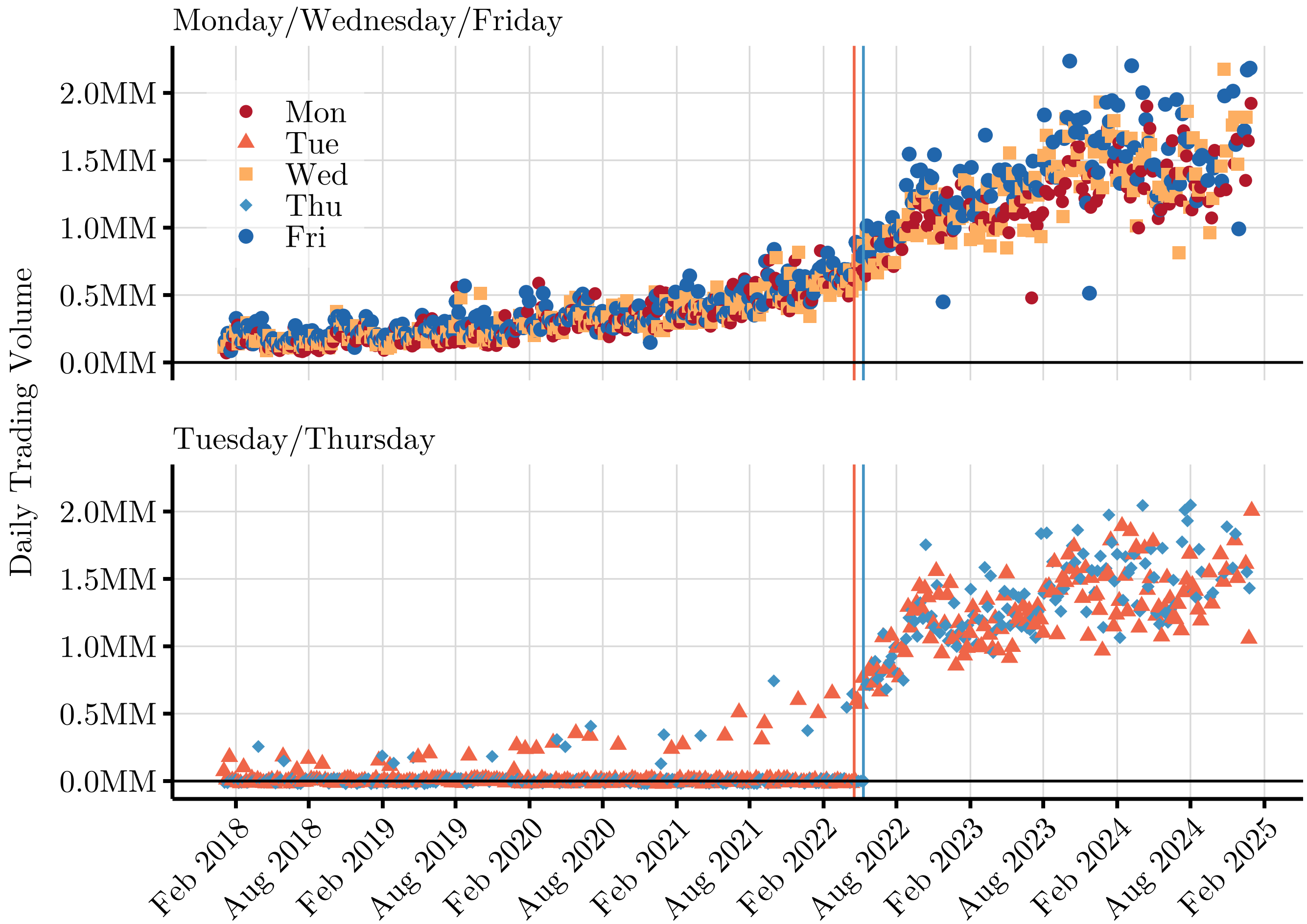


Figure 2: Daily 0DTE Trading Volume by Weekday, 2018-2024. Number of 0DTE contracts traded for every business day from 01/2018 to 12/2024. 0DTE contracts could trade on Tuesdays and Thursdays before 2022 when (i) end-of-month or end-of-quarter SPX contracts with PM settlement expired on a Tuesday or Thursday or (ii) when a Monday, Wednesday, or Friday was a holiday and the corresponding SPXW contracts expired on a neighboring Tuesday or Thursday. Regular SPXW contracts were introduced for Tuesdays and Thursdays in 2022 (vertical red lines). Days with a sudden drop in volume in the upper panel are due to U.S. Independence Day and Thanksgiving, when the Cboe's regular trading hours end at 1 pm. Markers that are visually close to the x-axis are exactly zero, but we introduce some visual variation so that the x-axis can be distinguished.

Alternative text: Daily 0DTE volume is concentrated on Monday, Wednesday, and Friday before 2022, then appears regularly on Tuesday and Thursday after contract introductions.

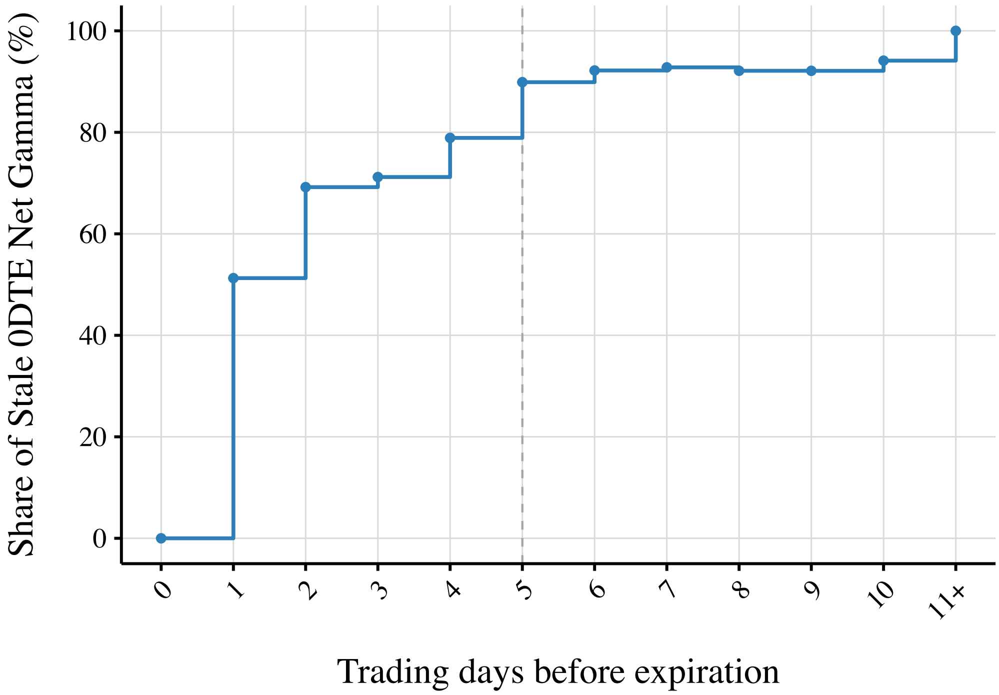


Figure 3: Origination of Stale 0DTE Net Gamma. Cumulative share of market makers' Stale 0DTE net gamma due to positions opened before the expiration date, on average in our sample, but disaggregated for each pre-expiration day. The horizontal axis is the distance in days from the expiration day. Zero is the expiration day, and "11+" collects positions opened eleven or more trading days earlier. The sample period is from May 19, 2022, to 12/2024.

Alternative text: The cumulative share of stale 0DTE net gamma increases with positions opened further before expiration, including positions opened eleven or more trading days earlier.

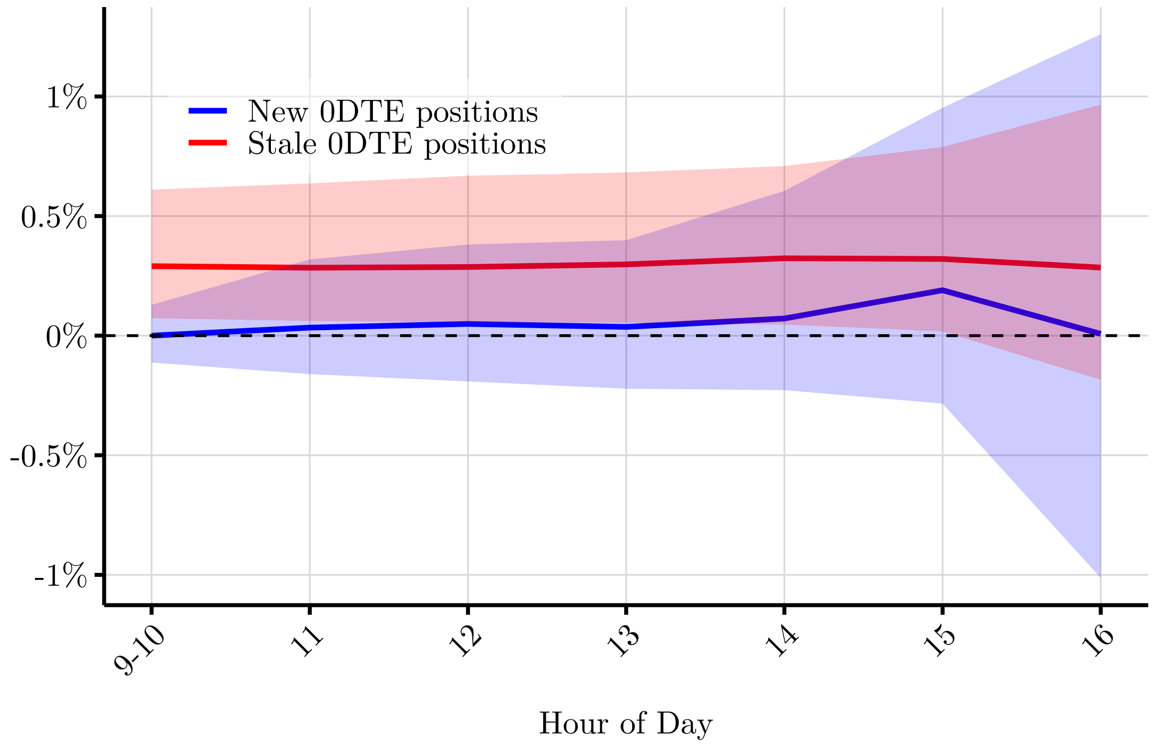


Figure 4: Market Makers' Net Gamma due to New and Stale 0DTE Positions. Median net gamma exposures of market makers' 0DTE positions, measured as a percentage share of the S&P 500 capitalization that market makers should sell to hedge after a 1% market return, for every hour of the trading day, separately for New (blue) and Stale (red) positions. New 0DTE positions are those opened after 4:00 p.m. on the trading day preceding expiration. Stale 0DTE positions are those opened earlier, when they were non-0DTE contracts. The solid lines indicate the medians, and the shaded bands indicate the hourly interquartile ranges. The sample period is from May 19, 2022, to 12/2024.

Alternative text: Median market-maker net gamma is positive for stale 0DTE positions throughout the day and is much smaller for newly opened 0DTE positions.

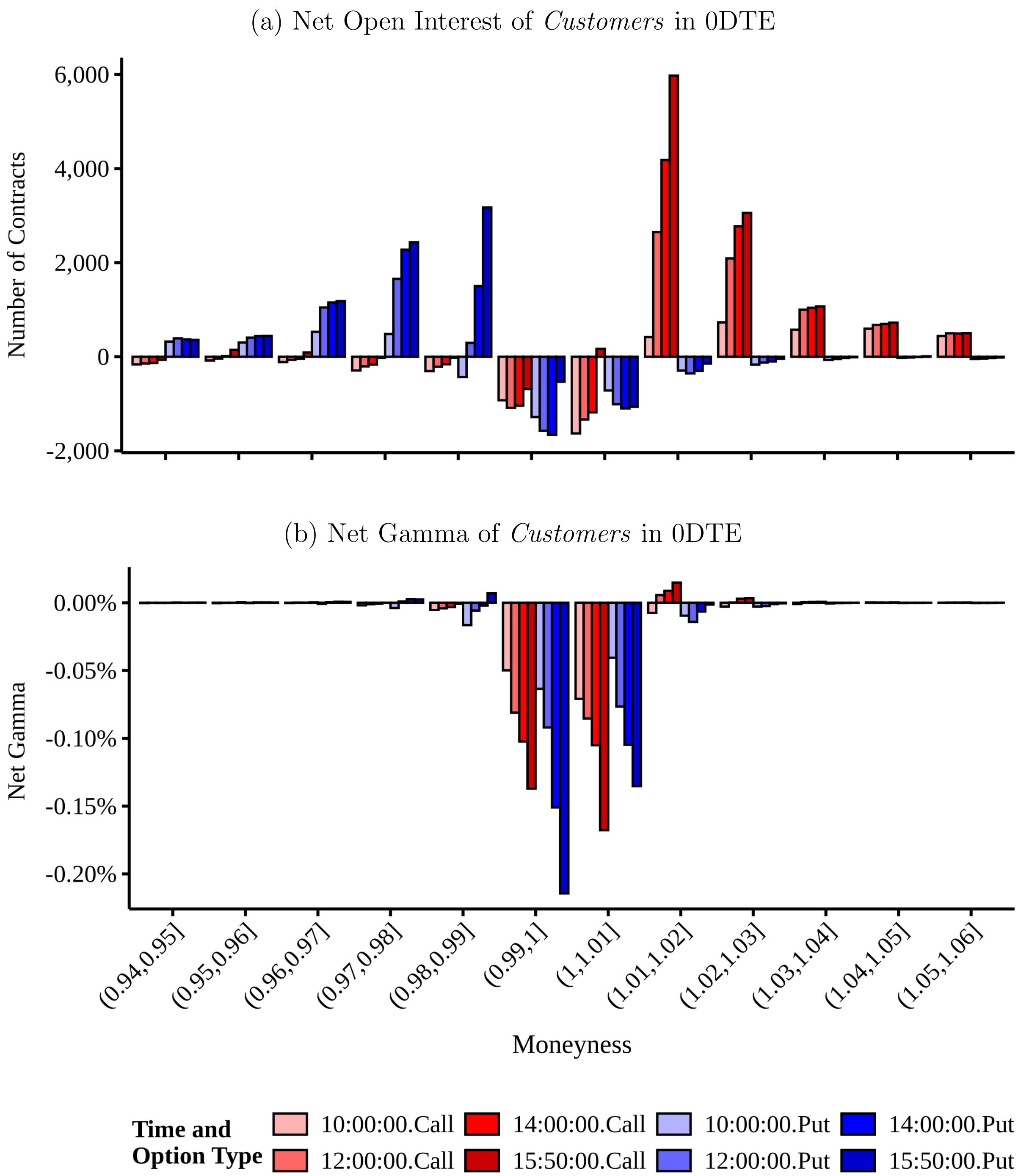


Figure 5: Intraday Net Open Interest and Net Gamma of End-users in 0DTE. Panel (a) shows the intraday *Customers* 0DTE net open interest. Panel (b) shows the *Customers* net gamma measured as a percentage share of the S&P 500 capitalization that market makers should sell to hedge after a 1% market return. We report the average values for put and call contracts and across moneyness by taking snapshots at 10:00, 12:00, 14:00, and 15:50 within the day. The 0DTE net gamma is largest for at-the-money options and quickly approaches zero for in-the-money or out-of-the-money options. Moneyness is defined as the strike price divided by the index price. The sample period is from May 19, 2022, to 12/2024.

Alternative text: Customer 0DTE net open interest and net gamma are largest near at-the-money strikes and decline toward in-the-money and out-of-the-money strikes.

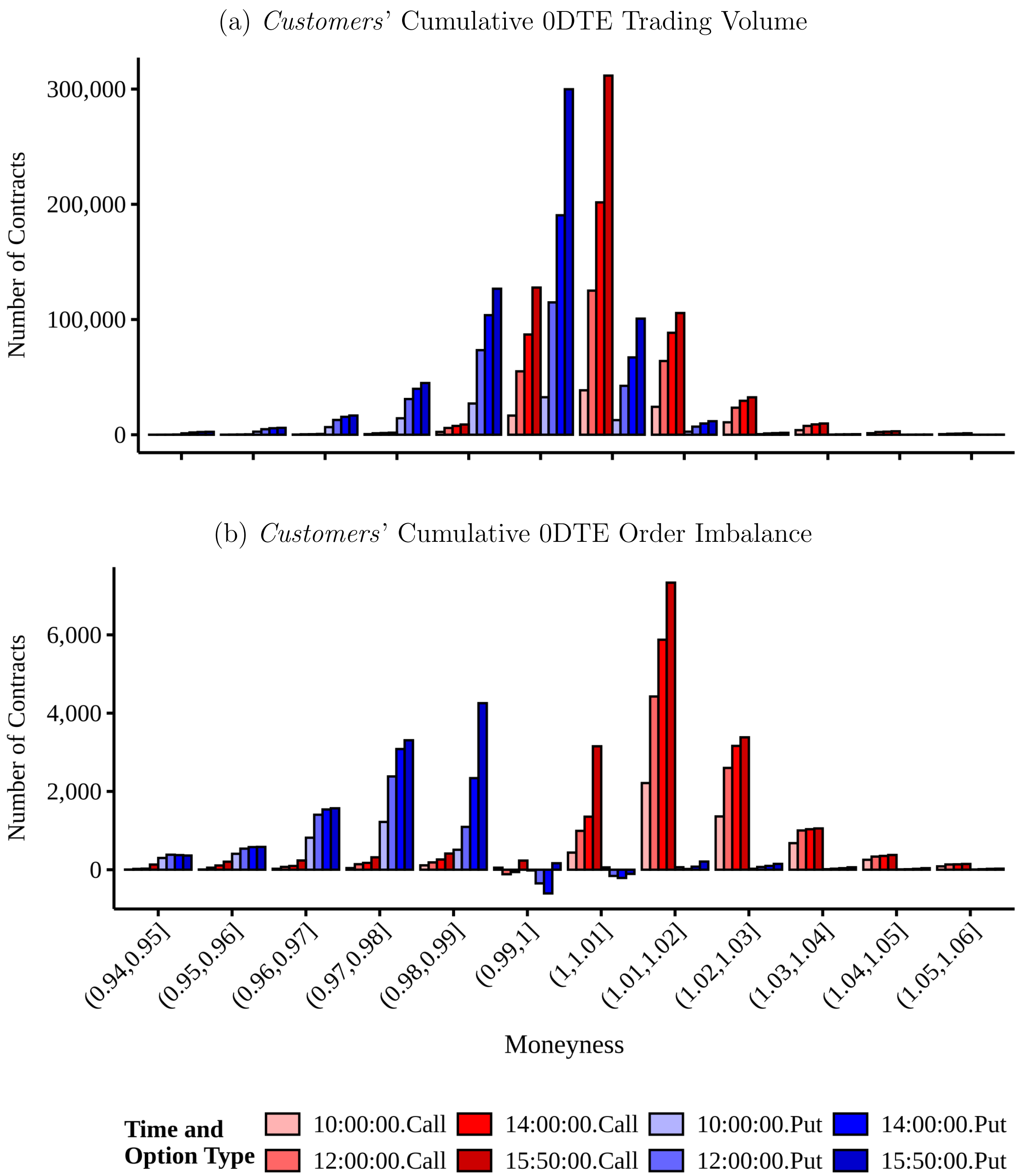


Figure 6: Customers' Intraday 0DTE Trading Volume and Order Imbalance. Panels (a) and (b) plot the intraday cumulative 0DTE trading volume and cumulative order imbalance of *Customers*. We plot averages across days for put and call contracts and across moneyness by taking snapshots within the day at 10:00, 12:00, 14:00, and 15:50. The gamma for short-maturity options is largest for at-the-money options and quickly approaches zero as moneyness moves toward in-the-money or out-of-the-money. Moneyness is the contract's strike price divided by the closing index price. The sample period is from May 19, 2022, to 12/2024.

Alternative text: Customer 0DTE trading volume and order imbalance accumulate through the day, with the largest activity near at-the-money strikes for both puts and calls.

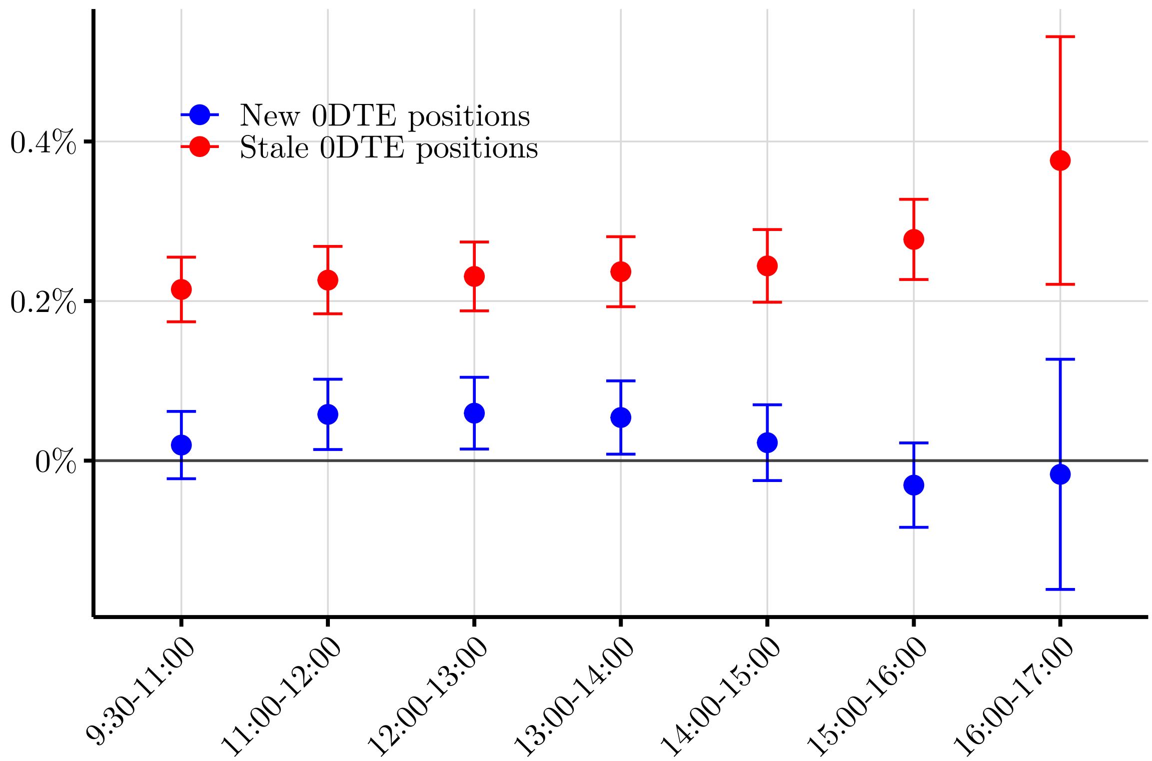


Figure 7: Effect of Expiring 0DTE Contracts on Market Makers' 0DTE Net Gamma. Estimated treatment effect of the presence of expiring 0DTE contracts on the hourly average market makers' 0DTE $Net\Gamma_t$ exposures, measured as a percentage share of the S&P 500 capitalization that market makers should sell to hedge after a 1% market return, separately for Stale (blue) and New (red) positions. New 0DTE positions are those opened after 4:00 p.m. on the trading day preceding expiration; Stale 0DTE positions are those opened earlier, when they were non-0DTE contracts. Each dot indicates a point estimate, and each range indicates its 95% confidence interval. The sample period is from 01/2018 to 12/2024.

Alternative text: Days with expiring 0DTE contracts raise stale market-maker net gamma throughout the trading day, while effects on new 0DTE net gamma are near zero.

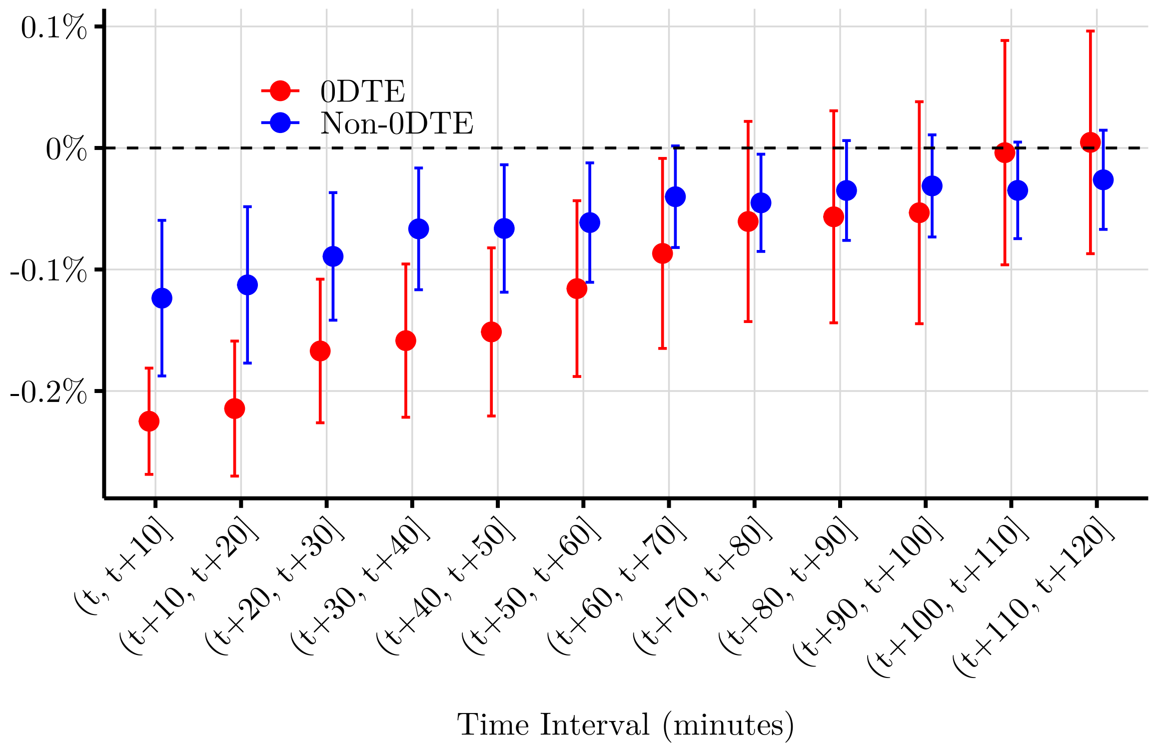


Figure 8: Predicted Response of Realized Volatility to Market Makers' Net Gamma. Predicted response of future realized volatility to a change in current market makers' net gamma. We combine a one-standard-deviation change in market makers' 0DTE or non-0DTE $Net\Gamma_t$ with the coefficient estimates from panel regression models that use the market makers' 0DTE or non-0DTE $Net\Gamma_t$ in a given intraday 10-minute interval t to predict the intraday realized volatility of the S&P 500 index in a future interval $t+n$, with $n = 1, \ldots, 12$. We use data after May 2022 to compute the standard deviation. Volatility is scaled to annualized percentage. Regression results are reported in Tables IA9-IA10 in the Internet Appendix. The x-axis indicates the forecast horizon. Two lags of the dependent variable are included in each regression, together with *Date* and *Year*$\times$ *Week*$\times$*Time* fixed effects. The 95% confidence intervals are calculated using Newey-West standard errors with 5 lags. The sample period is from 01/2018 to 12/2024.

Alternative text: A one-standard-deviation increase in market-maker 0DTE net gamma predicts lower realized volatility over subsequent intraday intervals than non-0DTE net gamma.

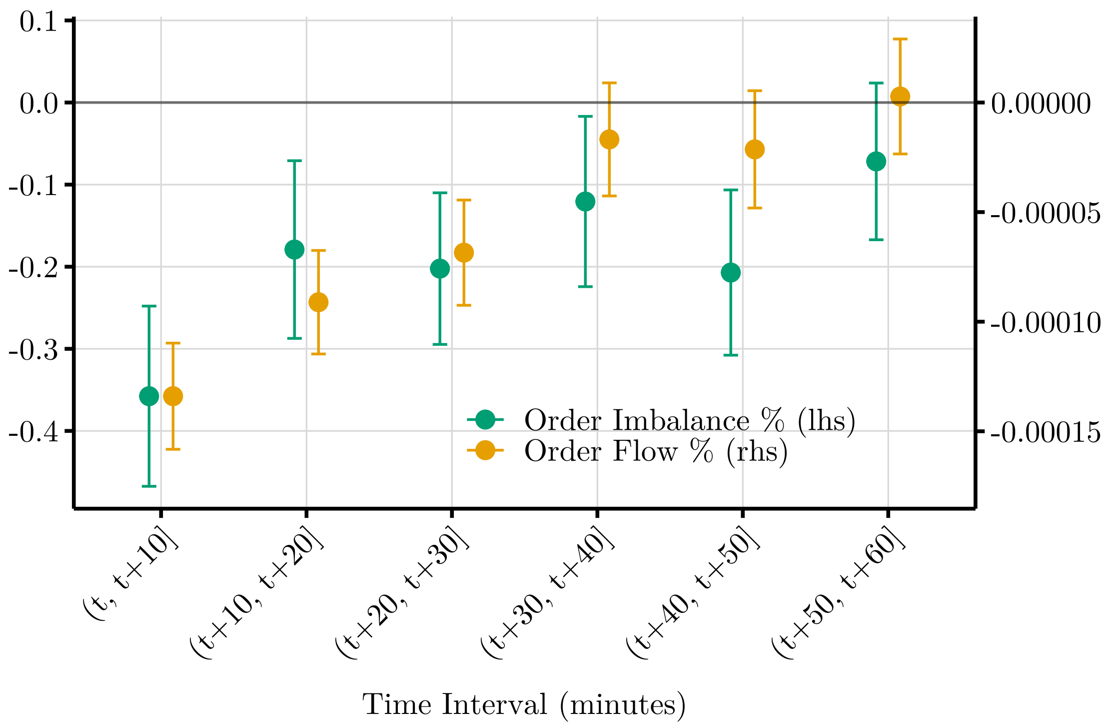


Figure 9: Stronger Order-Flow Reversal with Higher Market Makers' Net Gamma. Shifts in the predicted response of E-mini futures net order flows to positive S&P 500 returns when we raise the market makers' $Net\Gamma_t$ by one intraday standard deviation. We use data after May 2022 to compute the standard deviation. The shifts in responses are computed using the coefficient estimates from panel regressions estimated to predict the intraday *Order Flow* or *Order Imbalance* of the S&P 500 E-mini futures in a future interval $t+n$, with $n = 1, \ldots, 6$. *Order Flow* is the buy-minus-sell imbalance as a fraction of the S&P 500. *Order Imbalance* is the buy-minus-sell imbalance as a fraction of the gross order flow. Two lags of the dependent variable are included in each regression, along with *Date* and *Year*$\times$ *Week*$\times$*Time* fixed effects. The 95% confidence intervals are calculated using Newey-West standard errors with 5 lags. The sample period is from 01/2018 to 12/2024.

Alternative text: Higher market-maker net gamma strengthens E-mini order-flow reversal after positive S&P 500 returns, especially over short intraday horizons.

Tables

Dependent Variable:	Realized Volatility		
Model:	(1)	(2)	(3)
0DTE Expiration	-0.00456***	-0.00627***	-0.00613***
	(-4.9091)	(-3.0219)	(-2.9922)
Fixed-effects			
Year × Week × Time	Yes	Yes	Yes
Day-of-Week		Yes	
Year × Day-of-Week			Yes
Fit statistics			
Observations	42,831	42,831	42,831
R^2	0.71035	0.71162	0.71309
Within R^2	0.00217	0.00054	0.00051

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 1: Treatment Effect of Expiring 0DTE Contracts on S&P 500 Intraday Realized Volatility. Results from regression models of intraday return volatility of the S&P 500 E-mini futures (ES) on the presence of expiring 0DTE contracts. Each observation corresponds to a 10-minute interval of the trading day. The indicator variable *0DTE Expiration* is equal to 1 on days when there is an SPXW expiration and 0 otherwise. Intraday volatility is scaled to an annualized percentage. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 to May 19, 2022, when 0DTE options began expiring regularly on every weekday (*0DTE Expiration* becomes a constant afterward). Table IA2 of the Internet Appendix confirms these results using realized volatility computed for the S&P 500 cash index (Cash Index) or the SPDR S&P 500 ETF (SPY).

Dependent Variable:	Realized Volatility		
Model:	(1)	(2)	(3)
Tuesday/Thursday	0.0024***	0.0023***	0.0045***
	(3.646)	(3.557)	(4.874)
Introduction		-0.0124	-0.0097
		(-1.436)	(-1.123)
Tuesday/Thursday × Introduction			-0.0054***
			(-4.267)
Fixed-effects			
Year × Week × Time	Yes	Yes	Yes
Fit statistics			
Observations	66,656	66,656	66,656
R^2	0.69842	0.69848	0.69878
Within R^2	0.00081	0.00101	0.00200

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2: Introduction of Regular Tuesday and Thursday 0DTE Expirations. Results from a difference-in-differences analysis of the S&P 500 E-mini futures realized volatility around the introduction of SPXW contracts with Tuesday and Thursday expiration days. Each observation corresponds to a 10-minute trading interval. *Tuesday/Thursday* is an indicator variable for observations on Tuesdays or Thursdays. *Introduction* is an indicator variable equal to 1 for observations on or after April 26, 2022, the first regular Tuesday SPXW expiration (regular Thursday expirations followed on May 19, 2022). Realized volatility is scaled to an annualized percentage. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 to 12/2024.

	Mean	Median	SD	Intra SD	25th Pctl	75th Pctl
Before May 2022						
Realized Volatility	9.098	6.752	8.621	3.663	4.211	11.068
NetΔ_t	0.084	0.080	3.971	2.881	-0.235	0.446
0DTE NetΔ_t	0.025	0.000	2.620	1.421	-0.009	0.108
Non-0DTE NetΔ_t	0.058	0.051	4.087	2.886	-0.236	0.367
NetΓ_t	0.884	0.675	0.937	0.226	0.224	1.474
0DTE NetΓ_t	0.233	0.000	0.538	0.184	0.000	0.386
Stale 0DTE NetΓ_t	0.186	0.000	0.470	0.141	0.000	0.320
New 0DTE NetΓ_t	0.052	0.000	0.381	0.160	-0.005	0.095
Non-0DTE NetΓ_t	0.644	0.497	0.693	0.092	0.167	1.051
Before May 2022–Only 0DTE Days						
0DTE NetΔ_t	0.041	0.043	3.326	2.260	-0.160	0.294
0DTE NetΓ_t	0.376	0.268	0.642	0.278	0.026	0.630
Stale 0DTE NetΓ_t	0.293	0.220	0.567	0.222	0.003	0.492
New 0DTE NetΓ_t	0.083	0.036	0.481	0.251	-0.096	0.226
After May 2022						
Realized Volatility	8.292	6.913	5.412	3.472	4.749	10.208
NetΔ_t	0.281	0.220	5.559	4.224	-0.294	0.912
0DTE NetΔ_t	0.228	0.136	6.010	4.101	-0.261	0.725
Non-0DTE NetΔ_t	0.047	0.060	5.569	3.603	-0.258	0.417
NetΓ_t	1.424	1.049	1.413	0.547	0.474	2.098
0DTE NetΓ_t	0.542	0.316	0.957	0.512	0.000	0.875
Stale 0DTE NetΓ_t	0.392	0.296	0.579	0.233	0.052	0.665
New 0DTE NetΓ_t	0.159	0.027	0.857	0.515	-0.192	0.393
Non-0DTE NetΓ_t	0.867	0.722	0.751	0.129	0.338	1.250

Table 3: Summary Statistics. All variables are in percentage terms. Realized Volatility is scaled to an annualized percentage. Intraday SD is the time-series average of daily intraday standard deviation. 0DTE variables are zero on days without expiring 0DTE contracts. The sample period is from 01/2018 to 12/2024. We report the summary statistics separately in the sub-samples before and after 19 May 2022, when 0DTE options began expiring regularly on every weekday. We also report sub-sample results for days with 0DTE option expirations prior to May 19, 2022.

Dependent Variable:	$\text{Net}\Gamma_t$					Realized Volatility (2SLS)
Model:	0DTE	Stale 0DTE	New 0DTE	Non-0DTE	Overall	$\widehat{\text{Net}\Gamma_t}$ Overall
	(1)	(2)	(3)	(4)	(5)	(6)
0DTE Expiration	0.00275***	0.00247***	0.00029	-0.00137***	0.00153***	
	(9.1964)	(11.698)	(1.1753)	(-7.0152)	(4.6573)	
$\widehat{\text{Net}\Gamma_t}$ Overall						-4.0370***
						(-2.8955)
Fixed-effects						
Year × Day-of-Week	Yes	Yes	Yes	Yes	Yes	Yes
Year × Week × Time	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	42,929	42,929	42,929	42,822	42,822	42,820
R^2	0.44170	0.37259	0.32471	0.86532	0.77250	0.73229
Within R^2	0.01348	0.01265	0.00025	0.00838	0.00341	0.00060

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Treatment Effect of Expiring 0DTE Contracts on Market Makers' Net Gamma. Columns (1)–(5) report OLS results for panel regression models of intraday market makers' net gamma, separately for 0DTE positions, Stale and New 0DTE positions, non-0DTE positions, and all positions, respectively. Columns (1) and (4) do not add up to Column (5) because of a difference in the number of missing observations. Column (6) reports results of a 2SLS regression of intraday realized volatility on market makers' total net gamma. Each observation corresponds to a 10-minute interval of the trading day. The indicator variable *0DTE Expiration* is equal to 1 on days when there is an SPXW expiration and 0 otherwise. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 until May 19, 2022, when 0DTE options began expiring regularly on every weekday. Results using market makers' net delta are statistically insignificant.

Dependent Variable:	Realized Volatility (t+1)				
Model:	(1)	(2)	(3)	(4)	(5)
$\text{Net}\Gamma_t$	-0.4042***				
	(-13.16)				
$\text{Net}\Delta_t$	-0.0015				
	(-0.6116)				
0DTE $\text{Net}\Gamma_t$		-0.4392***		-0.4211***	-0.4231***
		(-8.816)		(-8.512)	(-8.597)
0DTE $\text{Net}\Delta_t$		-0.0040		-0.0032	-0.0031
		(-1.195)		(-0.9330)	(-0.9278)
Non-0DTE $\text{Net}\Gamma_t$			-0.9609***	-0.9173***	
			(-3.311)	(-3.283)	
Non-0DTE $\text{Net}\Delta_t$			0.0027	0.0012	0.0013
			(0.9462)	(0.4382)	(0.4464)
$[1,5]$DTE $\text{Net}\Gamma_t$					-0.7503***
					(-4.666)
$(5,\infty)$DTE $\text{Net}\Gamma_t$					-1.096*
					(-1.740)
Fixed-effects					
Year × Week × Time	Yes	Yes	Yes	Yes	Yes
Date		Yes	Yes	Yes	Yes
Fit statistics					
Observations	64,799	64,837	64,799	64,799	64,799
R^2	0.79028	0.81152	0.81157	0.81180	0.81180
Within R^2	0.32967	0.11682	0.11674	0.11780	0.11783

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Intraday Realized Volatility and Market Makers' Net Gamma. Results from panel regression models for S&P 500 intraday realized volatility. Each observation is a 10-minute interval within the trading day. The dependent variable is the realized volatility of the S&P 500 E-mini futures in the next 10-minute interval $t+1$, scaled to an annualized percentage. All independent variables are calculated with information up to time t. $Net\Delta_t$ and $Net\Gamma_t$ refer to market makers' net delta and net gamma, respectively. We report regression results using overall $Net\Delta_t$ and $Net\Gamma_t$ in Column (1), separately for 0DTE and non-0DTE positions in Columns (2)–(4), or for buckets with 0, $[1,5]$ and $(5,\infty)$ days to maturity in Column (5). Two lags of realized volatility are included. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 to 12/2024.

Dependent Variable:	Order Flow (t+1)	Order Imbalance (t+1)
Model:	(1)	(2)
Log Return	-0.0026***	-5.824***
	(-13.27)	(-18.93)
NetΓ_t	-0.0001	-0.2605
	(-1.465)	(-1.518)
Log Return × NetΓ_t	-0.1696***	-452.9***
	(-6.387)	(-10.84)
Fixed-effects		
Year × Week × Time	Yes	Yes
Date	Yes	Yes
Fit statistics		
Observations	56,148	56,148
R^2	0.78434	0.55813
Within R^2	0.20185	0.24316

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Intraday E-mini Order Flows and Market Makers' Net Gamma. Results from panel regression models for the S&P 500 E-mini intraday net order flows. Each observation is a 10-minute interval within the trading day. The dependent variable is the *Order Flow* or the *Order Imbalance* of S&P 500 E-mini futures in the next interval $t+1$. Each of the independent variables is calculated with information up to time t. $Net\Gamma_t$ refers to the market makers' net gamma aggregated across all SPX options. Two lags of the dependent variable are included in each case. Newey-West t-statistics with 5 lags are reported in parentheses. The sample period is from January 2018 to December 2024.

Interval (Minutes)	Quartiles of Market Makers' net gamma				
	Q1 (Low)	Q2	Q3	Q4 (High)	Q4−Q1 (Diff)
10	0.005	-0.010	0.084	-0.114	-0.119
	(0.04)	(-0.05)	(0.40)	(-0.52)	(-0.71)
30	0.449	0.029	-0.040	-0.606	-1.055***
	(1.58)	(0.07)	(-0.09)	(-1.34)	(-2.99)
60	0.633*	0.087	-0.271	-1.144**	-1.777***
	(1.73)	(0.17)	(-0.49)	(-1.97)	(-3.93)
120	0.730	0.181	-0.759	-2.158**	-2.888***
	(1.35)	(0.24)	(-0.92)	(-2.46)	(-4.18)

Fixed-effects: Year × Week × Time; Date
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 7: S&P 500 Momentum Returns and Market Makers' Net Gamma. Average intraday momentum returns in E-mini futures across quartiles of market makers' net gamma given by the coefficient β_i in the following regression model:

$$R_{t,t+n} - R_{t-n-1,t-1} = \sum_{i=1}^{4} \beta_i \cdot \mathbf{1}(\text{Net}\Gamma_t \in \text{Q}_i) + \text{Fixed Effect} + u_{t,n},$$

that we estimate without a constant, where each t corresponds to a 10-minute interval mark, $R_{t,t+n} = (\frac{ES_{t+n}}{ES_t} - 1) \times 10,000$ is the simple return in basis points from holding the E-mini futures between time t and $t+n$, and $\mathbf{1}(Net\Gamma_t \in \text{Q}_i)$ is the dummy variable equal to 1 if the market makers' net gamma at time t belongs to the Q_i quartile. Quartiles of market makers' net gamma are computed using a backward rolling window spanning 180 days. We include a rich set of fixed effects to isolate intraday variations in market makers' net gamma. Each row reports the estimates for a given return horizon n. Newey-West t-statistics in parentheses are calculated using $\min(5, n)$ lags. The sample period is from 01/2018 to 12/2024.

A1. Primary Data Sources

- Note: The sample period for the main analysis is from 01/2018 to 12/2024. All intraday data are collected during regular trading hours (9:30 AM–4:00 PM ET). Market maker positions sum the signed trading volumes from the start of each option series.
- **Cboe Open-Close Volume:** Intraday open-close volumes at 10-minute frequency from 01/2018 to 12/2024. End-of-day open-close volume at the daily frequency from 01/2012 to 12/2017. Includes open-buy, open-sell, close-buy, and close-sell volumes by trading capacity (market makers, customers, professional customers, proprietary firms, and broker-dealers). Used to calculate market maker positions in S&P 500 options.
- **Cboe Option Quotes:** Intraday quotes, price, implied volatility, delta, and gamma of each option contract at 1-minute frequency. Minute bar data from 01/2018 to 12/2024 with best bid and offer (BBO) quotes at the end of each minute. Used to calculate intraday hedging needs of market makers, e.g., net gamma and net delta.
- **CME E-mini Order Flow:** Top-of-book bid and ask prices, and trades. The front-month contract is used until 8 days to expiry, then rolled to the next quarterly contract. Used for calculating the *Order Flow* and *Order Imbalance* of the ES at 10-minute frequency. *Order Flow* is the aggregate of buy and sell orders at 10-minute frequency, calculated as (Buy − Sell) × 50 / M, where M is the number of shares in the S&P 500 index. *Order Imbalance* is the net order imbalance scaled by gross order flow at 10-minute frequency, calculated as (Buy − Sell) / (Buy + Sell).
- **Dividend Yields:** Daily option-implied S&P 500 index dividend yields for each expiration date, from OptionMetrics.
- **Interest Rates:** Daily term structure of zero-coupon interest rates, from OptionMetrics, interpolated to match option expiration dates.
- **Intraday Returns and Realized Volatilities:** Intraday close prices from DTN IQFeed for S&P 500 cash index and quotes (bid and ask) for E-mini S&P 500 Futures (ES) and SPDR S&P 500 ETF (SPY) at 1-minute frequency. Used to compute one-minute returns (from closing prices for the index and mid-quotes for ES and SPY) and 10-minute realized volatilities. ES is used in the main results. SPY and SPX are used as robustness checks.
- **Intraday Trades and Quotes:** Options Price Reporting Authority (OPRA) intraday best bid and offer (BBO), traded price, and quantity across all exchanges from 01/2012 to 12/2024. Used to calculate S&P 500 index options volume across all exchanges.

Internet Appendix to

Do S&P 500 Options Increase Market Volatility? Evidence from 0DTEs

IA1. Internet Appendix

IA1.1. Additional Figures and Tables

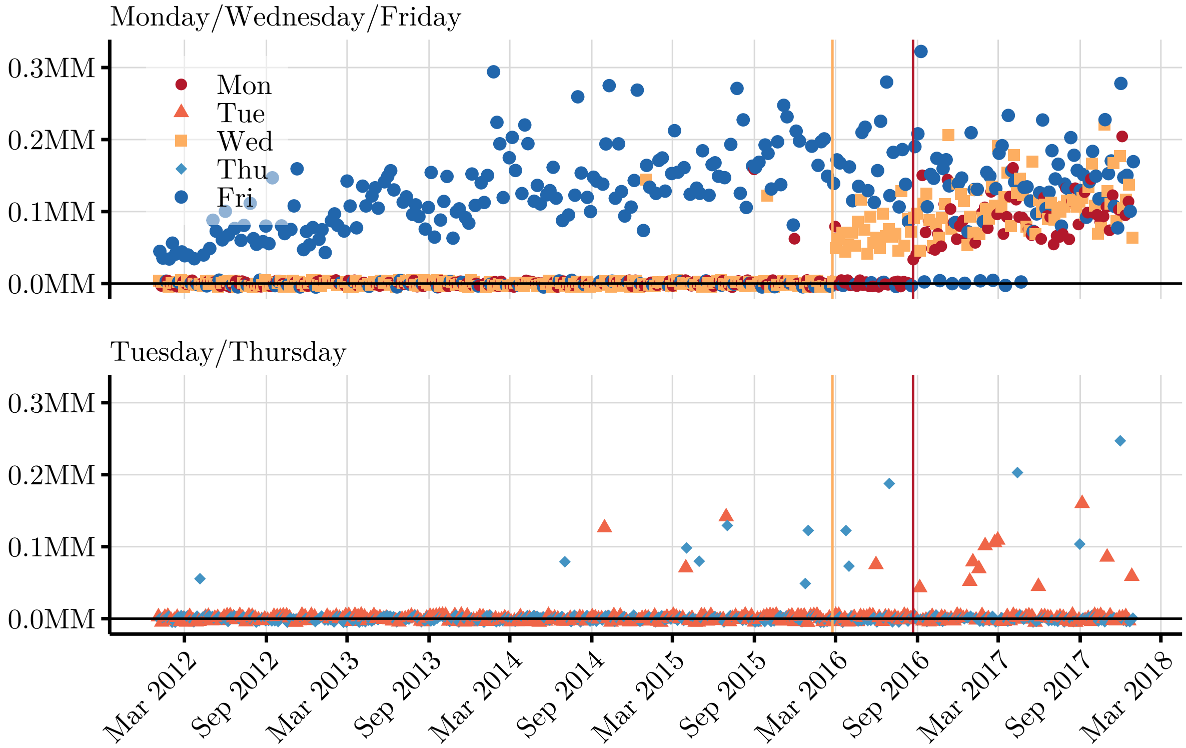


Figure IA1: 0DTE Trading Volume by Weekday, 2012-2018. Number of 0DTE contracts traded for every business day from 2012 to 2018. The vertical lines in the top panel indicate the introduction of regular weekly SPXW contracts expiring on Monday and Wednesday, respectively. 0DTE contracts could trade on weekdays before the corresponding weekly SPXW contracts were introduced either because (i) end-of-month or end-of-quarter SPX contracts with PM settlement expired that day or (ii) when a regular SPXW contract would have expired on a holiday. Markers that are visually close to the x-axis are exactly zero, but we introduce some visual variation so that the x-axis can be distinguished.

Alternative text: Before 2018, 0DTE volume appears mainly on regular expiration weekdays, with Monday and Wednesday activity increasing after weekly expirations are introduced.

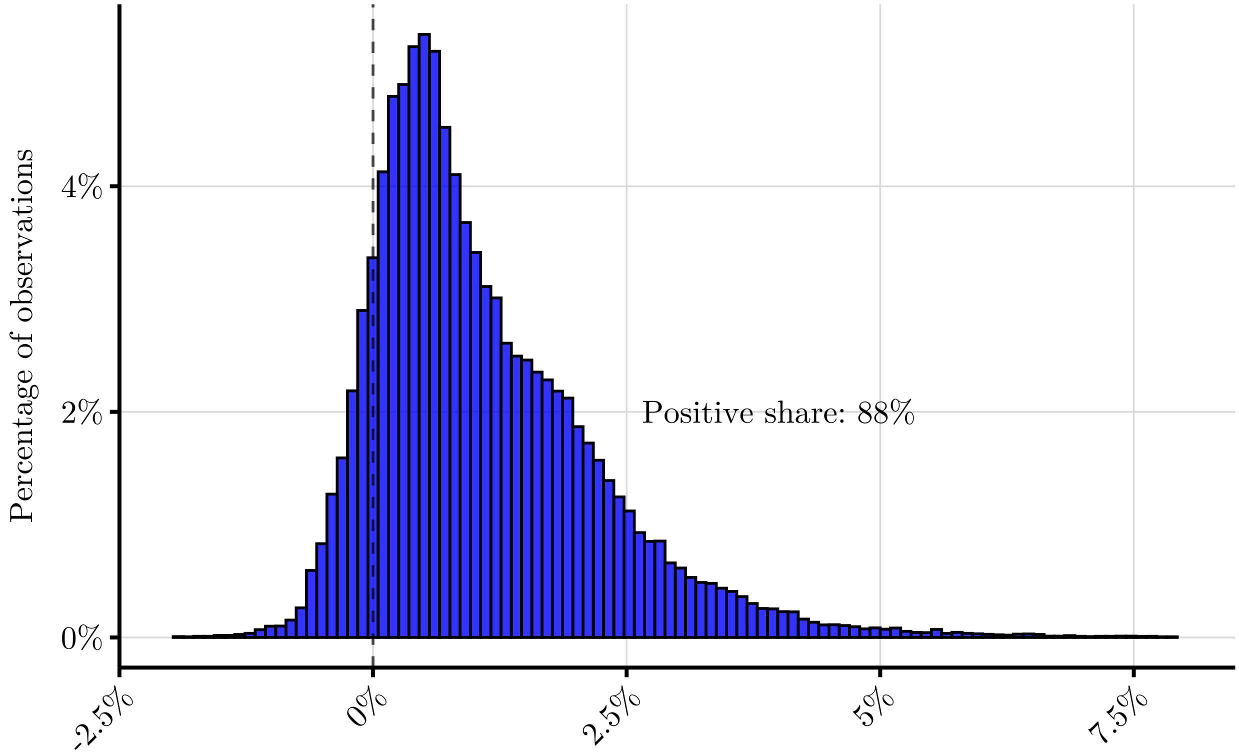


Figure IA2: Empirical Distribution of Intraday Market Makers' $\boldsymbol{Net\Gamma_t}$. Empirical distribution of market makers' net gamma in 10-minute intraday intervals during trading hours. The sample period is from 01/2018 to 12/2024.

Alternative text: The distribution of market-maker intraday net gamma is centered near zero but has both negative and positive tails across 10-minute intervals.

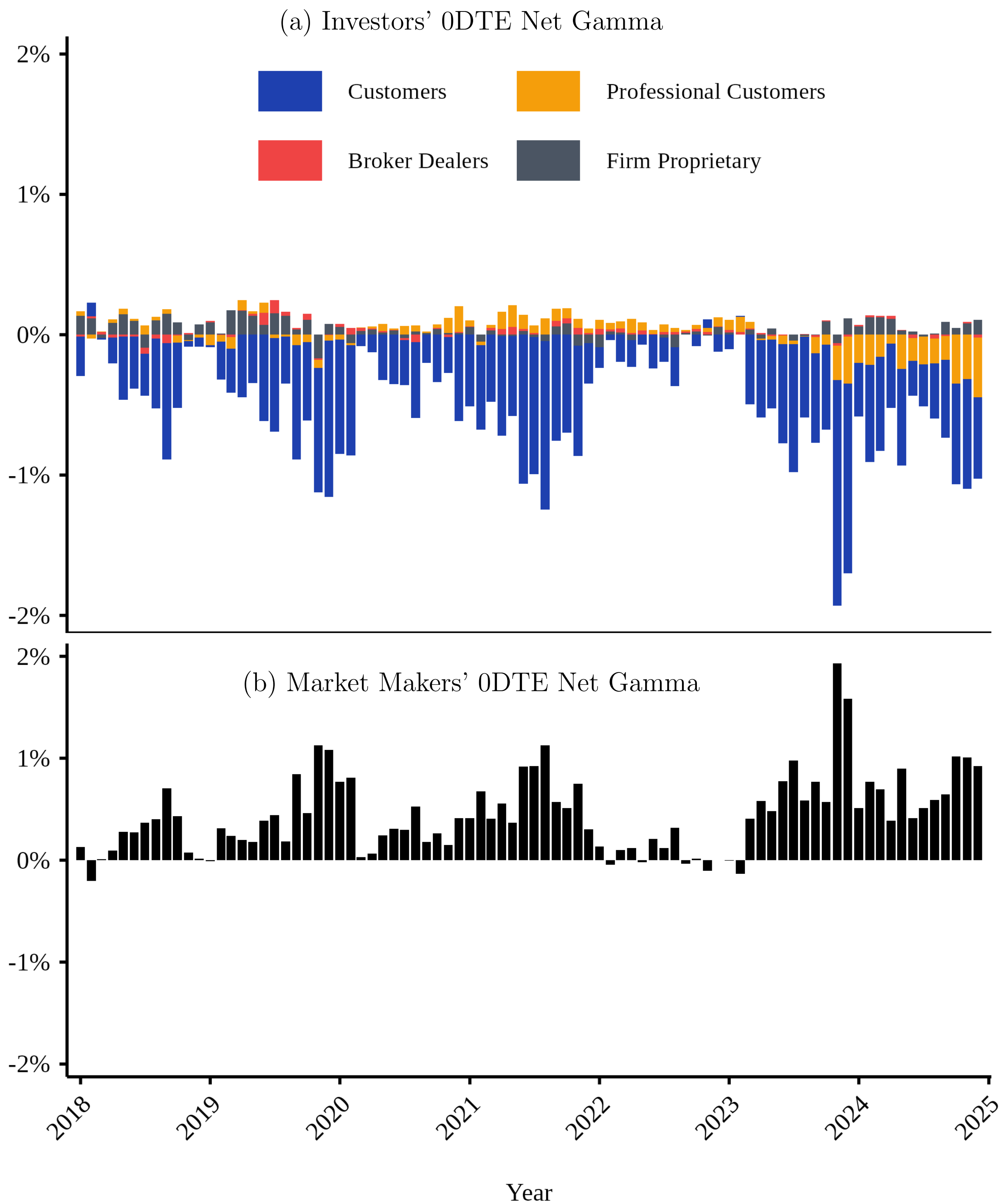


Figure IA3: Daily Average Values of 0DTE Net Gamma: A Decomposition. Time series of monthly averages of daily 0DTE net gamma. Panel (a): 0DTE net gamma by investor type. Panel (b): 0DTE net gamma of market makers, measured as a percentage share of the S&P 500 capitalization that market makers should sell to hedge after a 1% market return. The sample period is from 01/2018 to 12/2024. Market makers' net gamma mirrors the aggregated net gamma of *Customers*, *Professional Customers*, *Broker-Dealers*, and *Firm Proprietary.*

Alternative text: Customers, professional customers, broker-dealers, and firm proprietary traders have offsetting 0DTE net gamma positions mirrored by market makers over time.

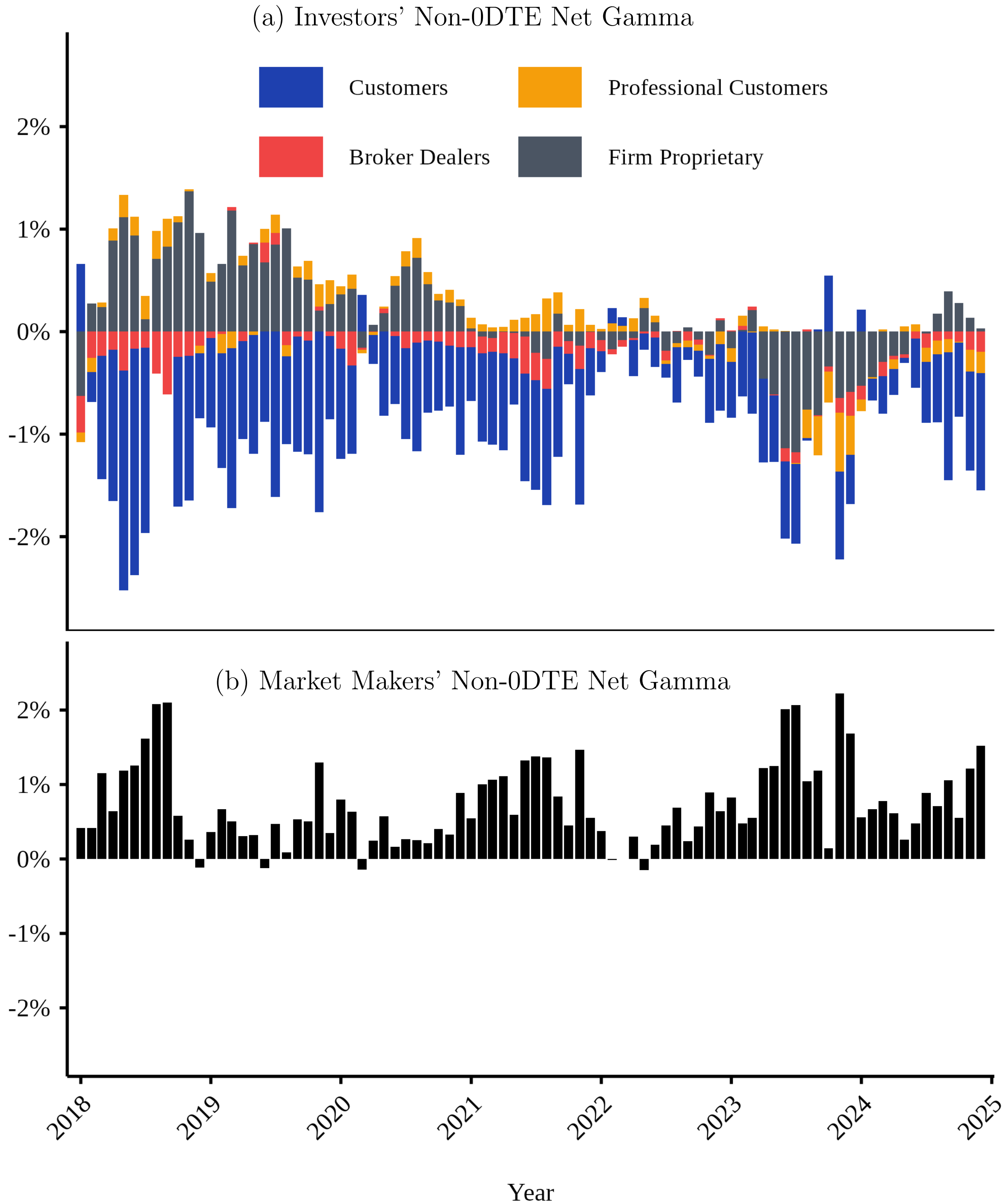
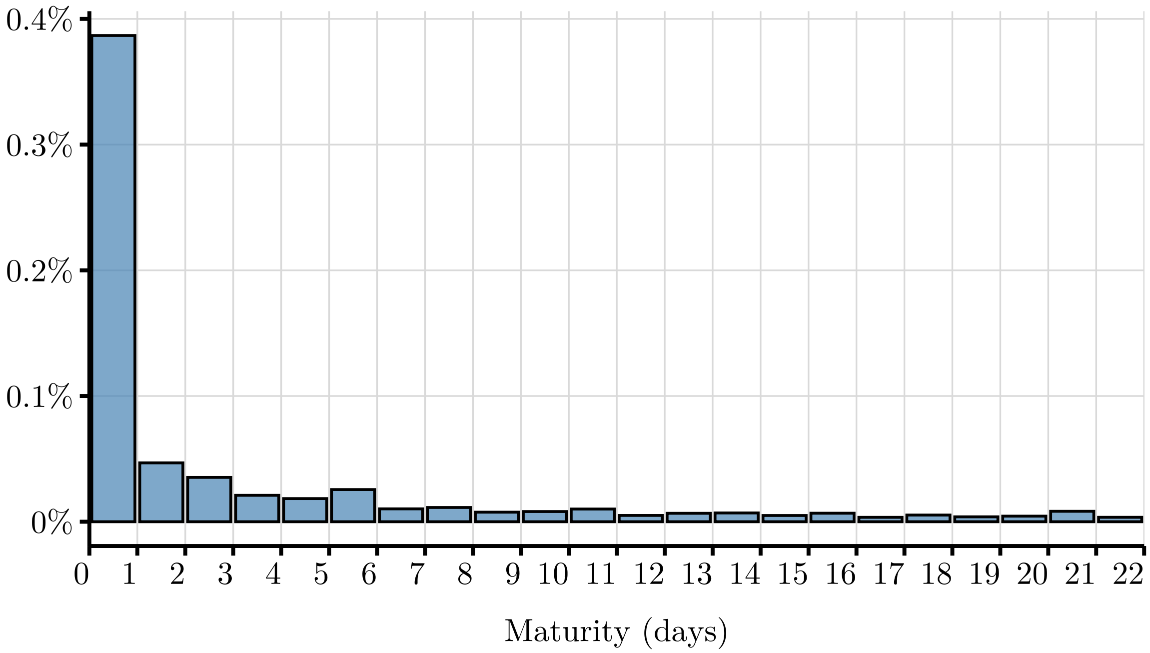
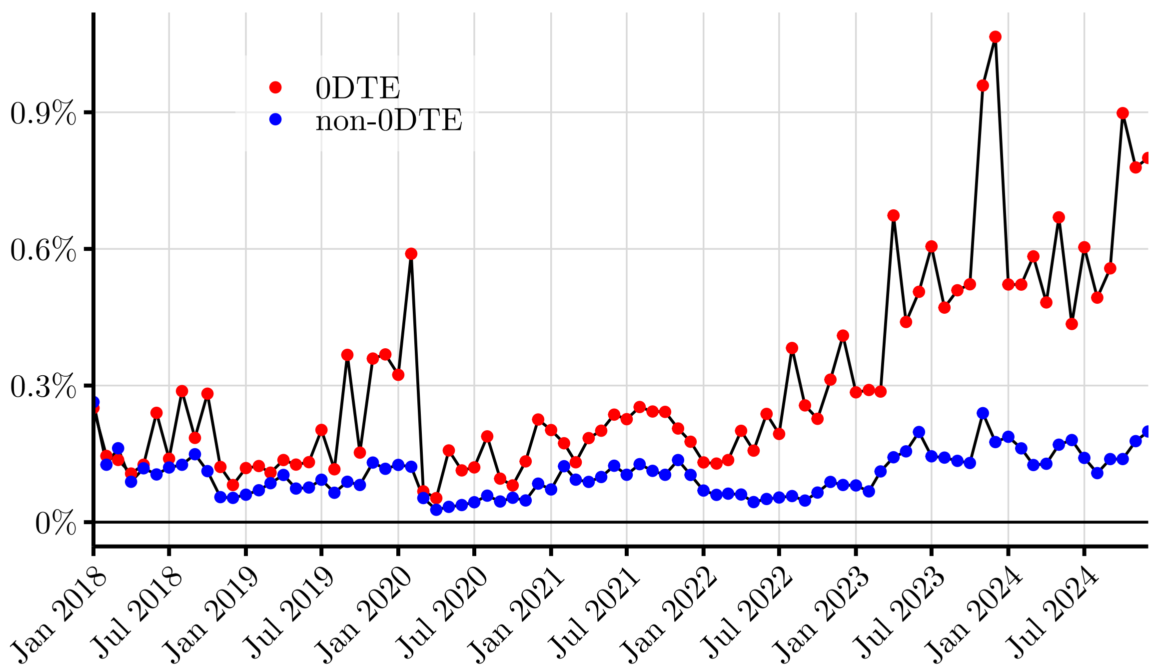


Figure IA4: Daily Average Values of Non-0DTE Net Gamma: A Decomposition. Time series of monthly averages of daily non-0DTE net gamma. Panel (a): non-0DTE net gamma by investor type. Panel (b): market makers' non-0DTE net gamma, measured as a percentage share of the S&P 500 capitalization that market makers should sell to hedge after a 1% market return. The sample period is from 01/2018 to 12/2024. Market makers' net gamma mirrors the aggregated net gamma of *Customers*, *Professional Customers*, *Broker-Dealers*, and *Firm Proprietary*.

Alternative text: Non-0DTE net gamma positions vary across investor types over time and are mirrored by market makers with the opposite aggregate exposure.



(a) Average daily intraday volatility across maturities



(b) Monthly average intraday volatility

Figure IA5: Volatility of Market Makers' Net Gamma. Panel (a) plots the average intraday volatility of 10-minute market makers' net gamma, measured as a percentage share of the S&P 500 capitalization that market makers should sell to hedge after a 1% market return, separately across contract maturities. Panel (b) plots the monthly averages of daily intraday volatility in market makers' net gamma separately for 0DTE and non-0DTE positions. The sample period is from 01/2018 to 12/2024.

Alternative text: Market-maker net gamma volatility is highest for the shortest maturities, with monthly 0DTE volatility moving differently from non-0DTE volatility.

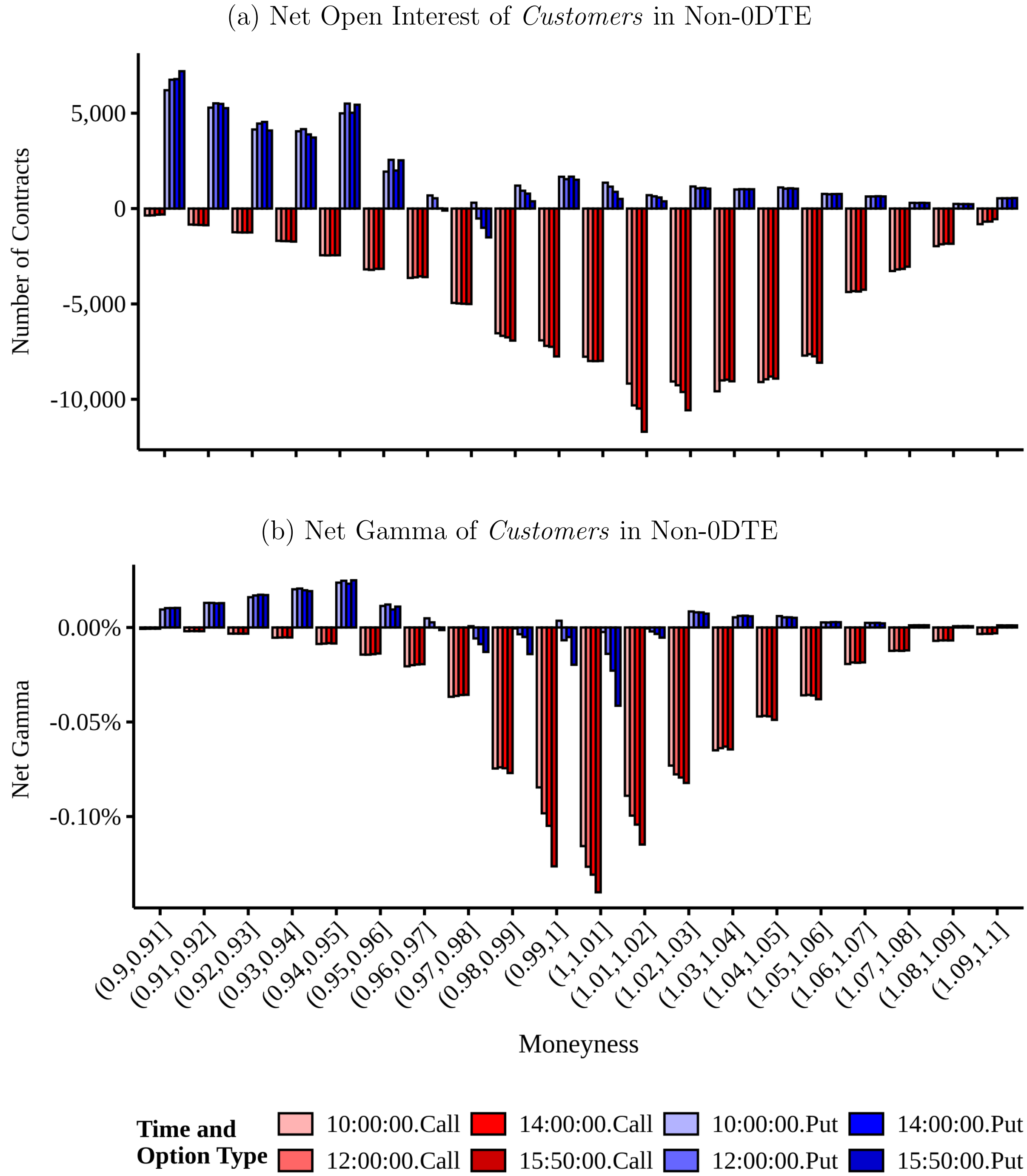


Figure IA6: Intraday Net Open Interest and Net Gamma of End-users in Non-0DTE. Panels (a) and (b) plot the *Customers*' intraday non-0DTE net open interest and net gamma, measured as a percentage share of the S&P 500 capitalization that market makers should sell to hedge after a 1% market return. We plot the average values for put and call contracts and across moneyness by taking snapshots within the day at 10:00, 12:00, 14:00, and 15:50. Moneyness is the contract's strike price divided by the closing index price. The sample period is from May 19, 2022, to 12/2024.

Alternative text: Customer non-0DTE net open interest and net gamma are concentrated near at-the-money strikes and vary across option type and intraday snapshots.

Dependent Variable:	Realized Volatility		
Model:	(1)	(2)	(3)
0DTE Expiration	-0.00363***	-0.00427***	-0.00326***
	(-6.7198)	(-5.9651)	(-3.2869)
Fixed-effects			
Year × Week × Time	Yes	Yes	Yes
Day-of-Week		Yes	
Year × Day-of-Week			Yes
Fit statistics			
Observations	101,350	101,350	101,350
R^2	0.70911	0.71037	0.71182
Within R^2	0.00146	0.00091	0.00026

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA1: Treatment Effect of Expiring 0DTE Contracts on Realized Volatility: 2012–2022 Sample. Results from panel regression models of intraday return volatility of the S&P 500 E-mini futures. Each observation corresponds to a 10-minute interval of the trading day. The indicator variable *0DTE Expiration* is equal to 1 on days when there is an SPXW expiration and 0 otherwise. Newey-West t-statistics calculated using 5 lags are reported in parentheses. Columns (1)–(3) report results across a range of fixed-effect specifications. Intraday volatility is scaled to an annualized percentage. The sample is from 01/2012 to May 19, 2022, when 0DTE options began expiring regularly on every weekday.

Dependent Variables:	Realized Volatility (SPY)			Realized Volatility (Cash Index)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
0DTE Expiration	-0.00490***	-0.00725***	-0.00712***	-0.00438***	-0.00586***	-0.00570***
	(-4.6004)	(-3.3701)	(-3.3861)	(-5.0025)	(-2.9579)	(-2.9092)
Fixed-effects						
Year × Week × Time	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-Week		Yes			Yes	
Year × Day-of-Week			Yes			Yes
Fit statistics						
Observations	42,924	42,924	42,924	42,845	42,845	42,845
R^2	0.65139	0.65228	0.65357	0.72456	0.72569	0.72716
Within R^2	0.00175	0.00051	0.00049	0.00240	0.00057	0.00053

Newey-West (L=5) covariance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA2: Treatment Effect of Expiring 0DTE Contracts on Realized Volatility – Cash Index & ETF. Results for regression models of intraday return volatility of the S&P 500 computed with the S&P 500 cash index (Cash Index) or the SPDR S&P 500 ETF (SPY). Each observation corresponds to a 10-minute interval of the trading day. The indicator variable *0DTE Expiration* is equal to 1 on days when there is an SPXW expiration and 0 otherwise. Intraday volatility is scaled to an annualized percentage. The sample period starts on 01/2018 and ends on May 19, 2022, when 0DTE options began expiring regularly on every weekday (*0DTE Expiration* becomes a constant afterward).

Dependent Variable:	Realized Volatility					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
0DTE Expiration	-0.00613***	-0.00613***	-0.00455***	-0.00455***	-0.00456***	-0.00456***
	(-2.7397)	(-5.8475)	(-4.1981)	(-9.4044)	(-4.2516)	(-9.2149)
Fixed-effects						
Year × Day-of-Week	Yes	Yes				
Year × Week × Time	Yes	Yes				
Year × Week			Yes	Yes	Yes	Yes
Time			Yes	Yes		
Week × Time					Yes	Yes
Co-variance	NW 10 lags	Year×Time	NW 10 lags	Year×Time	NW 10 lags	Year×Time
Fit statistics						
Observations	42,831	42,831	42,831	42,831	42,831	42,831
R^2	0.71309	0.71309	0.63064	0.63064	0.64591	0.64591
Within R^2	0.00051	0.00051	0.00169	0.00169	0.00177	0.00177

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA3: Treatment Effect of Expiring 0DTE Contracts on S&P 500 Intraday Realized Volatility – Robustness. Robustness of OLS regression results in Table 1 with respect to different fixed-effect specifications and alternative standard errors. The dependent variable is the 10-minute realized volatility of the S&P 500 E-mini futures (ES). The indicator variable *0DTE Expiration* equals 1 on days when there is an SPXW expiration and 0 otherwise. Each observation corresponds to a 10-minute interval of the trading day. The sample period starts on 01/2018 and ends on May 19, 2022, when 0DTE options began expiring regularly on every weekday (*0DTE Expiration* becomes a constant afterward).

	RV	Non-0DTE NetΔ	0DTE NetΔ	Non-0DTE NetΓ	0DTE NetΓ	New 0DTE NetΓ	Stale 0DTE NetΓ	Non-0DTE Net Speed	0DTE Net Speed	Non-0DTE NetΘ	0DTE NetΘ
RV	100.00	-0.10	0.81	-19.10	-13.40	-11.11	-4.53	1.27	-1.30	-0.54	0.84
Non-0DTE NetΔ	-0.10	100.00	-24.09	0.75	0.56	0.00	0.47	0.37	1.23	2.32	0.31
0DTE NetΔ	0.81	-24.09	100.00	-0.24	-0.54	-0.56	-0.88	-0.19	0.29	-4.70	-3.02
Non-0DTE NetΓ	-19.10	0.75	-0.24	100.00	7.37	2.48	8.99	10.55	1.14	-0.58	-0.55
0DTE NetΓ	-13.40	0.56	-0.54	7.37	100.00	69.24	31.60	0.62	7.05	0.54	-0.08
New 0DTE NetΓ	-11.11	0.00	-0.56	2.48	69.24	100.00	-22.29	-0.57	4.61	0.17	0.09
Stale 0DTE NetΓ	-4.53	0.47	-0.88	8.99	31.60	-22.29	100.00	2.47	4.06	-0.08	-0.57
Non-0DTE Net Speed	1.27	0.37	-0.19	10.55	0.62	-0.57	2.47	100.00	4.16	-10.54	-1.59
0DTE Net Speed	-1.30	1.23	0.29	1.14	7.05	4.61	4.06	4.16	100.00	0.18	-3.94
Non-0DTE NetΘ	-0.54	2.32	-4.70	-0.58	0.54	0.17	-0.08	-10.54	0.18	100.00	12.70
0DTE NetΘ	0.84	0.31	-3.02	-0.55	-0.08	0.09	-0.57	-1.59	-3.94	12.70	100.00

Table IA4: Intraday Correlation Matrix. Correlation matrix between 10-minute realized volatility (RV) and option market makers' portfolio sensitivities. RV is the realized volatility of the S&P 500 E-mini futures. Section 3 provides details of $Net\Gamma$, $Net\Delta$. Section IA1.2 provides details of the $NetSpeed$ and $Net\Theta$. For each trading day, we calculate pairwise correlations of variables using 10-minute intraday observations. We then average these daily correlations across the sample period from 01/2018 to 12/2024. All correlations are expressed in percentage terms.

Dependent Variable:	$\text{Net}\Delta_t$		
Model:	0DTE (1)	Non-0DTE (2)	Overall (3)
0DTE Expiration	0.00062	1.09×10^{-5}	0.00062
	(0.8679)	(0.0101)	(0.5935)
Fixed-effects			
Year × Day-of-Week	Yes	Yes	Yes
Year × Week × Time	Yes	Yes	Yes
Fit statistics			
Observations	42,929	42,817	42,817
R^2	0.20731	0.20621	0.21579
Within R^2	2.02×10^{-5}	2.60×10^{-9}	9.11×10^{-6}

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA5: Treatment Effect of Expiring 0DTE Contracts on Market Makers' Net Delta. This table reports OLS results for panel regression models of intraday market makers' net delta, separately for 0DTE positions, non-0DTE positions, and Overall positions. It is the net delta counterpart to the net gamma first stage in Table 4. Net delta is a flow that comes from the change in net open interest and is not split into stale and new positions, so the table has no stale component. Each observation corresponds to a 10-minute interval of the trading day. The indicator variable *0DTE Expiration* is equal to 1 on days with an SPXW expiration and 0 otherwise. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 until May 19, 2022, when 0DTE options began expiring regularly on every weekday. The presence of 0DTEs does not significantly change market makers' net delta on the expiration day, consistent with results in the main text.

Dependent Variable:	Realized Volatility (t+1)	
Model:	(1)	(2)
0DTE NetΓ_t $\times$ Hour = 9-10	-0.90015***	
	(-9.3215)	
0DTE NetΓ_t $\times$ Hour = 11	-0.58915***	
	(-7.2225)	
0DTE NetΓ_t $\times$ Hour = 12	-0.55064***	
	(-7.5918)	
0DTE NetΓ_t $\times$ Hour = 13	-0.47855***	
	(-6.9461)	
0DTE NetΓ_t $\times$ Hour = 14	-0.64563***	
	(-8.3781)	
0DTE NetΓ_t $\times$ Hour = 15	-0.34996***	
	(-6.6396)	
Non-0DTE NetΓ_t $\times$ Hour = 9-10		-1.2763***
		(-5.3784)
Non-0DTE NetΓ_t $\times$ Hour = 11		-0.94555***
		(-4.2120)
Non-0DTE NetΓ_t $\times$ Hour = 12		-0.70220**
		(-2.5059)
Non-0DTE NetΓ_t $\times$ Hour = 13		-0.82616***
		(-3.7433)
Non-0DTE NetΓ_t $\times$ Hour = 14		-1.1155***
		(-4.7705)
Non-0DTE NetΓ_t $\times$ Hour = 15		-1.2279***
		(-5.4341)
Fixed-effects		
Year $\times$ Week $\times$ Time	Yes	Yes
Date	Yes	Yes
Fit statistics		
Observations	64,837	64,837
R^2	0.81162	0.81156
Within R^2	0.11729	0.11702

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA6: Hourly Effects of Net Gamma on Realized Volatility. Robustness of panel regression models of S&P 500 intraday realized volatility across hours of the day. Each observation is a 10-minute interval within the trading day. The dependent variable is realized volatility of the S&P 500 E-mini futures in the next 10-minute interval, i.e., $t+1$. The independent variables are the interactions of a dummy variable for each trading hour with the market maker net gamma measures, respectively. The independent variables are calculated with information up to time t. Volatility is scaled to annualized percentage. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period starts on 01/2018 and ends on 12/2024.

Dependent Variable:	Realized Volatility $(t+1)$			
Model	(1)	(2)	(3)	(4)
0DTE NetΓ_t	-0.4536***		-0.4378***	-0.4443***
	(-8.050)		(-7.745)	(-7.871)
0DTE NetΔ_t	-0.0036		-0.0031	-0.0031
	(-1.088)		(-0.9251)	(-0.9263)
Non-0DTE NetΓ_t		-1.184***	-1.109***	
		(-5.603)	(-5.258)	
Non-0DTE NetΔ_t		0.0023	0.0009	0.0008
		(0.8006)	(0.3155)	(0.2738)
$[1,5]$DTE NetΓ_t				-0.4822**
				(-2.298)
$(5,\infty)$DTE NetΓ_t				-4.406***
				(-6.998)
Fixed-effects				
Year × Week × Time	Yes	Yes	Yes	Yes
Date	Yes	Yes	Yes	Yes
Fit statistics				
Observations	64,837	64,318	64,318	64,318
R^2	0.81154	0.81209	0.81235	0.81260
Within R^2	0.11693	0.11671	0.11789	0.11906

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table IA7: Hedging Needs and Future Realized Volatility: Alternative Net Gamma. Robustness of our panel regression results in Table 5, but using intraday option delta and gamma calculated using the Black-Scholes formula with VIX as the annualized implied volatility of each contract. Each observation is a 10-minute interval within the trading day. The dependent variable is the return volatility of the S&P 500 E-mini futures in the next 10-minute interval, i.e., $t+1$. All independent variables are calculated with information up to time t. $Net\Delta_t$ and $Net\Gamma_t$ refer to the market makers' net delta and net gamma, respectively. We report regression results using overall $Net\Delta_t$ and $Net\Gamma_t$ for non-0DTE or 0DTE positions in Columns (1)–(3), or for buckets with 0, $[1,5]$, and $(5,\infty)$ days to maturity in Column (4). Volatility is scaled to annualized percentage. Two lags of realized volatility are included. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 to 12/2024.

Dependent Variable:	Realized Volatility $(t+1)$	
Model:	(1)	(2)
0DTE NetΓ_t	-0.4211***	-0.4213***
	(-8.512)	(-8.533)
0DTE NetΔ_t	-0.0032	-0.0032
	(-0.9330)	(-0.9373)
Non-0DTE NetΓ_t	-0.9173***	-0.9287***
	(-3.283)	(-3.291)
Non-0DTE NetΔ_t	0.0012	0.0013
	(0.4382)	(0.4497)
Higher-order Greeks		
0DTE NetSpeed$_t$		-0.2736**
		(-2.192)
0DTE NetΘ_t		0.0379
		(0.8926)
Non-0DTE NetSpeed$_t$		-0.8295***
		(-3.638)
Non-0DTE NetΘ_t		0.0120
		(0.3593)
Fixed-effects		
Year × Week × Time	Yes	Yes
Date	Yes	Yes
Fit Statistics		
Observations	64,799	64,799
R^2	0.81180	0.81187
Within R^2	0.11780	0.11813

*Sign. codes: ***: 0.01, **: 0.05, *: 0.1.*

Table IA8: Robustness to Higher-Order Greeks: Impact on Intraday Realized Volatility. Robustness of results from panel regression models of S&P 500 intraday realized volatility when controlling for market makers' higher-order Greek exposures. Each observation is a 10-minute interval within the trading day. The dependent variable is the return volatility of the S&P 500 E-mini futures in the next 10-minute interval, i.e., $t+1$. $Net\Gamma_t$ and $Net\Delta_t$ represent standard delta-hedging exposures. $NetSpeed_t$ represents the gamma of gamma (second-order convexity). $Net\Theta_t$ represents charm, the time decay of delta. See Internet Appendix IA1.2 for details. All exposures are calculated separately for 0DTE and non-0DTE positions. Volatility is scaled to annualized percentage. Two lags of realized volatility are included. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 to 12/2024.

Dependent Variable:	Realized Volatility $(t+n)$					
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
0DTE NetΓ_t	-0.4394***	-0.4190***	-0.3264***	-0.3097***	-0.2958***	-0.2261***
	(-8.818)	(-6.614)	(-4.841)	(-4.302)	(-3.742)	(-2.735)
Observations	64,837	63,078	61,319	59,560	57,801	56,042
R^2	0.81151	0.80061	0.79881	0.79481	0.79092	0.79023
Within R^2	0.11680	0.07012	0.05345	0.03251	0.01430	0.00856

Fixed-effects: Year × Week × Time; Date
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

(a) Predicting Realized Volatility in the First Hour

Dependent Variable:	Realized Volatility $(t+n)$					
	$t+7$	$t+8$	$t+9$	$t+10$	$t+11$	$t+12$
0DTE NetΓ_t	-0.1695*	-0.1182	-0.1106	-0.1041	-0.0075	0.0090
	(-1.896)	(-1.253)	(-1.107)	(-0.9938)	(-0.0707)	(0.0859)
Fit statistics						
Observations	54,283	52,524	50,765	49,006	47,247	45,488
R^2	0.78881	0.78904	0.79169	0.79261	0.79366	0.79441
Within R^2	0.00316	0.00079	0.00131	0.00074	0.00176	0.00235

Fixed-effects: Year × Week × Time; Date
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

(b) Predicting Realized Volatility in the Second Hour

Table IA9: Predicting Realized Volatility with Market Makers' 0DTE Net Gamma. Results from predictive regression models for the S&P 500 E-mini futures realized volatility in the $t+n$ interval, where $n = 1 \cdots 12$, using the market makers' 0DTE $Net\Gamma_t$ in the current period t as the predictive variable. Each period corresponds to a 10-minute interval. Two lags of the dependent variable are included. Realized volatility is scaled to an annualized percentage. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 to 12/2024.

Dependent Variable:	Realized Volatility ($t+n$)					
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$
Non-0DTE NetΓ_t	-0.9615***	-0.8765***	-0.6941***	-0.5178**	-0.5154**	-0.4776**
	(-3.309)	(-3.000)	(-2.911)	(-2.274)	(-2.161)	(-2.136)
Observations	64,837	63,078	61,319	59,560	57,801	56,042
R^2	0.81148	0.80060	0.79882	0.79479	0.79092	0.79024
Within R^2	0.11667	0.07008	0.05349	0.03240	0.01425	0.00864
Fixed-effects: Year × Week × Time; Date						
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1						

(a) Predicting Realized Volatility in the First Hour

Dependent Variable:	Realized Volatility ($t+n$)					
	$t+7$	$t+8$	$t+9$	$t+10$	$t+11$	$t+12$
Non-0DTE NetΓ_t	-0.3119	-0.3512*	-0.2720	-0.2427	-0.2713	-0.2037
	(-1.638)	(-1.926)	(-1.452)	(-1.265)	(-1.495)	(-1.091)
Fit statistics						
Observations	54,283	52,524	50,765	49,006	47,247	45,488
R^2	0.78881	0.78906	0.79170	0.79262	0.79368	0.79442
Within R^2	0.00317	0.00088	0.00136	0.00078	0.00184	0.00240
Fixed-effects: Year × Week × Time; Date						
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1						

(b) Predicting Realized Volatility in the Second Hour

Table IA10: Predicting Realized Volatility with Market Makers' Non-0DTE Net Gamma. Results from predictive regression models for the S&P 500 E-mini futures realized volatility in the $t+n$ interval, where $n = 1 \cdots 12$, using the market makers' non-0DTE $Net\Gamma_t$ in the current period t as the predictive variable. Each period corresponds to a 10-minute interval. Two lags of the dependent variables are included in each regression. Realized volatility is scaled to an annualized percentage. Newey-West t-statistics calculated using 5 lags are reported in parentheses. The sample period is from 01/2018 to 12/2024.

Interval	Panel A. Market Makers' 0DTE NetΓ Quartiles				
(Minutes)	Q1 (Low)	Q2	Q3	Q4 (High)	Q4−Q1 (Diff)
10	0.155*	0.027	-0.174	-0.097	-0.252*
	(1.88)	(0.23)	(-1.29)	(-0.62)	(-1.90)
30	0.285	0.070	-0.414	-0.491	-0.776***
	(1.62)	(0.28)	(-1.41)	(-1.47)	(-2.74)
60	0.534**	0.101	-0.561	-0.967**	-1.502***
	(2.36)	(0.31)	(-1.49)	(-2.25)	(-4.11)
120	0.394	0.140	-0.871	-1.855***	-2.249***
	(1.16)	(0.29)	(-1.49)	(-2.83)	(-4.01)
Interval	Panel B. Market Makers' Non-0DTE NetΓ Quartiles				
(Minutes)	Q1 (Low)	Q2	Q3	Q4 (High)	Q4−Q1 (Diff)
10	-0.057	-0.000	-0.120	-0.157	-0.100
	(-0.44)	(-0.00)	(-0.56)	(-0.63)	(-0.47)
30	0.471*	-0.002	-0.239	-0.558	-1.030**
	(1.66)	(-0.01)	(-0.51)	(-1.05)	(-2.30)
60	0.866**	-0.006	-0.626	-1.449**	-2.315***
	(2.34)	(-0.01)	(-1.04)	(-2.14)	(-4.07)
120	1.247**	-0.011	-1.752*	-3.429***	-4.676***
	(2.25)	(-0.01)	(-1.87)	(-3.21)	(-5.12)

Fixed-effects: Year × Week × Time; Date
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table IA11: Relative Returns of E-mini and Net Gamma: 0DTE vs Non-0DTE. This table reports the average momentum or reversal returns of E-mini futures at different quartiles of the market makers' net gamma, from the lowest (Q1) to the highest (Q4). We report estimates of the coefficient β_i in the following regression model without a constant:

$$R_{t,t+n} - R_{t-n-1,t-1} = \sum_{i}^{4} \beta_i \cdot \mathbf{1}(\text{Net}\Gamma_t \in \text{Q}_i) + \text{Fixed Effect} + u_{t,n},$$

Each period t represents a 10-minute interval mark. The dependent variable is the difference in simple returns (in bps) of E-mini futures (ES) from t to $t+n$ relative to $t-n-1$ to $t-1$. We sort market makers' $Net\Gamma_t$ at time t into quartiles using a 180-day backward rolling window. $\mathbf{1}(Net\Gamma\ \text{Q} = i)_t$ is the dummy variable equal to 1 if the market makers' $Net\Gamma_t$ is in the ith quartile. Panel A uses only 0DTE options gamma, and Panel B uses only non-0DTE options gamma. We include a rich set of fixed effects in the regression model. Newey-West t-statistics, calculated using $\min(5, n)$ lags, are reported in parentheses. The sample period is from 01/2018 to 12/2024.

IA1.2. Delta Hedging with Higher-Order Greeks

This section examines the higher-order Greeks associated with delta-hedging activity. We keep the discrete-hedging setting and notation of Section 3. The market maker rebalances at discrete intervals indexed by t. She computes her Greeks from the Black-Scholes model, using the implied volatility observed at t. Write the pre-existing rebalancing component q_t from Equation (4), omitting the contract subscript i:

$$q_t \;=\; -w_{t-1} \cdot (\Delta_t - \Delta_{t-1}). \tag{IA1}$$

In Section 3.2 we approximated the change in delta by its leading (gamma) term, $\Delta_t - \Delta_{t-1} = \Gamma_t \, \Delta S_t + O(\Delta S_t^2)$, where $\Delta S_t \equiv S_t - S_{t-1}$. Here we carry that discrete expansion to second order. We take a Taylor expansion of the delta function $\Delta(S,t)$ in the realized price change ΔS_t and the time step Δt. The expansion is in the realized change over the interval, not along a continuous path. It gives

$$\Delta_t - \Delta_{t-1} \;=\; \frac{\partial \Delta_t}{\partial S_t}\,\Delta S_t + \frac{1}{2}\frac{\partial^2 \Delta_t}{\partial S_t^2}\,(\Delta S_t)^2 + \frac{\partial \Delta_t}{\partial t}\,\Delta t + O\big((\Delta S_t)^3\big).$$

Substituting this expansion into Equation (IA1) and factoring out the return $\Delta S_t / S_t$, we obtain

$$\begin{aligned} q_t \;&=\; -w_{t-1} \cdot S_t \cdot \left[\frac{\partial \Delta_t}{\partial S_t} + \frac{1}{2}\frac{\partial^2 \Delta_t}{\partial S_t^2}\Delta S_t + \frac{\partial \Delta_t}{\partial t}\frac{\Delta t}{\Delta S_t}\right] \cdot \frac{\Delta S_t}{S_t} \\ &=\; -w_{t-1} \cdot \left[S_t \cdot \Gamma_t + \frac{1}{2}\frac{\partial \Gamma_t}{\partial S_t} S_t\,\Delta S_t + \Theta_t \frac{S_t}{\Delta S_t}\Delta t\right] \cdot \frac{\Delta S_t}{S_t}, \end{aligned} \tag{IA2}$$

where $\Gamma_t \equiv \frac{\partial \Delta_t}{\partial S_t}$ is the option's gamma, $\frac{\partial \Gamma_t}{\partial S_t}$ is its speed, and $\Theta_t \equiv \frac{\partial \Delta_t}{\partial t}$ is its charm, the time decay of delta. Here $(\Delta S_t)^2$ is a realized squared price change, so we do not use Ito's lemma.

IA1.3. Decomposing the Rebalancing Effect

From Equation (IA2), we decompose the rebalancing impact of delta-hedging an option position into three components:

$$\Delta q_t^{\Gamma} \;=\; -w_{t-1} \cdot (S_t \Gamma_t) \cdot \frac{\Delta S_t}{S_t}, \tag{IA3}$$

$$\Delta q_t^{\text{Speed}} \;=\; -w_{t-1} \cdot \left(\frac{1}{2}\frac{\partial \Gamma_t}{\partial S_t} S_t\,\Delta S_t\right) \cdot \frac{\Delta S_t}{S_t}, \tag{IA4}$$

$$\Delta q_t^{\Theta} \;=\; -w_{t-1} \cdot \left(\Theta_t \frac{S_t}{\Delta S_t}\Delta t\right) \cdot \frac{\Delta S_t}{S_t}, \tag{IA5}$$

where

$$q_t = \Delta q_t^{\Gamma} + \Delta q_t^{\text{Speed}} + \Delta q_t^{\Theta}. \tag{IA6}$$

The gamma component Δq_t^{Γ} is the standard gamma-hedging term and reproduces the $Net\Gamma_t$ measure of Section 3.2. We now examine the speed and charm components separately.

IA1.4. The Rebalancing Effect of Speed

For $\Delta q_t^{\text{Speed}}$, we use the analytical relationship between option speed and gamma. The speed $\equiv \frac{\partial \Gamma_t}{\partial S_t}$ can be expressed in the Black-Scholes framework with dividend yield q as:

$$\text{Speed} = -\frac{\Gamma}{S}\left[\frac{d_1}{\sigma\sqrt{\tau}} + 1\right] \tag{IA7}$$

$$\text{Speed} = -\frac{\Gamma}{S} \cdot d_3 \tag{IA8}$$

where $d_3 = \frac{d_1}{\sigma\sqrt{\tau}} + 1$, $d_1 = \frac{\ln(S/K)+(r-q+\sigma^2/2)\tau}{\sigma\sqrt{\tau}}$ and $d_2 = d_1 - \sigma\sqrt{\tau}$. Note that speed is identical for both call and put options with the same parameters, as gamma is identical for calls and puts. For computational purposes, we obtain d_1 from observed delta values:

$$d_1 = N^{-1}\left(\frac{\Delta + \mathbf{1}_{\text{Put}}}{\exp(-q\tau)}\right), \tag{IA9}$$

where $N^{-1}(\cdot)$ is the inverse cumulative standard normal distribution function, Δ is the option delta, and $\mathbf{1}_{\text{Put}}$ is an indicator variable equal to 1 if the option is a put, 0 otherwise. Substituting the expression for speed into Equation (IA4), we get:

$$\begin{aligned}
\Delta q_t^{\text{Speed}} &= -w_{t-1} \cdot \left(\frac{1}{2}\frac{\partial \Gamma_t}{\partial S_t} S_t\, \Delta S_t\right) \cdot \frac{\Delta S_t}{S_t} \\
&= -w_{t-1} \cdot \left(\frac{1}{2}\left(-\frac{\Gamma_t \cdot d_{3,t}}{S_t}\right) S_t\, \Delta S_t\right) \cdot \frac{\Delta S_t}{S_t} \\
&= \frac{w_{t-1}}{2} \cdot (\Gamma_t \cdot d_{3,t}\, \Delta S_t) \cdot \frac{\Delta S_t}{S_t} && \text{(IA10)} \\
&= \frac{w_{t-1}}{2} \cdot (\Gamma_t \cdot d_{3,t} \cdot S_t\, R_t) \cdot \frac{\Delta S_t}{S_t} && \text{(IA11)}
\end{aligned}$$

where $R_t \approx \frac{\Delta S_t}{S_t}$, so that $\Delta S_t = S_t\, R_t$, and $d_3 = \frac{d_1}{\sigma\sqrt{\tau}} + 1$.

IA1.5. Net Speed

We are now ready to quantify the hedging impact against the speed component from the market maker's perspective. We define *Net Speed* as

$$\begin{aligned}
\text{Net Speed}_t &\equiv \left(\frac{-100 \cdot \sum_i \Delta q_{i,t}^{\text{Speed}}}{M}\right) / \left(\frac{\Delta S_t}{S_t}\right) && \text{(IA12)} \\
&= \frac{-100}{M}\sum_i w_{i,t-1} \cdot \frac{\Gamma_{i,t} \cdot d_{3,i,t} \cdot S_t\, R_t}{2} && \text{(IA13)} \\
&= \frac{-50 \cdot S_t\, R_t}{M}\sum_i w_{i,t-1} \cdot \Gamma_{i,t} \cdot d_{3,i,t} && \text{(IA14)}
\end{aligned}$$

where $w_{i,t-1}$ is the market maker's position in option contract i at time $t-1$, M is the number of outstanding shares on the underlying security, and each option contract represents 100 underlying shares. Like the $Net\Gamma_t$, *Net Speed* is a fraction of the shares outstanding, normalized by the one-percent change in the underlying price. The factor of S_t is necessary for *Net Speed* to be a unit-free share fraction comparable to the $Net\Gamma_t$.[19] Because the speed contribution to the share rebalancing is quadratic in ΔS_t, dividing by a single power of the return leaves *Net Speed* proportional to R_t: the speed-hedging demand grows with the size of the price move within the interval.

IA1.6. Net Charm

We now examine the hedging impact from the time-decay component of delta, known as charm. From the decomposition in Equation (IA5), the charm-related rebalancing component is:

$$\Delta q^{\Theta}_{i,t} = -w_{i,t-1} \cdot \left(\Theta_{i,t} \frac{S_t}{\Delta S_t} \Delta t\right) \cdot \frac{\Delta S_t}{S_t} \tag{IA15}$$

This can be rewritten as:

$$\Delta q^{\Theta}_{i,t} = -w_{i,t-1} \cdot \left(\frac{\Theta_{i,t}}{R_t} \cdot \Delta t\right) \cdot \frac{\Delta S_t}{S_t} \tag{IA16}$$

with the usual substitution of $1/R_t \approx \frac{S_t}{\Delta S_t}$. The *charm* effect measures how delta changes with time. Charm $\equiv \Theta$ is defined as:

$$\Theta_t = \frac{\partial \Delta}{\partial t} = \frac{\partial^2 V}{\partial S \partial t} \tag{IA17}$$

Given Γ_t of the option contract, we can write charm as follows:

$$\text{Charm}_{\text{call}} = -e^{-q\tau} \frac{\phi(d_1)}{\sigma\sqrt{\tau}} \left[(r-q)\sqrt{\tau} - \frac{d_2 \sigma}{2\sqrt{\tau}}\right] - q e^{-q\tau} N(d_1) \tag{IA18}$$

$$\text{Charm}_{\text{put}} = -e^{-q\tau} \frac{\phi(d_1)}{\sigma\sqrt{\tau}} \left[(r-q)\sqrt{\tau} - \frac{d_2 \sigma}{2\sqrt{\tau}}\right] + q e^{-q\tau} N(-d_1) \tag{IA19}$$

where r is the risk-free rate and we can recover d_2 from the option delta

$$d_1 = N^{-1}\left(\frac{\Delta_t + \mathbf{1}_{\text{Put,i}}}{e^{-q\tau}}\right) \tag{IA20}$$

$$d_2 = d_1 - \sigma_t \sqrt{\tau} \tag{IA21}$$

We are now ready to define *Net Charm* as:

$$\text{Net}\Theta_t \equiv \left(\frac{-100 \cdot \sum_i \Delta q^{\Theta}_{i,t}}{M}\right) \Big/ \left(\frac{\Delta S_t}{S_t}\right) \tag{IA22}$$

$$= \frac{100 \cdot \Delta t}{M \cdot R_t} \sum_i w_{i,t-1} \cdot \Theta_{i,t} \tag{IA23}$$

[19] Without the factor of S_t, the speed component carries a residual dimension of one over price and is not comparable in units to the $Net\Gamma_t$. The factor arises because the speed contribution to the share rebalancing is quadratic in ΔS_t: writing $(\Delta S_t)^2 = S_t \, \Delta S_t \cdot (\Delta S_t / S_t)$ leaves one factor of S_t inside the bracket after the return $\Delta S_t / S_t$ is factored out.

where $w_{i,t-1}$ is the market maker's position in option contract i at time $t-1$, Δt is the 10-minute time step expressed in annual units, and M is the number of outstanding shares on the underlying security. Each option contract represents 100 underlying shares. Because the charm-hedging trade is independent of the price increment ΔS_t, *Net Charm*, like the $Net\Delta_t$, carries the return in the denominator and is computed using the same rescaling of near-zero-interval returns described in Section 3.3.