

The Price Impact of Hedging Expiring Index Options[☆]

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Abstract

A previously unrecognized channel through which index options trading impacts the underlying market is that delta hedges of expiring cash-settled index options are unwound at expiration. This contrasts with physically-settled options, where the delta hedge positions in the underlier are used to settle the options position. We use proprietary data to determine market maker positions in expiring S&P 500 index options, and show that hedge unwinding trades have important impacts on index futures returns and volatility during the 30 minutes before options expiration. We also study the impact of options market maker hedge rebalancing trades on market volatility.

JEL Classification: G12, G13, G23, G24

Keywords: 0DTE options, S&P 500 index options, hedge unwinding, hedge rebalancing, gamma squeeze, options trading

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1. Introduction

A developing literature explores the impact of options market maker (OMM) hedge trading on underlier prices, focusing on OMM trading to rebalance delta hedges of their options positions (Avellaneda and Lipkin (2003), Ni, Pearson, and Poteshman (2005), Golez and Jackwerth (2012), Ni et al. (2021), Baltussen et al. (2021), and Baltussen, Terstegge, and Whelan (2023)). The recent explosion in the growth of trading in 0DTE S&P 500 index options has increased interest in this topic, as the very large trading volumes suggest that OMM positions might be large, and thus that their hedge trading might be large enough to materially impact S&P 500 index values and volatility.¹ In a recent paper, Adams et al. (2025) test the hypothesis that it does. Focusing on the average impact, they find that OMM hedge rebalancing trading decreases underlier volatility.

These analyses focus on the hedge rebalancing trades that occur as options deltas change due to changes in underlier prices and the passage of time. But the research literature overlooks the impact of trading to unwind delta hedges that are carried into options expiration, which is important for cash-settled index options. For a cash-settled index option that expires in-the-money (ITM), the option delta disappears upon settlement, but the underlier position that comprises the delta hedge remains. The disappearance of the options position upon settlement leaves OMMs with unhedged underlier positions, that must be liquidated just before option settlement. This can result in large volumes of underlier trading shortly before expiration, potentially impacting prices during the most volatile part of the trading day.

We exploit novel data on signed trades by trader type to compute OMM positions and examine whether OMM hedging affects the price level and volatility of the underlier, and through which mechanism. Our findings reveal a clear separation between the two channels. Hedge unwinding, which is determined by the delta of expiring options, affects price levels. We

¹ Examples of such concern include “Are 0DTE options creating the next ‘Volmageddon’” (Gunjan Banerji, *Wall Street Journal*, February 15, 2023); “JP.M.org’s Kolanovic warns of ‘Volmageddon 2.0’ risk in options” (*Bloomberg*, February 15, 2023); “A potential stock-market catastrophe in the making: The popularity of these risky option bets has Wall Street on edge” (Joseph Adinolfi, *MarketWatch*, February 21, 2023); “Explainer: The rise of 0DTE stock options and how they could be a risk to markets” (Saqib Iqbal Ahmed, Reuters, February 22, 2023); “Forget Volmageddon: Gammageddon Is Coming...” (Toby Hayes, *AlphaWeek*, April 29, 2024); “Let there be gamma” (Robin Wigglesworth, *Financial Times*, May 30, 2024); “After the selloff, competing theories on dealer gamma” (Faye Kilburn, *Risk.net*, August 12, 2024); and “Dispelling false narratives about 0DTE options” (Ambrus Capital, undated).

estimate the aggregate OMM position in p.m.-expiring S&P 500 (SPXW) options 30 and 15 minutes before expiration, compute the associated index futures positions that must be unwound upon settlement, and show that these estimated trades predict movements in S&P 500 futures prices over the corresponding pre-expiration intervals. In contrast, hedge rebalancing, which is driven by the gamma of the OMM position, predicts a relation between gamma and volatility. We compute the net gammas of the aggregate OMM position throughout the day and find that its average effect on volatility is negative, and that even the largest estimated effects are modest.

Thus, the empirical finding is sharp: hedge unwinding at index options settlement causes directional price movements, whereas rebalancing throughout the day impacts volatility. Accordingly, concerns about the market impact of 0DTE options should focus primarily on hedge unwinding at options settlement rather than hedge rebalancing. The relevant measure of the impact of OMM hedge unwinding trades is the delta of the aggregate OMM position shortly before options expiration.

We begin with a discussion of trades that unwind hedges of expiring cash-settled index options. When an OMM carries the delta hedge of a cash-settled index option into expiration, the option delta disappears upon settlement, and leaves the OMM with an unhedged position in the hedge instrument. Thus, cash-settled index options that expire in the money require market makers to unwind their remaining delta hedges before expiration. In contrast, physically-settled options on individual equities and exchange-traded funds (ETFs) can be settled through delivery of the underlier held as a hedge, and do not require the same immediate pre-expiration trades to unwind the hedge positions.

We then turn to a careful discussion of hedge rebalancing trades. In the Black-Scholes-Merton setting, the underlier follows geometric Brownian motion and the value of an option or options portfolio $V(S, t)$ is a function of the underlying price S and time t . The delta hedge position is the negative of the option or portfolio delta, $\Delta(S, t) = \partial V(S, t) / \partial S$. Using Itô's lemma,

$$d\Delta(S, t) = \frac{\partial \Delta}{\partial S} dS + \frac{1}{2} \frac{\partial^2 \Delta}{\partial S^2} (dS)^2 + \frac{\partial \Delta}{\partial t} dt \quad (1)$$

$$= \Gamma dS + \frac{1}{2} \frac{\partial^2 \Delta}{\partial S^2} \sigma^2 S^2 dt + \frac{\partial \Delta}{\partial t} dt. \quad (2)$$

The first term captures changes in the hedge induced by movements in the underlying price. The terms $\partial^2 \Delta / \partial S^2 = \partial^3 V / \partial S^3$ and $\partial \Delta / \partial t = \partial^2 V / \partial S \partial t$ are speed and charm. Equation (1) explains why papers such as Ni, Pearson, and Poteshman (2005) and Golez and Jackwerth (2012) that study

pinning focus on charm. In pinning, as expiration approaches the underlier can be trapped near an option strike price, the term $dS \approx 0$, and charm determines the hedge rebalancing trades.

Outside this special situation, the dS term dominates the dt terms that appear in equation (2), which motivates the usual focus on gamma. In practice, however, hedge adjustments occur over finite intervals, and speed and charm individually can be large for very short-dated options. This raises the question of whether they should enter empirical analysis as separate determinants of hedge rebalancing.

We show that the combined contribution of speed and charm is proportional to gamma. Thus, even though speed and charm may each be large near expiration, and hedging may take place over non-infinitesimal intervals, their joint effect is captured by gamma. Consequently, aggregate gamma is a sufficient statistic for model-implied hedge rebalancing over the empirical intervals we study. This result provides the theoretical justification for our empirical specification and for the exclusive focus on gamma in studies such as Ni et al. (2021) and Adams et al. (2025), even though very short-term options for which speed and charm are large can comprise a large fraction of OMM positions.

Our empirical analysis exploits Cboe data on signed trades by trading capacity (e.g., customer, firm proprietary trader, market maker), that allow us to compute the aggregate OMM position in both expiring (0DTE) and non-expiring (non-0DTE) S&P 500 index options at every point in time. Given the OMM positions, we compute the key variables that determine the magnitudes of hedge unwinding and hedge rebalancing trading: (a) the deltas of the aggregate OMM position in 0DTE options at times shortly before the options expiration, which determine the hedge unwinding trades; and (b) the gammas of the aggregate OMM positions in all S&P 500 index options throughout the day, which determine the magnitude of the hedge rebalancing trades. These variables allow us to study the impact of both hedge unwinding and hedge rebalancing trades.

Our first empirical analyses study the impact of hedge unwinding trades. When the delta of the aggregate options market maker position in the expiring options is positive (negative), the hedge position is short (long) the index futures, and the hedge unwinding trades involve buying (selling) index futures contracts. Thus, we predict that the index futures return during the period shortly before the 4:00 p.m. options settlement is positive (negative) when the delta of the aggregate OMM position in the expiring options is positive (negative).

We test this prediction by exploiting the signed trade data to compute the deltas of the aggregate OMM position in the 0DTE index options at 3:30 p.m.. We sort the trading dates into five quintiles based on the delta of the aggregate OMM position in the 0DTE options at 3:30 p.m., and examine the index futures returns from 3:30 to the 4:00 p.m. options expiration. Consistent with the prediction, the average 30-minute return prior to expiration on the high-delta dates is 17 bps greater than the average return on the low-delta dates. We repeat the analysis using the OMM delta positions at 3:45 p.m. and find a 12.5 bps return differential during the period from 3:45 p.m. to 4:00 p.m..

The results of regressions in which returns are regressed on the delta of the aggregate market maker position at 3:30 p.m. or 3:45 p.m. and control variables are consistent with the results based on sorting dates into groups.

If hedge unwinding trades impact returns during the immediate pre-expiration period, then they should also impact volatility during the same period. We find that return volatility over the last 30 (15) minutes prior to the 4:00 p.m. option expiration is significantly positively related to the absolute value of the delta of the aggregate market maker position at 3:30 (3:45) p.m..

A 17 (12.5) bps return differential over a 30-minute (15-minute) period is large, and S&P 500 index options expire at 4:00 p.m. on every trading day. Thus, our estimates imply that hedge unwinding trading has frequent, important impacts on market movements during the last 30 minutes of trading, except when the delta of the aggregate OMM position in the expiring options is small in magnitude. The only circumstance when 0DTE options do not impact prices is when the delta of the aggregate OMM position prior to expiration is zero or close to zero.

We then turn to the hedge rebalancing channel. As an initial matter, we show that the typically positive OMM gamma is due to the OMM positions resulting from complex trades. OMMs sell gamma through their single-leg trades, because customers are generally buying through the single-leg trades. But customers and other market participants sell gamma, and thus OMMs buy gamma, through multi-leg trades, and especially through vertical spreads. The gamma of the positions that OMMs acquire through complex trades is typically far greater than the gamma of the positions they acquire through single-leg trades, resulting in an aggregate OMM position that typically has positive gamma.

We study the impact of hedge rebalancing trades by estimating GARCH models that are augmented to allow realized variance to depend on OMM gamma throughout the day. The

models specify the conditional variance of each one-minute return to be a function of the previous squared return, the previous conditional variance, and lagged OMM gammas. They also allow the return variance to differ across days, and for a diurnal pattern within each day. The results are consistent with the hypothesis that hedge rebalancing trading impacts return volatility in the expected directions.

We use the estimated models to carry out counterfactual analyses to estimate the largest impact of OMM gamma on realized volatility during our sample period. We use the models to generate simulated returns under the counterfactual assumption that the return volatility is unrelated to the lagged gammas. We then use the simulated returns to compute realized volatility for each trading day, and compare these counterfactual volatilities to the realized volatilities computed from one-minute returns. The differences between the volatilities based on actual and counterfactual simulated returns provide measures of the impact of OMM gamma on volatility. We use the same approach to compute simulated and actual realized volatilities for non-overlapping 30-minute periods starting at 9:30 am each day.

The results show that the typical impact of gamma is to reduce volatility, consistent with results in Adams et al. (2025). The median impact is to reduce daily volatility by 0.08 percentage points. Negative impacts on volatility are to be expected, given the negative relation with gamma and the typically positive values of OMM gamma. But OMM gamma is sometimes negative, and at these times volatility is elevated. We find that the maximum impact of OMM gamma on volatility is to increase annualized daily volatility by 2.3 percentage points. Changes in annualized daily realized volatility of about 2.3 percentage points or greater occur reasonably frequently, on about 20% of the days, or on average about once per week. Given this, our interpretation of the results is that a gamma-induced change of about 2.3 percentage points is not large.

Other papers that study hedge rebalancing or related trading include Ni, Pearson, and Poteshman (2005), who show that hedge rebalancing trading on expiration dates of single-name options causes stocks to “pin” on option strike prices, and Golez and Jackwerth (2012), who provide evidence that index option hedge rebalancing and expiration-related trading impact index futures prices on index options expiration dates. Baltussen et al. (2021) present evidence consistent with the hypothesis that hedge rebalancing contributes to intraday market momentum, and Barbon et al. (2021) present a range of related results. Lipson, Tomio, and Zhang (2023)

show that retail trading of single-name options is associated with increases in the volatility of the options' underlying stocks, and suggest that this is caused by OMMs hedging their options exposure. O'Donovan, Yu, and Zhang (2023) provide evidence that market makers with positive portfolio gammas supply liquidity and stabilize markets for individual stocks.

Papers that study other aspects of 0DTE options include Bandi, Fusari and Reno (2024), who present closed-form pricing formulae based on a local-in-time approach that captures 0DTE prices and the implied-volatility surface. Almeida, Freire, and Hizmeri (2024) explore the risk premia investors can expect to earn holding 0DTE options. Brogaard, Han, and Won (2023) find that stock market return volatility, as measured by the return volatility of an S&P 500 exchange-traded fund, is correlated with the ratio of 0DTE trading volume to total trading volume in S&P 500 index options.

The remainder of the paper is as follows. Section 2 discusses hedge unwinding and rebalancing trades. Section 3 describes the data, and how we use it to determine OMM positions and compute the delta and gamma of the aggregate OMM position at various times throughout the trading day. Section 4 presents the results showing that hedge unwinding trading impacts returns shortly before the expiration of the 0DTE options. Section 5 describes the GARCH model we use to analyze hedge rebalancing and presents the estimation results. Section 6 describes how we simulate the models to estimate the maximum impact of gamma on realized volatility, and how the estimated gamma-induced increases in volatility compare to typical changes in volatility. Section 7 briefly concludes.

2. Delta-hedge Rebalancing and Unwinding Trades

Options trading can have non-informational impacts on underlier prices through the hedge trades of OMMs and possibly other market participants, if the market for the underlier is not infinitely liquid. These trades can be categorized into hedge unwinding trades at expiration of cash-settled options, which have not previously been considered in the research literature; hedge rebalancing trades; and hedge trades that adjust delta hedges in response to options trades. This section first discusses hedge unwinding trades, and then turns to the other trades.

2.1 Hedge unwinding trades at expiration of cash-settled options

Hedge unwinding trades at the expiration of cash-settled index options arise due to an important difference between cash- and physically-settled options. Consider a physically-settled option that expires in-the-money. Upon exercise or assignment of the option, a delta-hedging

OMM who carries the hedge position into expiration can deliver the shares of underlying stock or ETF that comprise the delta hedge to the options counterparty to meet its obligations if the delta-hedge position is long the underlying stock or ETF. Or, if the delta-hedge position involves being short the underlier, the stock or ETF shares received from the options counterparty are used to cover the short position. Thus, the expiration of a physically-settled option does not create any need to trade the underlier.

In contrast, for a cash-settled index option, the underlier is not delivered or received at expiration. Rather, the options settlement involves a cash payment and the options position and its related delta exposure cease to exist, while the underlier position, and the delta exposure created by it, continue. The result is that an OMM who has a delta-neutral position in cash-settled index options would be left with an unhedged position in the underlier upon the expiration of the options.² Unless the OMM wants the delta exposure, he or she must trade to dispose of the underlier position.

A trader who holds a cash-settled index option and a related hedge position in the underlier can mimic the situation of the holder of a physically-settled option, and minimize the settlement risk, by trading out of the hedge position at a price as close as possible to the index settlement price. OMMs typically hedge the S&P 500 index options positions using the S&P 500 e-mini index futures contract. Thus, for the p.m.-expiring SPXW options, OMMs can minimize the settlement risk by liquidating the index futures hedge position shortly before the 4:00 p.m. options settlement.

When the delta of the aggregate options market maker position in the expiring options is positive, the hedge position is short the index futures, and the hedge unwinding trades involve buying index futures contracts. When the delta of the aggregate options market maker position in the expiring options is negative, the hedge position is long the index futures, and the hedge unwinding trades involve selling index futures contracts. This leads to the prediction that the index futures return during the period shortly before the 4:00 p.m. options settlement is positive (negative) when the delta of the aggregate OMM position in the expiring options is positive (negative).

² The easiest way to understand this is to recognize that the underlier position hedges the options position, and simultaneously, the options position hedges the underlier position. Thus, a trader who is delta hedging a cash-settled index option is left with an unhedged position in the underlier when the index option expires.

2.2 Delta-hedge rebalancing trades

The delta (Δ) of an options position is the derivative of the position value with respect to the underlying price S , $\Delta = \partial V / \partial S$, where V is the model value of the position. OMMs often buy or sell the underlier to make the net delta of the combined position of options and underlier be within an acceptable range, often within some neighborhood of zero. This entails holding a position in the underlier such that the number of units of the underlying asset n is approximately equal to the negative of the delta of the options positions, i.e. such that $n \approx -\Delta$. Under the assumption that market makers hold such (approximately) delta-neutral positions, and rebalance their delta hedges to maintain (approximate) delta neutrality, the hedge rebalancing trades are determined by the negative of the changes in the delta of the options position. We focus on the change in delta.

Assume that the movement of the underlier price is described by the stochastic differential equation

$$dS = \mu S dt + \sigma S dW, \quad (3)$$

where μ is the expected return on the underlier, σ is the volatility, and W is a standard Brownian motion. In the setting of Black and Scholes (1973) and Merton (1973) both the value of an option or options portfolio $V(S, t)$ and delta $\Delta(S, t)$ are functions of S and t . From Itô's lemma, the movement of Δ is given by

$$d\Delta(S, t) = \frac{\partial \Delta}{\partial S} dS + \frac{1}{2} \frac{\partial^2 \Delta}{\partial S^2} (dS)^2 + \frac{\partial \Delta}{\partial t} dt \quad (4)$$

$$= \frac{\partial \Delta}{\partial S} dS + \frac{1}{2} \frac{\partial^2 \Delta}{\partial S^2} \sigma^2 S^2 dt + \frac{\partial \Delta}{\partial t} dt. \quad (5)$$

In the limit dt is small relative to dS , and the terms $\partial^2 \Delta / \partial S^2 = \partial^3 V / \partial S^3$ (“speed”) and $\partial \Delta / \partial t = \partial^2 V / \partial S \partial t$ (“charm”) do not contribute to the change in delta and the required hedge rebalancing trade. But actual hedge rebalancing inherently takes finite time, so these terms can contribute. For options with short remaining times to expiration these terms can be material for reasonable values of the volatility σ and other parameters.

This is illustrated in Figure 1, which shows the gamma, speed, and charm for options with one hour (Panel A) and 15 minutes (Panel B) to expiration. In each panel, the solid black line displays ΓdS , and the blue and red dashed lines display $\frac{1}{2} \frac{\partial \Gamma}{\partial S} \sigma^2 S^2 dt$ and $\frac{\partial \Delta}{\partial t} dt$, respectively.

The term $dt = 15 \text{ minutes} = 15/(60 \times 24 \times 365) \text{ years}$, and dS is set equal to the standard deviation per 15 minutes, $\sigma S \sqrt{dt}$. The other parameters are $K = 100$, $\sigma = 0.4$, and $r = 0.04$.

Examination of equations (4)-(5), together with the recognition that speed and charm can be material for very short-term options, might make one wonder whether Ni et al. (2021), Adams et al. (2025), and others are correct to focus exclusively on gamma, disregarding the other two terms. And what is assumed by Ni, Pearson, and Poteshman (2005), Golez and Jackwerth (2012), and Baltussen, Terstegge and Whelan (2023) when they focus on charm, disregarding gamma and speed?

In addition to showing that the speed and charm of very short-term options can be large, Figure 1 suggests that these two terms might offset one another. Speed and charm do not quite offset one another, but their sum is proportional to gamma, and equation (5) becomes

$$d\Delta(S, t) = \Gamma dS - \Gamma(\sigma^2 + r)S dt = \Gamma(S, t)S(\sigma dW - (\sigma^2 + r)dt). \quad (6)$$

An implication of equation (6) is that hedge rebalancing trades are proportional to gamma, even when rebalancing hedges takes time and speed and charm are large.

To obtain equation (6), we exploit the Black-Scholes (1973) partial differential equation (p.d.e.)

$$\frac{1}{2}\sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} + rS \frac{\partial V}{\partial S} + \frac{\partial V}{\partial t} - rV = 0. \quad (7)$$

This p.d.e. applies to both single-name and index options, despite the slightly different p.d.e. in Merton (1973) for the case of a continuous dividend yield. Dividends on the index portfolio are not paid continuously, but only during the overnight period, and analysis at an intraday time scale should recognize this. Accounting for the discreteness of dividend payments, the value of an index option is the solution of a system of p.d.e.'s of the form of equation (7), connected through time boundary conditions at the ex-dividend times.³

Differentiating equation (7) with respect to S yields

$$\frac{1}{2}\sigma^2 S^2 \frac{\partial^3 V}{\partial S^3} + \sigma^2 S \frac{\partial^2 V}{\partial S^2} + rS \frac{\partial^2 V}{\partial S^2} + r \frac{\partial V}{\partial S} + \frac{\partial^2 V}{\partial S \partial t} - r \frac{\partial V}{\partial S} = 0. \quad (8)$$

Rearranging, the sum

$$\frac{1}{2}\sigma^2 S^2 \frac{\partial^3 V}{\partial S^3} + \frac{\partial^2 V}{\partial S \partial t} = \frac{1}{2} \frac{\partial \Gamma}{\partial S} \sigma^2 S^2 + \frac{\partial \Delta}{\partial t}$$

³ Wilmott (1998, Section 47.10.2) describes the handling of boundary conditions across ex-dividend dates.

is given by

$$\frac{1}{2}\sigma^2S^2\frac{\partial^3V}{\partial S^3} + \frac{\partial^2V}{\partial S\partial t} = -\sigma^2S\frac{\partial^2V}{\partial S^2} - rS\frac{\partial^2V}{\partial S^2} - r\frac{\partial V}{\partial S} + r\frac{\partial V}{\partial S} \quad (9)$$

$$= -(\sigma^2 + r)S\frac{\partial^2V}{\partial S^2}. \quad (10)$$

Substituting into equation (5) yields equation (6).

As indicated above, an implication of equation (6) is that hedge rebalancing trades are proportional to gamma. This justifies the focus of Baltussen et al. (2021), Ni et al. (2021), Barbon et al. (2021), O'Donovan, Yu, and Zhang (2023), and Adams et al. (2025) on gamma.

At first glance, this may seem inconsistent with the focus on charm in Ni, Pearson, and Poteshman (2005), Golez and Jackwerth (2012), and Baltussen, Terstegge, and Whelan (2023). The difference, however, reflects the specific mechanisms examined in those papers.

The analyses in Ni, Pearson, and Poteshman (2005) and Golez and Jackwerth (2012) are based on the theoretical analysis of Avellaneda and Lipkin (2003), who study how hedge rebalancing trades of short-term at-the-money options can cause the underlier price to “pin” at the options strike price. Charm is central to this mechanism because it changes sign as the underlier crosses the strike. Just above (below) the strike, the charms of both calls and puts are positive (negative), as the call delta goes from approximately one-half to one (zero) at expiration and the put delta goes from approximately negative one-half to zero (negative one) at expiration. For an OMM who is long options, the charm component of hedge rebalancing trades entails selling (buying) the underlier when it is above (below) the strike. This trading can “pin” the underlier at the strike. Once the underlier is pinned, the terms $\frac{\partial\Delta}{\partial S}dS$ and $\frac{1}{2}\frac{\partial^2\Delta}{\partial S^2}(dS)^2$ that appear in equations (2) and (6) become negligible.

Baltussen, Terstegge and Whelan (2023) present evidence of an upward drift in the S&P 500 index during the overnight period leading into the expiration of the am-settled SPX options.⁴ They attribute this to the charm of OMM written positions in slightly out-of-the-money SPX puts. The mechanism is that written put positions have positive deltas, which go to zero as expiration approaches. The delta-hedge positions are short the underlier, and rebalancing them

⁴ Baltussen, Terstegge, and Whelan (2023) do not find any evidence of upward price drift explained by charm going into the expiration of the p.m.-settled SPXW options. This suggests that the expiration of the a.m.-settled SPX options is special, perhaps either because of the large magnitude of SPX options or because of the lesser liquidity of the e-mini futures during the overnight period as compared to during regular trading hours.

involves buying the underlier as expiration approaches, creating upward pressure on the underlier price.

2.3 Hedge trades in response to options trades

OMMs also execute delta hedge trades as they trade options, to either establish or close out delta hedges of their added or closed options positions. These trades can impact prices both through the information they convey and non-informational price pressure. Research studying the price impact of initial delta hedge trades (for example, Hu (2014)) has interpreted the price impacts as evidence that they convey information to the market. Golez and Jackwerth (2012) and Amaya et al. (2026) provide evidence consistent with the hypothesis that such unwinding trades on the expiration dates of index futures options and equity and ETF options, respectively, impact underlier prices.⁵

3. Data and the Computation of the Delta and Gamma of the Aggregate OMM Position

The main data we use are records of all trades in S&P 500 index options with symbols SPX and SPXW during the period running from January 2020 through June 2023. The SPX options settle at the market open on the third Friday of each month, while the SPXW options settle at 4:00 p.m. each day. We first describe these data, and how we use them to compute the aggregate option market maker (OMM) net position in every SPX and SPXW options series at one-minute frequency throughout the trading day. Then we describe how we compute the delta and gamma of the OMM position. This involves using quote data to compute the implied volatilities at one-minute frequency of all SPX and SPXW option series in the aggregate OMM position, using the implied volatilities and other data to compute the deltas and gammas of each options series, and then aggregating the deltas and gammas to compute the delta and gamma of the aggregate OMM position.

3.1 SPX and SPXW options trade data

The records of trades in S&P 500 index options are provided by Cboe Global Markets. Each single-leg trade, and each leg of each complex trade, appears as at least two trade records, one for the buyer and one for the seller. A trade or trade leg appears as more than two trade records when the passive side of the trade is shared among two or more traders. Each trade

⁵ Conceptually, such hedge unwinding trades are not different from initial delta hedge trades. Hu (2014) shows that such trades impact the prices of underlying stock through the information they convey. One difference is that there is evidence that closing trades contain much less information than opening trades (Ge, Lin, and Pearson (2016)).

record includes the option series traded, the trade date and time, trade price, number of contracts, trading capacity of the trader, and whether the option is purchased or sold. We group the trading capacities provided in the Cboe data into the broader categories of customer, market maker, professional customer, firm, and broker-dealer. For the non-market maker capacities, each trade record also indicates whether the trade opened a new options position or closed an existing position. The dataset contains a total of 442,589,991 trade records. A detailed description of the data and the construction of complex trades are provided in the Internet Appendix A.

Table 1 shows the average percentages of trading volume due to the buys and sells of each trading capacity, for options with different numbers of days to expiration (DTE). We report trading for options with 0DTE, 1-5 DTE, 6-21 DTE, and > 21 DTE in four panels. Other than the sums in the last row and column of each panel, each entry is the average percentage of total SPX and SPXW volume due to buys by the trading capacity indicated in the row label and sells by the capacity indicated in the column heading. We compute the average percentages by first computing the percentage for each trading date, where the denominator is the total trading volume on that date, across all SPX and SPXW option series. We then average the daily percentages across the trading days during our sample period. The last row and last column of each panel display the sums of the entries across rows or columns, respectively.

For example, the entry in the row labeled “Customer” and column headed “Market maker” in Panel A shows that on average 15.0% of total SPX and SPXW option trading volume is due to trades in 0DTE options which a customer bought and a market maker sold. The entry in the row “Customer” and column “Customer” indicates that on average 1.7% of volume comes from trades in which a customer bought and another customer sold. The other entries in this row show that 0.2%, 0.3%, and < 0.1% of volume comes from trades in which a customer bought and a firm, professional customer, or broker dealer sold, respectively. The last entry in the row shows that 17.2% of total SPX and SPXW trading volume is due to trades in which a customer bought a 0DTE option. The entry in the column headed “Customer” and row labeled “Sum” indicates that a similar, but slightly smaller, percentage of trading volume, 16.0% consisted of trades in which a customer sold a 0DTE option. The lower right-hand entry in Panel A is the sum of the 25 entries for the different trading capacities. It shows that on the average day in our sample trading

in 0DTE options accounted for 34.8% of total SPX and SPXW trading volume. The results displayed in Panels B-D are interpreted similarly.⁶

The results in Table 1 show that trading in SPX and SPXW options is dominated by customers and market makers. On an average day, trades in which a customer buys and a market maker sells account for 34.9% ($= 15.0\% + 9.5\% + 5.1\% + 5.3\%$) of trading volume, and trades in which a customer sells and a market maker buys account for 33.9% ($= 14.1\% + 9.4\% + 5.1\% + 5.3\%$) of volume. Thus, on the average day, 68.8% of volume involves a customer trading with a market maker. An additional 9.0% ($= 1.5\% + 2.6\% + 1.9\% + 3.0\%$) involves a market maker trading with another market maker, and 2.2% ($= 1.7\% + 0.4\% + <0.1\% + <0.1\%$) involves a customer trading with another customer. Trading volume due to customers trading with other customers is a much larger fraction of 0DTE volume as compared to trading volume in options with one or more days to expiration.

Customers and market makers of course also traded with other capacities. Summing the entries in the rows and columns labeled “Firm,” “Professional Customer,” and “Broker Dealer” across the four panels, on the average day only 2.9% of trades involved neither a customer nor a market maker.

3.2 ETF options trade data

For some analyses we include the deltas or gammas of the positions in the S&P 500 ETF options (symbols SPY, IVV, and VOO) resulting from trades executed on one of the Cboe exchanges. These trade data are also obtained from Cboe Global Markets. A limitation of these data is that they cover only trades on the four Cboe exchanges.

3.3 Computing the aggregate OMM position

Because the trade records include every trade in which an OMM participated, and indicate whether the OMM bought or sold, we can compute the aggregate OMM net position at any time for most options series. At the inception of trading in each option series, the aggregate OMM position in that series must be zero. Then each OMM buy increases the aggregate OMM position in that option series by the trade size, and each OMM sell decrements the aggregate net position by the trade size. Thus, we can determine the aggregate position at any time by

⁶ The sum of the entries in the lower right-hand corners of the four panels, $34.8\% + 29.2\% + 18.3\% + 27.1\% = 109.4\%$, does not sum to 100% because the results are averages of ratios and total trading volume in SPX and SPXW options differs considerably across dates.

cumulating the market maker trades from the inception of trading up to that time, where a buy is a positive increment and a sell is a negative increment.

We cannot compute the aggregate OMM net position for option series that began trading before January 2, 2020, which is the first date for which we have the Cboe trade data. For these options, computing OMM positions by cumulating the trades starting from January 2020 results in an error equal to the aggregate OMM net position at the beginning of January 2020. We limit the impact of this on our results by carrying out the statistical analysis using our estimates of OMM deltas and gammas starting from July 2020. Of the option series that are available for trading at the beginning of July 2020, relatively few are available for trading on January 2, 2020. These are the SPX options with expirations in September, October, November, and December 2020, March, June, September, and December 2021, and December 2022. For the series expiring at these times, the error consists of the market maker positions that existed at the beginning of January 2020, more than six months before the expiration of the first of these option series. Because open interest in options with six months or more to expiration tends to be small relative to open interest in other expirations, and the aggregate OMM net position must be less than or equal to open interest, our approach of carrying out the statistical analysis using only the estimates starting from July 2020 limits the magnitude of the error in our estimates of aggregate OMM net positions. During the latter part of the sample period the errors are smaller or non-existent, because there are few or no options that began trading before January 2020.

We perform the computation described above for every minute during regular trading hours (RTH) starting from July 2020. Specifically, for each minute during RTH starting from the beginning of trading on July 1, 2020, and for each option series, we cumulate the signed market maker trading volumes starting from January 2020 to estimate the aggregate market maker net position in that series. The result is, for each option series, a time-series of aggregate market maker net positions at one-minute frequency that consists of the positions at each minute from 9:30 am to 4:00 p.m. on each date, starting from the first day the option series traded.

3.4 Computing the delta and gamma of the aggregate OMM position

Given the OMM positions, for each options series and minute we compute the delta and gamma by multiplying the position (in contracts) by the contract multiplier of 100 and the delta or gamma of the series as of that minute. The delta and gamma are the first and second

derivatives of the Black-Scholes formula. Computing the delta and gamma requires a dividend yield, an interest rate, and an implied volatility.

For each trade date, OptionMetrics provides the option-implied S&P 500 index dividend yield for each SPX or SPXW expiration date. For each option series j and minute on date d , we use the OptionMetrics dividend yields from the preceding date $d - 1$. OptionMetrics also provides, for each date, a term structure of zero-coupon interest rates, for a set of maturity dates that are not necessarily options expiration dates. For each option series j and minute on date d , we interpolate the date d OptionMetrics interest rates to obtain a zero-coupon rate for the expiration date of series j .

In contrast to the dividend yields and interest rates, which are treated as constant during each date, we compute implied volatilities for each series for each minute during the trading day. We do this using “minute bar” data for the SPX and SPXW options obtained from Algoseek LLC. Each minute bar includes, among other data items, the prevailing BBO quotes at the end of the minute. For each minute, and each SPX and SPXW series in which the aggregate OMM position is non-zero, we use the midpoints of these quotes to compute the implied volatility of the option series as of the end of the minute by (numerically) inverting the Black-Scholes-Merton formula. We obtain the spot price needed for this calculation from the price of the e-mini futures contract (symbol ES) that has the greatest trading volume on that date, adjusted from the futures maturity to the current date. The calculation of implied volatility uses the dividend yield and interest rates obtained from OptionMetrics.

Finally, for each minute on each date, we compute the appropriate weighted sum of the deltas and gammas of the option series that are available for trading on that date to obtain the delta and gamma of the aggregate OMM position as of that date and minute. The results consist of OMM deltas and gammas at one-minute frequency from 9:30 a.m. to 4:00 p.m. on each date, during the period running from July 2020 through June 2023.⁷ Throughout the paper, a timestamp refers to the beginning of the corresponding one-minute interval. For example, observations labeled 3:59 p.m. use data from 3:59:00 through 4:00:00 p.m. For some analyses,

⁷ The 9:30 a.m. delta and gamma reflect all trades up through 9:30 a.m., that is, they include the trades during the overnight period. Even though our delta and gamma estimates include all SPX and SPXW options, we stop computing gamma at 4:00 p.m. on each date because our analysis is motivated by the possible impact of large 0DTE positions, and the 0DTE options expire at 4:00 p.m..

we also compute and use the delta or gamma of subsets of the OMM positions, for example OMM positions in expiring 0DTE options.

4. Impact of Hedge Unwinding trades on Underlying Futures Prices

As discussed in Section 2, hedge unwinding at the expiration of cash-settled index options generates a clear prediction for index futures returns. When the delta of the aggregate OMM position in expiring options is positive, the hedge position is short index futures, so unwinding the hedge requires buying futures. When OMM delta is negative, hedge unwinding requires selling futures. We therefore predict that index futures returns shortly before the 4:00 p.m. options expiration are positive (negative) when OMM delta in expiring 0DTE options is positive (negative). In this section, we test this prediction using the delta of the aggregate OMM position in expiring SPXW options shortly before expiration.

4.1 OMM deltas prior to options expiration

The solid red line in Figure 2 plots the delta of the aggregate OMM position in the expiring (0DTE) SPXW options during the sample period running from July 2020 through June 2023. The delta is expressed in billions of U.S. dollars; it is computed by taking the usual delta, expressed in numbers of index futures contracts, converting to dollars by multiplying by the notional value of one index futures contract, and then dividing by 10^9 . The time series of 0DTE delta, shown by the red line, suggests it would be difficult or impossible for other market participants to reliably predict the delta of the aggregate OMM position without knowledge of OMM positions, which they are unlikely to have. The 3:30 deltas appear random, and the time series is not highly persistent, with a first-order serial correlation of only 0.207.

The dashed purple line plots the delta of the aggregate OMM position in the other (non-0DTE) SPX and SPXW options.⁸ The time series of non-0DTE delta is obviously highly persistent. Consistent with the visual impression left by the figure, the first-order serial correlation is 0.969. There also appears to be much more variability in the non-0DTE delta compared to the 0DTE delta.

The two panels of Figure 3 display histograms showing the distributions of the deltas of the aggregate OMM position in the expiring (0DTE) SPXW options at 3:30 and 3:45 p.m. The lines superimposed on the histograms display density functions of Normal distributions with the

⁸ Internet Appendix Figure IAB1 plots the deltas of the OMM positions in the 0DTE and non-0DTE options as of 3:45 p.m.. Visually, it is difficult to distinguish Figure IAB1 from Figure 2.

same mean and variance as the distributions shown in the histograms. Comparison of the histograms to the density functions reveals that the distributions of the OMM deltas are approximately Normal, with a slightly larger probability of a delta close to zero compared to the Normal distribution with the same mean and variance.

In Table 2 we report statistics describing the distributions of the 0DTE deltas displayed in Figure 3. Table 2 also displays the same statistics describing the distributions of the deltas of the OMM positions in non-0DTE options. Comparing the statistics describing the distribution of non-0DTE deltas to the same statistics describing the distribution of 0DTE deltas, the distribution of non-0DTE delta is much more variable than the distribution of 0DTE deltas. For example, the standard deviation of the non-0DTE delta at 3:30 p.m. (denoted $\Delta_{\text{non-0DTE}}(3:30 \text{ p.m.})$) is 19.05, more than eight times the 2.22 standard deviation of the 3:30 p.m. 0DTE delta (denoted $\Delta_{\text{0DTE}}(3:30 \text{ p.m.})$). The interquartile range of the 3:30 p.m. non-0DTE delta is approximately 24, as compared to approximately 2 for the 3:30 p.m. 0DTE delta.

What positions contribute to the delta of the OMM position in 0DTE options? We explore this in Figure 4, Panel A, which displays for each month in the sample period the average contributions to the delta of the 3:30 p.m. 0DTE OMM positions resulting from single- and multi-leg trades. The blue bars show the net delta of the OMM positions resulting from single-leg trades, with light (dark) shading when the net delta is positive (negative). The red bars display the net delta of the OMM positions resulting from complex trades, with light (dark) shading when the net delta is positive (negative). The display consists predominantly of dark blue bars and light red bars, indicating that OMMs generally sell delta through single-leg trades and buy delta through multi-leg trades. Thus, other market participants, primarily customers, mostly buy delta through single-leg trades and sell delta through multi-leg trades. This is especially the case toward the end of the sample period, where the figure displays only light red and dark blue bars.⁹

Panel B displays for each month the average contributions to the delta of the 3:30 p.m. non-0DTE OMM positions resulting from single- and multi-leg trades. The results displayed in this panel are quite different from those in Panel A. This panel consists primarily of light blue

⁹ Internet Appendix Figure IAB4 shows monthly volume of vertical spreads, other two-leg complex trades (for example, calendar, diagonal, and ratio spreads), three-leg complex trades, four-leg complex trades, and other complex trades, during our sample period.

and dark red bars, indicating that OMMs are generally buying delta (and thus others are selling delta) through single-leg trades and selling delta (and thus others are buying delta) through complex trades.

4.2 Returns for groups of days sorted by OMM delta

As discussed above, we predict that the index futures return during the period shortly before the 4:00 p.m. options settlement is positive (negative) when the delta of the aggregate OMM position in the expiring SPXW options is positive (negative).

We test this prediction by first using the deltas of the aggregate OMM position in the expiring SPXW options as of 3:30 p.m. to sort the trading dates into five quintiles. We then compute the average index futures returns from 3:30 to 4:00 p.m. for each group of dates. Specifically, we use the one-minute log returns on the front-month e-mini futures contract to compute the cumulative log return from 3:30 p.m. to each subsequent minute up to 4:00 p.m.. We then average the cumulative log returns within each quintile, yielding five sets of average cumulative log returns.

We report the results in Figure 5. Panel A displays the average cumulative one-minute log returns on the front-month futures contract for each minute over the period running from 3:30 to 4:00 p.m. for the five quintiles. By 4:00 p.m., the average cumulative return on the highest-delta quintile is about 6.5 bps, and the average cumulative return on the lowest-delta quintile is about -10.5 bps, for a return difference of about 17 bps. The average cumulative returns on the middle three quintiles lie between those of the low and high delta groups, and are all small, with the largest in absolute magnitude being only about -2 bps. The average returns between 3:30 and 4:00 p.m. on all five groups of days are monotonically increasing from the lowest to the highest quintile.

To the extent that OMMs use marketable orders to unwind their delta hedge trades, we expect to find that the cumulative order imbalance (buys minus sells) for the high-delta quintiles exceeds the cumulative order imbalance for the low-delta quintile. We explore this hypothesis by computing the average cumulative order imbalance from 3:30 p.m. to each subsequent minute up to 4:00 p.m. for each of the five groups, where the direction (buy/sell) of each trade is estimated using the Lee and Ready (1991) algorithm.

Panel B of Figure 5 displays the average cumulative order imbalances for the five quintiles. A limitation of the Lee and Ready (1991) algorithm in this context is that it tends to

incorrectly sign customer trades executed using non-marketable limit orders. Despite this limitation, the average cumulative order imbalance at 4:00 p.m. for the low-delta group of days is the smallest, approximately $-1,700$ contracts. The average cumulative order imbalance for the high-delta group of days is the greatest after 3:40 p.m., except for at exactly 4:00 p.m., when it is the second greatest, just slightly below the greatest order imbalance. Thus, the average order imbalances are generally consistent with the average cumulative returns.

Figure IAB2 displays the results of a similar analysis in which we sort the dates in five groups using the deltas at 3:45 p.m. rather than 3:30 p.m., and examine the average cumulative log returns over the period from 3:45 p.m. to 4:00 p.m. Consistent with the results in Panel A of Figure 5, the average cumulative return in Panel A of Figure IAB2 is greatest for the highest-delta days, and least for the lowest-delta quintile, and the return difference is about 12.5 bps.

The average order imbalances displayed in the bottom panel of Figure IAB2 are consistent with those shown in Figure 5. The average order imbalance of the low delta quintile is the smallest of the five quintiles for the 15 minutes before expiration. The average order imbalance in the high delta quintile is the greatest for most of the 15 minutes prior to expiration, except for the last minute.

4.3 Regressions using the delta of the OMM position in expiring SPXW options

To control for other potential determinants of index futures returns, we complement the sorting analyses reported in Figure 5 with multivariate regressions that include control variables. While OMMs do not need to unwind delta hedges on non-0DTE options, their non-0DTE delta may still predict returns if OMM positioning reflects information about future index movements. Because non-0DTE delta is also correlated with 0DTE delta, we include it in the regressions, along with lagged index futures returns and minute-of-day fixed effects.

In these regressions the unit of observation is a minute, the dependent variable is the log return R_t on the front-month index futures contract during the minute ending at time t , in basis points (bps), and the sample consists of the minutes ending at times $t = 12:01$ p.m., $12:02$ p.m., ..., $4:00$ p.m. during the sample period running from July 2020 through June 2023. The main explanatory variable of interest is the interaction term $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$, where τ is either 3:30 or 3:45 p.m. and $\tau+1$ is 1 minute later, $\Delta_{0DTE}(\tau)$ is the delta of the OMM position in the expiring (0DTE) options at time τ , and the indicator variable $I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ equals one if t (the end of the minute) is in the set $\{\tau+1, \dots, 4:00 \text{ p.m.}\}$. Thus, this

indicator variable equals one for the 30 or 15 minutes before expiration, and the interaction term $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ equals $\Delta_{0DTE}(\tau)$ for the 30 or 15 minutes before expiration. Some specifications also include the interaction $\Delta_{\text{non-0DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$, where $\Delta_{\text{non-0DTE}}(\tau)$ is the delta of the OMM position in the non-expiring options at time τ . All specifications include the lagged return R_{t-1} and minute-of-day fixed effects.

We report the results in Table 3, Panel A. Column (1) presents the results for the full model when $\tau = 3:30 \text{ p.m.}$ The coefficient on $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ is positive and highly significant (t -statistic 4.09), as expected. The coefficient on the lagged return R_{t-1} is statistically significant (t -statistic 2.17), but small in magnitude and economically insignificant. The coefficient on $\Delta_{\text{non-0DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$, the interaction term involving the delta of the OMM position in non-0DTE options, is insignificant. Columns (2) and (3) display the results after dropping $\Delta_{\text{non-0DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ and $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$, respectively. The coefficient on $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ in column (2) is close to that in column (1), and highly significant. The coefficient on the control variable $\Delta_{\text{non-0DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ in column (3) is close to zero and insignificant, indicating that including this control variable was unnecessary.

The specifications in columns (4)-(6) are identical to those in columns (1)-(3), except that $\tau = 3:45 \text{ p.m.}$ The coefficient on the key variable of interest $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ is highly significant in the two specifications in columns (4) and (5) that include this variable, and the coefficient on the control variable $\Delta_{\text{non-0DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ is small and insignificant in the two models in which it appears. Thus, across columns (1)-(6), the coefficient on the key variable of interest $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ is highly significant in every specification in which it appears, and the coefficient on the control variable $\Delta_{\text{non-0DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ is close to zero and insignificant in every specification in which it appears.¹⁰

When $\tau = 3:30 \text{ p.m.}$, the estimated coefficient on $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ implies that a one-standard-deviation change in $\Delta_{0DTE}(\tau)$ increases each of the 30 one-minute

¹⁰ We report the results of placebo regressions that show that the delta of the OMM position in expiring options does not explain index futures returns during periods other than the 30 minutes prior to expiration in Internet Appendix Table IAB1.

returns during the window from 3:30 p.m. to 4:00 p.m. by 0.198 bps.¹¹ This implies that the 30-minute return over the interval is impacted by approximately $30 \times 0.198 \text{ bps} = 5.94 \text{ bps}$. When $\tau = 3:45 \text{ p.m.}$, the estimated coefficient on $\Delta_{0\text{DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ implies that a one-standard-deviation change in $\Delta_{0\text{DTE}}(\tau)$ increases each of the 15 returns during the window from 3:45 p.m. to 4:00 p.m. by 0.314 bps, which implies that the return over the 15-minute interval is impacted by 4.71 bps.¹² Recognizing that $\Delta_{0\text{DTE}}(\tau)$ will frequently be one standard deviation above or below its mean, and will be two standard deviations above or below its mean on about 11 days per year, the estimated relation implies that hedge unwinding trades frequently have economically important impacts on the index futures market during 30 and 15 minutes prior to options expiration.¹³ This is consistent with the results displayed in Figure 5.

4.4 Regressions using the delta of the OMM position in expiring ETF options

As discussed above, OMMs must unwind delta hedges for cash-settled options held to expiration, but not for physically settled options. However, when customers and other non-OMM participants close option positions on the afternoon before expiration, OMMs may take the other side and close some of their own positions before expiration. If so, OMMs may unwind the associated delta hedges, potentially affecting index futures returns. If OMM deltas in expiring ETF options correlate with those in expiring SPXW options, omitting ETF-option deltas may bias the estimated impact of SPXW-option deltas.

We explore whether unwinding delta hedges on expiring ETF options affects index futures returns by adding two interaction terms to the specifications in Table 3, Panel A: $\Delta_{0\text{DTE}}^{\text{ETF}}(\tau) \times I(t \in \{2:01 \text{ p.m.}, \dots, 4:00 \text{ p.m.}\})$ and $\Delta_{\text{non-}0\text{DTE}}^{\text{ETF}}(\tau) \times I(t \in \{2:01 \text{ p.m.}, \dots, 4:00 \text{ p.m.}\})$. These variables are defined analogously to the corresponding SPXW measures, except that they use OMM deltas in expiring and non-expiring ETF options and apply from 2:01 p.m. onward to allow for earlier customer liquidations.

Table 3, Panel B reports the results. The coefficient estimates on $\Delta_{0\text{DTE}}^{\text{ETF}}(\tau) \times I(t \in \{2:01 \text{ p.m.}, \dots, 4:00 \text{ p.m.}\})$ are positive in all specifications but small and statistically

¹¹ The standard deviation of $\Delta_{0\text{DTE}}(3:30 \text{ p.m.})$ in Table 2 is 2.22. The product of this and the estimated coefficient on $\Delta_{0\text{DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ in column (1) of Table 3, Panel A is $0.0889 \times 2.223 = 0.198 \text{ bps}$.

¹² The standard deviation of $\Delta_{0\text{DTE}}(3:45 \text{ p.m.})$ in Table 2 is 2.20. The product of this and the estimated coefficient on $\Delta_{0\text{DTE}}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ in column (4) of Table 3, Panel A is $0.143 \times 2.196 = 0.314 \text{ bps}$.

¹³ The calculation of 11 days relies on the approximate normality of $\Delta_{0\text{DTE}}(3:30 \text{ p.m.})$ evident in Figure 3. Letting $N(\bullet)$ denote the standard normal distribution function, $(N(-2) + (1 - N(2))) \times 252 \text{ days} = 11.47 \text{ days}$.

insignificant. Although inconclusive, their positive signs are consistent with some OMMs closing expiring ETF-option positions and unwinding the associated delta hedges in ways that affect index futures returns. More importantly, adding the expiring and non-expiring ETF-option delta measures has little effect on the coefficients for the corresponding SPXW variables. Indeed, the estimates of $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ are slightly larger in Panel B than in Panel A.

4.5 Impacts on volatility

The results in Figure 5 and Table 3 show that positive (negative) OMM 0DTE delta is associated with positive (negative) index futures returns. If OMM delta has a large impact on returns, then it should also impact volatility. We explore the impact of OMM delta by regressing realized volatility over the final 30 (15) minutes before the 4:00 p.m.. expiration on the absolute OMM 0DTE delta measured at 3:30 (3:45) p.m..

The unit of observation in these regressions is a day, and the sample consists of all days during the sample period running from July 2020 through June 2023. The dependent variable is the annualized realized volatility of the one-minute log returns on the front-month e-mini index futures contract during the period from τ to 4:00 p.m., where τ is either 3:30 p.m. or 3:45 p.m.. Realized volatility is annualized by multiplying the realized variance during the 30-minute period from 3:30 to 4:00 p.m. (15-minute period from 3:45 to 4:00 p.m.) by 13×252 (26×252) and taking the square root. The key explanatory variable is $|\Delta_{0DTE}(\tau)|$, the absolute delta of the OMM position in the expiring (0DTE) options at time τ . On days with no 0DTE options, $\Delta_{0DTE}(\tau)$ equals zero. Deltas are multiplied by 10^{-12} so that the coefficients are in convenient units. We include controls for non-expiring option positions, hedge rebalancing, and systematic variation in volatility. Specifically, we include $|\Delta_{\text{non-0DTE}}(\tau)|$, the absolute delta of OMM positions in non-expiring options at time τ ; OMM gamma in 0DTE and non-0DTE options; and week and day-of-week fixed effects.

Table 4 reports the regression results. Panel A uses OMM deltas in S&P 500 index options, while Panel B also includes OMM deltas in S&P 500 ETF options (symbols SPY, VOO, and IVV). The results show a positive relation between the magnitude of OMM 0DTE delta and realized volatility before expiration. When $\tau = 3:30 \text{ p.m.}$, the coefficients on $|\Delta_{0DTE}(\tau)|$ are positive and statistically significant across both panels, with t -statistics ranging from 1.97 to 2.90. The coefficient estimates are also consistently larger in Panel B, which includes ETF

options. When $\tau = 3:45$ p.m., the coefficients remain positive but are weaker in Panel A; in Panel B, they remain statistically significant, with t -statistics between 2.00 and 2.23. The coefficients on OMM gamma in both 0DTE and non-0DTE options are negative and statistically significant, consistent with hedge rebalancing dampening volatility. In contrast, $|\Delta_{\text{non-0DTE}}(\tau)|$ is not significant at the 5% level in any specification, although several estimates are significant at the 10% level. This lack of a strong relation is expected because non-expiring options positions do not require hedge unwinding at expiration. The results for $\tau = 3:45$ p.m. are slightly weaker, with both smaller point estimates of the coefficients on $|\Delta_{\text{0DTE}}(\tau)|$ and smaller t -statistics.

5. Impact of Hedge Rebalancing Trades

We next examine the impact of OMM hedge rebalancing on index futures volatility. Section 2 shows that hedge rebalancing trades are proportional to OMM gamma, even when hedging occurs over finite intervals and speed and charm are large. Aggregate OMM gamma therefore provides the relevant measure of the hedge rebalancing pressure generated by OMM positions. In this section, we first describe the level, variation, and trading-strategy origins of OMM gamma and then estimate its relation with the volatility of one-minute index futures returns.

5.1 Summary statistics for OMM gamma

We begin by reporting summary statistics that describe some features of the estimates of OMM gamma. We first scale all the OMM gamma estimates by dividing them by 10^9 . For each date, we compute the mean, median, standard deviation, maximum, and minimum of the (scaled) gamma estimates at one-minute frequency. The result is a sample of daily values of each statistic, for example, a sample of daily means. We then compute the mean, standard deviation, and several percentiles of the samples of daily values, and report the results in Table 5.

Panel A displays the results for all days during the period running from July 2020 through June 2023. The results show that gamma is typically positive, with a mean of the daily means equal to 343.3 (that is, 343.3×10^9). It also displays considerable variation, with a standard deviation of 321.6, almost as large as the mean of the daily means. The distribution of daily minima shows that gamma is negative on at least 25% of the days (the 25th percentile of the daily minima is -92.5). The gamma is negative for the entire day on at least 1% of the days, as the first percentile of the daily maxima is -46.2 . The minimum of the daily minima is $-3,548.2$, and the maximum of the daily maxima is even larger, 16,743.4.

Panels B and C display the results for subsamples of days for two periods: July 2020 through April 2022 and May 2022 through June 2023. The dividing point, the beginning of May 2022, is approximately the time when the Tuesday and Thursday expirations are introduced.¹⁴ The results show that OMM gamma is generally higher before the introduction of Tuesday and Thursday expirations. For example, the means of the daily means are 411.1 before, and 235.9 after, the Tuesday and Thursday expirations were introduced. Negative gammas are also more frequent. After the Tuesday and Thursday expirations are introduced, the median of the daily minima is negative (−44.3), implying that gamma is negative at some point during at least half of the trading days.

Figure 6 illustrates one feature of the variation in gamma by plotting the average OMM gamma on each trading date. Specifically, for each trading date we average the OMM gammas at one-minute frequency, resulting in a single average value for each day. We then scale these by dividing by 10^{12} , and plot the scaled daily average values. The figure shows considerable day-to-day variation in OMM gamma. One feature apparent in the plot is that daily average gamma is rarely negative before 2022, but is often negative starting in early 2022. Figure IAB3 illustrates the intraday variation in OMM gamma for seven representative days.

5.2 Single-leg trades, multi-leg trades, and OMM gamma

We examine whether OMM gamma is associated with single-leg (simple) or multi-leg (complex) trades. We find that customers are generally buying when they execute single-leg trades. Because OMMs typically take the other side of the customer trades (see Table 1), the single-leg trades contribute negatively to OMM gamma. Customers are generally selling gamma through the multi-leg book, and these trades contribute positively to OMM gamma. The net gamma traded via multi-leg trades typically exceeds the net gamma traded in the single-leg protocols. As a result, net OMM gamma is typically positive.

Table 6 displays the average OMM gamma, in billions, due to positions created by single-leg trades, vertical spreads in calls and puts, and other multi-leg trades. We report vertical spreads separately because Internet Appendix Figure IAB4 shows that they are the most common multi-leg trade. To construct Table 6, we first aggregate the OMM trades of different strategies

¹⁴ The first Tuesday expiration was on April 26, 2022 and the first Thursday expiration was on May 19, 2022. These options began trading on April 18 and May 11, 2022, respectively. See <https://ir.cboe.com/news/news-details/2022/Cboe-to-Add-Tuesday-and-Thursday-Expirations-for-SPX-Weeklys-Options-04-13-2022/default.aspx>.

to find the net OMM position resulting from the different strategies. We then compute the gammas of the strategy positions at one-minute frequency, and average the one-minute frequency gammas across the sample. The first column displays the gammas resulting from trades in the SPX and SPXW options, which make the largest contribution to OMM gamma. The next three columns show the gammas of the OMM positions resulting from trades in the S&P 500 ETFs with symbols SPY, IVV, and VOO executed on the Cboe exchanges. The last column (row) provides the sum across the symbols (strategies).

The first column shows that the average gamma of the OMM positions resulting from single-leg trades in the SPX and SPXW is negative and large, with an average value of -106.64 billion. This negative gamma is more than offset by the positive gamma resulting from vertical calls, vertical puts, and other multi-leg trades, yielding an average OMM gamma of 342.59 billion in SPX and SPXW options.

Among the ETFs, only the positions resulting from trades in SPY make a material contribution to the average OMM gamma. OMM positions resulting from single-leg SPY trades on average contribute negatively to gamma, with an OMM gamma of -54.85 billion. The average net gamma of positions resulting from multi-leg trades is close to zero ($1.66 - 7.59 + 5.86 = -0.07$), so the overall average contribution of the SPY positions to OMM gamma is -54.92 billion, close to the contribution of the SPY positions resulting from single-leg trades.

The negative contribution of the SPY positions to OMM gamma, while material (-54.92 billion), is not large enough to offset the positive gamma resulting from the SPX and SPXW positions. As a result, the total OMM gamma is 287.89 billion.

Figure 7 shows the average contribution of OMM positions resulting from single- and multi-leg trades in SPX and SPXW options to OMM gamma during each month of the sample period. The dark blue bars in the negative region show the magnitudes of the contribution of single-leg trades when the contribution is negative; the light blue bars in the positive regions show the single-leg contributions when they are positive. The contribution of single-leg trades to OMM gamma is almost always negative, and large, with exceptions of positive contributions occurring in February, March, September, and November of 2021. The pink bars display the contribution of complex trades to OMM gamma, which is always positive, though occasionally small.

Figure 8, Panel A decomposes the gamma contribution of positions resulting from single-leg SPX and SPXW trades into positions in 0DTE options and positions in options with more than zero days to expiration. The plot shows that the negative gamma of positions resulting from single-leg trades rapidly increased in magnitude after Tuesday and Thursday expirations are introduced in April-May 2022. The gamma resulting from single-leg trades in options with greater than zero days to expiration remains close to zero. Panel B decomposes the gamma contribution of positions resulting from multi-leg SPX and SPXW trades. The positive gamma contributions of positions resulting from multi-leg trades with both zero and greater than zero days to expiration increase rapidly after June 2022. These increases more than offset the increasingly negative gamma contribution from 0DTE single-leg positions.

5.3 GARCH model

Our goal is to estimate the impact of the aggregate OMM net gamma on volatility, or equivalently, variance. We use a flexible version of a generalized autoregressive conditional heteroskedasticity (GARCH) model that incorporates lagged OMM gammas as additional explanatory variables, to allow for a relation between the conditional variance of returns and lagged OMM gammas. The model also incorporates ideas from the GARCH model proposed by Engle and Sokalska (2012) to allow the level of variance to differ across days, and for a diurnal variance pattern within each day.

The one-minute index return is modelled as

$$r_{t,d} = h_d s_t q_{t,d} \varepsilon_{t,d}, \quad (11)$$

where $(h_d s_t q_{t,d})^2$ is the return variance. In this equation d indexes the day, t indexes the minute within the day, $r_{t,d} = \ln(F_{t,d}/F_{t-1,d})$ is the log change in the midpoint price of the S&P 500 futures contract with highest trading volume on day d , $\varepsilon_{t,d}$ is an innovation with mean zero and variance one, h_d^2 is the daily variance component, s_t^2 is the diurnal variance pattern, and $q_{t,d}^2$ is the intraday variance component.

Following the two-step estimation approach of Engle and Sokalska (2012), we first estimate the daily variance component h_d^2 and the diurnal variance pattern s_t^2 using non-parametric methods. For the daily component, we compute the daily realized variance using one-minute returns. For the diurnal pattern, we use the daily realized standard deviation to standardize the one-minute returns on each day and then compute the sample variance for each minute across the full sample.

In the second step, we normalize returns by the daily and diurnal volatility components, and model the residual intraday variance component $q_{t,d}^2$ as a multi-component GARCH model:

$$\sigma_{t,d}^2 = (1 - \alpha - \beta) + \alpha \frac{z_{t-1,d}^2}{\tau_{t-1,d}} + \beta \sigma_{t-1,d}^2, \quad (12)$$

$$\ln(\tau_{t,d}^2) = m + \gamma \sum_{l=1}^K \varphi_l(\omega_1, \omega_2) \Gamma_{t-l,d}, \quad (13)$$

$$q_{t,d}^2 = \tau_{t,d}^2 \sigma_{t,d}^2, \quad (14)$$

$$z_{t,d} = \frac{r_{t,d}}{\hat{h}_d \hat{s}_t}. \quad (15)$$

The specification for the τ component builds on the MIDAS specification proposed in Engle, Ghysels, and Sohn (2013), which allows the model to incorporate information from an economic variable in the spirit of a MIDAS regression. In our model, the economic variable of interest is $\Gamma_{t,d}$, representing the gamma exposure of the aggregate OMM net position at minute t on day d . Lags of this variable are included in the τ component according to the weighting scheme φ_l , governed by two parameters that can represent various shapes, including monotonically increasing (or decreasing) patterns and unimodal, hump-shaped schemes. We use the “Beta” weighting function proposed in Engle, Ghysels, and Sohn (2013).

We also introduce parameters representing the initial variance for each day. Including initial variance as a parameter to be estimated, together with the daily variance component h_d^2 , implies that only information for a given day is used in the variance forecast, as no information about past variables is carried over across days. We predict that γ is negative and that the largest weights fall on the shortest lags.

We estimate the model in equations (11)-(15) with five lags of gamma for each month from July 2020 to June 2023, using the one-minute returns and quasi-maximum likelihood estimation based on the assumption that $\varepsilon_{t,d} \sim N(0, 1)$. We obtain model parameters for each month, and compute average parameter values across the 36 months. To obtain conveniently scaled parameter estimates, we divide OMM gammas by 10^{12} and measure returns in basis points.

5.4 GARCH model results

We report the results of estimating the GARCH model in equations (11)-(15) in Table 7. The table presents averages across the 36 months of the coefficients on $r_{t-1,d}^2$ and $\sigma_{t-1,d}^2$, the

parameters m and γ , and the implied weights on the lagged gammas $\Gamma_{t-l,d}$. Standard errors of the average coefficient estimates are in parentheses below the coefficient estimates. These standard errors are computed as the standard deviation of the 36 monthly estimates, divided by the square root of 36. Column (1) displays the results for a version of the model that does not include the lagged gammas. Columns (2) and (3) present the results of specifications that include either one or five lags of gamma, respectively. To assess the statistical performance of these two models, for each month, and each model, we compute a likelihood ratio test (LRT) statistic to test the hypothesis that all parameters except α and β equal zero. The last row of the table reports the average likelihood ratio test statistic across the 36 months.

The average coefficient estimates are 0.044–0.045 for $r_{t-1,d}^2(\alpha)$ and 0.922–0.923 for $\sigma_{t-1,d}^2(\beta)$, values typical of GARCH(1,1) models estimated using index returns. The standard errors of these averages indicate that there is relatively little variation in the estimates of these coefficients across months.

Turning to the estimates of the coefficient γ , its average across the 36 months is -0.499 for model (2) and -0.516 for model (3), indicating a negative relation between OMM net gamma and index return variance. The small standard errors indicate little variation in these estimates across months. These results are consistent with the prediction that delta-hedging by market makers in S&P 500 index options affects index variance at the minute level. This impact persists, as evidenced by the non-negative weights $\varphi_1, \dots, \varphi_5$, with the largest weight on the first lag.

The likelihood ratio test statistics in the last row test the hypotheses that except α and β are jointly zero. Under the null hypothesis that these coefficients are zero, the test statistics are distributed χ^2 , with two degrees of freedom. The 5%, 2.5%, and 1% critical values of the χ^2_2 test statistic are 5.99, 7.38, and 9.21, respectively. The average values of the test statistic in columns (2) and (3) are 8.62 and 8.85, providing on average some statistical evidence against the hypothesis that $m = \gamma = 0$. Thus, the likelihood ratio tests provide evidence against the hypothesis of no relation between index return variance and OMM gamma.

The likelihood ratio tests also indicate little statistical benefit from including more than one lag of gamma. The difference between the likelihood ratio test statistics in columns (2) and (3) tests whether the additional gamma lags improve model fit. Because the Beta lag structure of Engle, Ghysels, and Sohn (2013) introduces two additional parameters, the difference in the

monthly likelihood ratio statistics is distributed as χ^2_2 under the null. The difference between the average statistics is only $8.85 - 8.62 = 0.23$, far below the 5% critical value, providing no evidence that the additional gamma lags improve the model.

Models (4) through (8) explore whether the results are robust to reasonable variations in the specification. In column (4), we restrict the initial variance to be the same across all days of the month. This specification is more restrictive than that in column (3). The estimates of α and β are close to those in columns (2) and (3), but slightly higher for α and slightly lower for β . The estimate of γ is slightly smaller in magnitude than the estimates in columns (2) and (3). We do not report an LRT statistic because the specification in column (4) does not nest the model in column (1).

Model (5) replaces Γ_{t-1} with an estimate of the expected OMM gamma at $t+10$, $E[\Gamma_{t+10}]$. We compute this expectation by assuming that the change in the log price of the e-mini futures over the next 10 minutes is normally distributed and approximate this distribution with a discrete distribution. Next, we compute the gamma for each point in the discrete distribution and calculate the expectation $E[\Gamma_{t+10}]$ as the probability weighted average of these gammas. Results for model (5) are very close to those for model (3). Model (8) extends model (3) by adding 30 lagged gammas instead of five. We obtain similar results to those in model (3).

Models (6) and (7) incorporate the gammas of positions in the S&P 500 ETFs SPY, VOO, and IVV. Model (6) uses positions resulting from trades on the Cboe exchanges, while model (7) scales these positions by the ratio of average ETF trading volume across all exchanges to average volume on the Cboe exchanges to account for trading in all option exchanges. The results for both models are very similar to those for model (3).

Finally, we examine whether our conclusions are specific to the GARCH framework by estimating linear models in which variance depends on aggregate OMM net gamma. As reported in Internet Appendix Table IAB2, the results are qualitatively unchanged, suggesting that our findings are not driven by the choice of the statistical model.

5.5 Distinguishing between gammas of initial and new positions

Our estimates of the relation between return variance and OMM gamma are possibly impacted by a “reverse causality” in which trades are partly explained by expectations of market variance. Because OMMs participate in many trades, expectations of market variance may generate a correlation between market variance and OMM gamma independent of OMM hedge

rebalancing. In risk management applications, such as using OMM gamma to forecast intraday market variance, reverse causality is not a concern because the source of the association is not important. However, reverse causality is important when assessing whether OMM gamma causes market volatility.

To address the reverse causality, we decompose gamma at minute t of day d , $\Gamma_{t,d}$, into two components: (i) the gamma due to OMM positions at the 9:30 am market open, denoted $\Gamma_{0,d}$, and (ii) the gamma of the incremental positions generated by trades from 9:30 am up through minute t , equal to $\Gamma_{t,d} - \Gamma_{0,d}$. While the positions that enter $\Gamma_{0,d}$ are fixed throughout the day, $\Gamma_{0,d}$ varies with the index level, implied volatility, and the remaining time to option expiration. This decomposition should mitigate concerns about reverse causality because the relation between $\Gamma_{0,d}$ and market variance is not driven by intraday trading.

Using this decomposition, we re-estimate the model described in equations (11)-(15), replacing the specification of $\ln(\tau_{t,d}^2)$ in equation (13) with

$$\ln(\tau_{t,d}^2) = m + \gamma_{\text{initial}} \sum_{l=1}^K \varphi_l(\omega_1, \omega_2) \Gamma_{0,d} + \gamma_{\text{new}} \sum_{l=1}^K \varphi_l(\omega_1, \omega_2) (\Gamma_{t-l,d} - \Gamma_{0,d}). \quad (16)$$

We report the results in Table 8. Column (1) reproduces the specification without OMM gamma from Table 7, column (1). Model (2) includes one lag of gamma computed from OMM positions in SPX and SPXW options. Model (3) also includes one lag but adds positions in S&P 500 ETF options to the gamma measure. Models (4) and (5) use five and 30 lags of gamma, respectively; we do not report the estimated lag-weight parameters ϕ_1 through ϕ_5 .

The estimates of γ_{new} range from -0.557 to -0.872 and are consistently larger in magnitude than the corresponding estimates of γ_{initial} . This pattern is consistent with some of the association between OMM gamma and return variance arising because intraday option trades respond to expectations of future volatility. Importantly, however, the relation between initial OMM gamma and return variance remains strong: the estimates of γ_{initial} range from -0.372 to -0.416 . Because initial positions are determined before the trading day begins, these estimates provide evidence that the negative relation between OMM gamma and return variance is not driven solely by intraday trading in anticipation of future volatility.

6. Estimating the Impact of OMM Gamma on Market Return Variance

We now turn to using the GARCH models to estimate the impact of OMM gamma on the variance of S&P 500 index returns. One cannot do this by computing the partial derivatives of variance with respect to the lagged gammas in the GARCH model, because the lagged gamma at time t impacts not only the time t conditional variance but also all future variances through the dynamic variance models. For example, in the GARCH model, at time t lagged gamma $\Gamma_{t-1,d}$ impacts σ_t^2 and thus r_t directly through the coefficient γ . Then $\sigma_{t,d}^2$ and $r_{t,d}$ impact $\sigma_{t+1,d}^2$ and $r_{t+1,d}$ through the coefficients β and α ; these in turn impact $\sigma_{t+2,d}^2$ and $r_{t+2,d}$, which in turn impact $\sigma_{t+3,d}^2$ and $r_{t+3,d}$, and so forth. The process continues until the impact of $\Gamma_{t-1,d}$ eventually decays. Through this process, the variance at any time t is impacted by many lags of gamma, with the magnitude of the impact determined by the coefficients on the lagged gammas and the other model parameters in a complicated way.

We estimate the impact of gamma on return variance by simulating the GARCH model to generate simulated returns or squared returns under the counterfactual assumption that the lagged gammas are all zero, or equivalently, under the assumption that the coefficients m and γ are all zero. These simulations yield time series of simulated squared returns at one-minute frequency based on the counterfactual assumption that OMM gammas do not impact variance. We then use the simulated squared returns to compute realized variance over horizons of one day and 30 minutes and compare them to the realized variances computed from the actual observed one-minute returns. The differences between the realized volatilities based on actual and simulated returns provide measures of the impact of option market maker gamma on volatility.

6.1 Simulating the GARCH models

We begin by constructing a comprehensive measure of daily total variability, which includes the price impact induced by OMM gammas. This involves generating one-minute returns derived from bid-ask midpoint futures prices, followed by the computation of the realized variance for each trading day and for each half hour during the day. The realized variance captures the total variability observed in the market, reflecting both the volatility due to fundamental factors (for example, news) and any additional volatility arising from market dynamics, including the impact of hedge rebalancing by OMMs.

Letting t index the minute during regular trading hours on a day d , the realized variance during regular trading hours for day d is

$$RV_d = \sum_{t=1}^n r_{t,d}^2, \quad (17)$$

where $r_{t,d}$ represents the one-minute return at minute t of date d , and n is the total number of one-minute intervals during regular trading hours.

We identify the effect of gamma by simulating a gamma-free realized variance. For each minute, we compute an estimate $\hat{\varepsilon}_{t,d}$ of the GARCH model innovation $\varepsilon_{t,d}$. We recover the estimated innovation $\hat{\varepsilon}_{t,d}$ from equation (11) using the actual return and the model estimate of the conditional standard deviation, that is, $\hat{\varepsilon}_{t,d} = z_{t,d}/(\hat{\tau}_{t,d}\hat{\sigma}_{t,d})$. We then use these innovations to simulate one-minute returns, $\hat{r}_{t,d}$, under the counterfactual assumption that returns are not influenced by the gammas. The simulation involves multiplying the recovered one-minute innovations by the estimated conditional variance from the GARCH model in Table 7 column (3), while setting the coefficients associated with lagged values of net gamma, m and γ , to zero. This removes the influence of gamma from the returns, thereby yielding estimated gamma-free returns.

Then, we use the simulated returns to compute a gamma-free realized variance,

$$RV_d^{GF} = \sum_{t=1}^n \hat{r}_{t,d}^2, \quad (18)$$

for each day d . The impact of gamma on index volatility is then estimated by comparing the annualized observed realized volatility and the annualized gamma-free realized volatility. The day d impact is calculated as the difference between the realized volatility and the annualized gamma-free realized volatility:

$$Impact_d = \sqrt{252 \times RV_d} - \sqrt{252 \times RV_d^{GF}}. \quad (19)$$

With this definition, positive impacts mean that the actual realized volatility, which reflects the impact of OMM delta hedging, exceeds the counterfactual volatility computed under the assumption that OMM delta hedging does not impact returns.

We use the same approach to compute the gamma impacts over shorter, 30-minute intraday periods, allowing for a more granular analysis of gamma's influence on market volatility throughout the trading day.

We report summary statistics describing the distribution of the impacts of OMM gamma on annualized daily volatility and annualized 30-minute volatility in Table 9, Panel A. The average daily and 30-minute impacts are negative for both horizons, with means of -0.21 and -0.19 percentage points, respectively. Thus, realized volatility is, on average, lower than it would have been in the absence of OMM delta hedging. This result follows from the negative relation between return variance and OMM gamma, combined with the fact that OMM gamma is positive on most days (Table 5). However, the 75th percentiles are positive at both horizons, indicating that OMM delta hedging increases volatility on approximately 25% of days and 25% of 30-minute periods.

The last column of Table 9, Panel A shows that the largest estimated impact is an increase of 2.31 percentage points in annualized daily volatility. The second row shows that the largest impact on 30-minute volatility is to increase annualized volatility by 5.86 percentage points. This impact of 5.86 percentage points is an outlier, given that the 99th percentile of the 30-minute impacts is only 1.55 percentage points.

Figure 9 displays the daily time series of impacts on the annualized daily volatilities. These impacts are generally negative, consistent with the results that the OMM gammas are typically positive. Comparing the daily gamma-induced impacts in Figure 9 to the average daily gammas in Figure 6 shows that the impacts tend to be positive when OMM gamma is negative, as expected. Figure IAB5 displays histograms of the distributions of the daily and 30-minute impacts.

We obtain qualitatively similar results when estimating the effects of OMM delta hedging using a linear model rather than the GARCH specification. These results are reported in Internet Appendix Table IAB3 and Figure IAB6.

6.2 Discussion

Should one think of a gamma-induced increase in annualized daily realized volatility of 2.31 percentage points as large or small? Similarly, should one think of a gamma-induced increase in annualized 30-minute realized volatility of 5.86 percentage points as large or small?

The distributions of changes in annualized daily and 30-minute realized volatilities provide benchmarks for thinking about these questions. For example, suppose daily changes in annualized realized volatility of about 2.31 percentage points or greater occur frequently, for whatever reason. If this is the case, then market participants are likely used to dealing with such

changes, and the fact that OMM delta hedging can increase annualized realized volatility by 2.31 percentage points might not be a source of concern. But if increases of about 2.31 percentage points are rare, then the fact that OMM delta hedging can cause such an increase might merit more attention.

Figure IAB7, Panel A displays the histogram of daily changes in annualized daily realized volatility. To construct this histogram, we use one-minute log futures returns to calculate the realized variance during regular trading hours, annualize the realized variance by multiplying by 252, and take the square root to convert the result to a volatility. Then we subtract the previous day's annualized realized volatility, and construct the histogram displayed in Panel A. Panel B of Table 9 presents various percentiles of the distribution of daily changes in annualized daily realized volatility, along with the mean, standard deviation, minimum, and maximum of the daily changes.

The standard deviation of daily changes in annualized realized volatility is 4.5 percentage points, and the change in annualized realized volatility from the previous day exceeds 2.31 percentage points on about 20% of the trading days. Thus, changes in annualized realized volatility of about 2.31 percentage points or greater occur reasonably frequently, on about 20% of the days, or on average about once per week. Given this, our interpretation of the results is that a gamma-induced change of 2.31 percentage points is not large.

Figure IAB7, Panel B displays the histogram of changes in annualized 30-minute realized volatilities. For this figure, each daily change is the difference between the annualized realized volatility during a 30-minute period, say 10:00-10:30 am, and the previous 30-minute period, 9:30-10:00 am. The histogram displays changes between -20 and 20 percentage points, as there are few changes outside that range. Table 9, Panel C includes several percentiles of the distribution of these daily changes, along with the mean, standard deviation, minimum, and maximum. The minimum and maximum changes are -52.2 and 63.4 percentage points.

The results in Table 9, Panel C show that the standard deviation of the changes in annualized 30-minute realized volatility is 4.6 percentage points, and the 1st and 99th percentiles of the daily changes in annualized 30-minute realized volatilities are -11.6 and 14.2 percentage points. Using these as benchmarks, the maximum gamma-induced change of 5.86 percentage points does not seem large.

7. Conclusion

We exploit data on the trades of different market participants obtained from Cboe Global Markets to estimate both the impact of hedge unwinding trading on market returns during the last 30 minutes of the trading day, and the relation between OMM gamma and volatility throughout the trading day, during the period running from July 2020 through June 2023. Importantly, the Cboe data allow us to compute OMM positions, and the delta and gamma of the aggregate net OMM position, throughout the trading day, both in the aggregate and separately for positions arising from single-leg and multi-leg option trades. This allows us to study the impact of OMM hedge trading on the index futures market.

We find that the impacts of hedge unwinding trading on the returns during the last 30 minutes of trading can be large. Specifically, we estimate that a one-standard deviation increase (decrease) in the delta of the OMMs' position in expiring options as of 3:30 p.m. increases (decreases) market returns over the last 30 minutes of trading by about 6 bps. Because 0DTE S&P 500 index options expire every day, it is common for the delta to be one standard deviation from its mean, and deviations of two or more standard deviations happen several times per year. Thus, our estimates imply that hedge unwinding trading has frequent, important impacts on market movements during the last 30 minutes of trading.

We also find a significant relation between OMM gamma and market volatility throughout the trading day. We estimate the maximum impact of OMM gamma on S&P 500 index volatility over one-day and 30-minute periods, as compared to a counterfactual situation in which OMM gamma does not impact market volatility. We do this by using the GARCH models to generate simulated returns under the counterfactual assumption that the return variance is unrelated to the lagged gammas. We then use the simulated returns to compute realized variance for each trading day, and compare these counterfactual realized volatilities to the realized volatilities computed from the actual one-minute returns. The differences between the realized volatilities based on actual and simulated returns provide measures of the impact of market maker gamma on volatility. We use the same approach to compute simulated and actual realized volatilities for non-overlapping 30-minute periods starting at 9:30 am each day.

The results show that the typical impact of gamma is to reduce volatility, with the mean impact being to reduce volatility by 0.2 percentage points. But OMM gamma is sometimes negative, and at these times volatility is elevated. We find that the maximum impact of OMM

gamma on annualized daily volatility is to increase annualized daily volatility by 2.31 percentage points. The maximum impact of OMM gamma on annualized 30-minute volatility is to increase it by 5.86 percentage points.

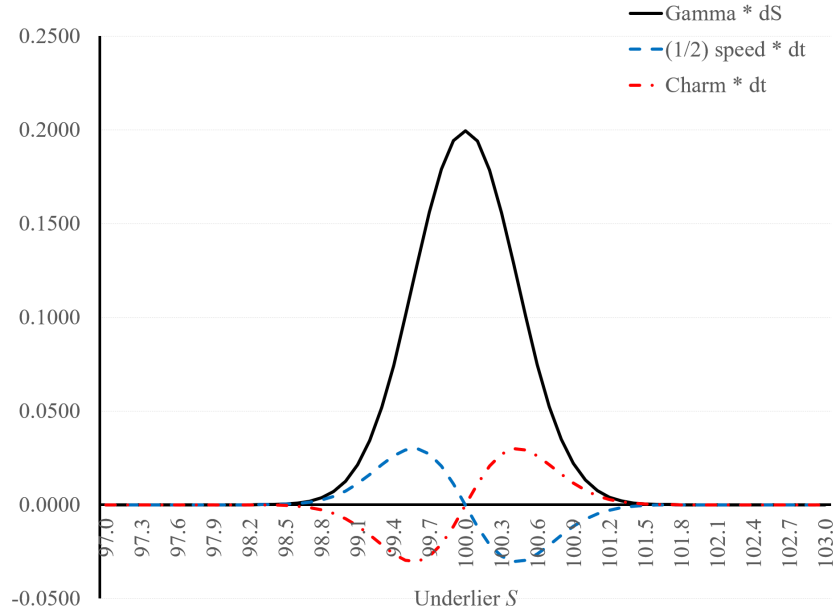
Taken together, our results reveal a clear distinction between the two channels through which OMM hedge trading affects the underlying market. Hedge unwinding at the settlement of cash-settled index options generates directional price pressure shortly before expiration, while hedge rebalancing throughout the trading day affects volatility. The impact of hedge unwinding is economically more important. Thus, concerns about the market impact of 0DTE index options should focus primarily on the unwinding of delta hedges at expiration rather than on gamma-driven hedge rebalancing. In particular, the delta of the aggregate OMM position in expiring options shortly before settlement is the relevant measure of the potential price impact of 0DTE options.

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Panel A. Greeks 1 hour before expiration



Panel B. Greeks 15 minutes before expiration

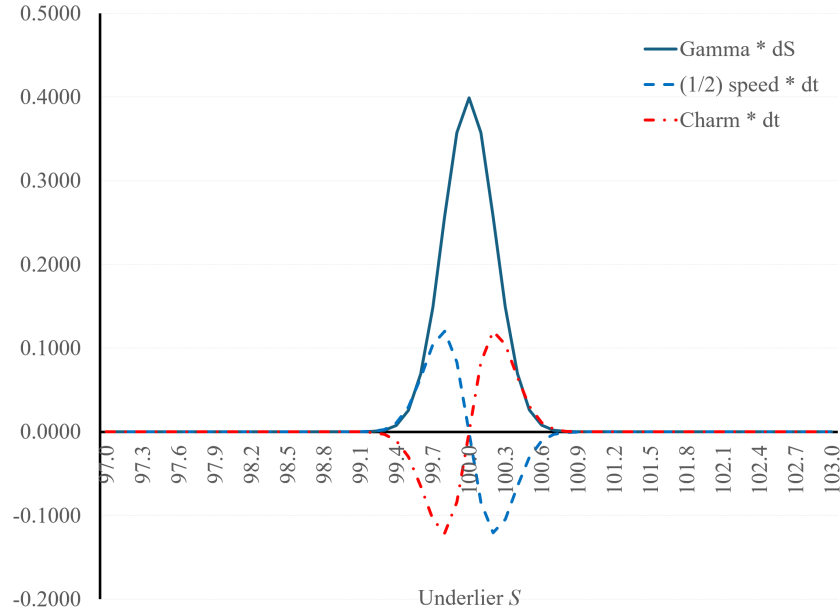


Figure 1

Terms that comprise $d\Delta$

In each panel, the solid line displays ΓdS , and the blue and red dashed lines display $\frac{1}{2}(\partial\Gamma/\partial S)\sigma^2 S^2 dt$ (“speed”) and $(\partial\Delta/\partial t)dt$ (“charm”), respectively. The time to expiration is $\tau = 1$ hour $= 1/(24 \times 365)$ years in Panel A and $\tau = 15$ minutes $= 15/(60 \times 24 \times 365)$ years in Panel B. The term $dt = 15$ minutes $= 15/(60 \times 24 \times 365)$ years, and dS is set equal to the standard deviation of the change in the underlying price over 15 minutes, $\sigma S\sqrt{dt}$. The other parameters are $K = 100$, $\sigma = 0.4$, and $r = 0.04$.

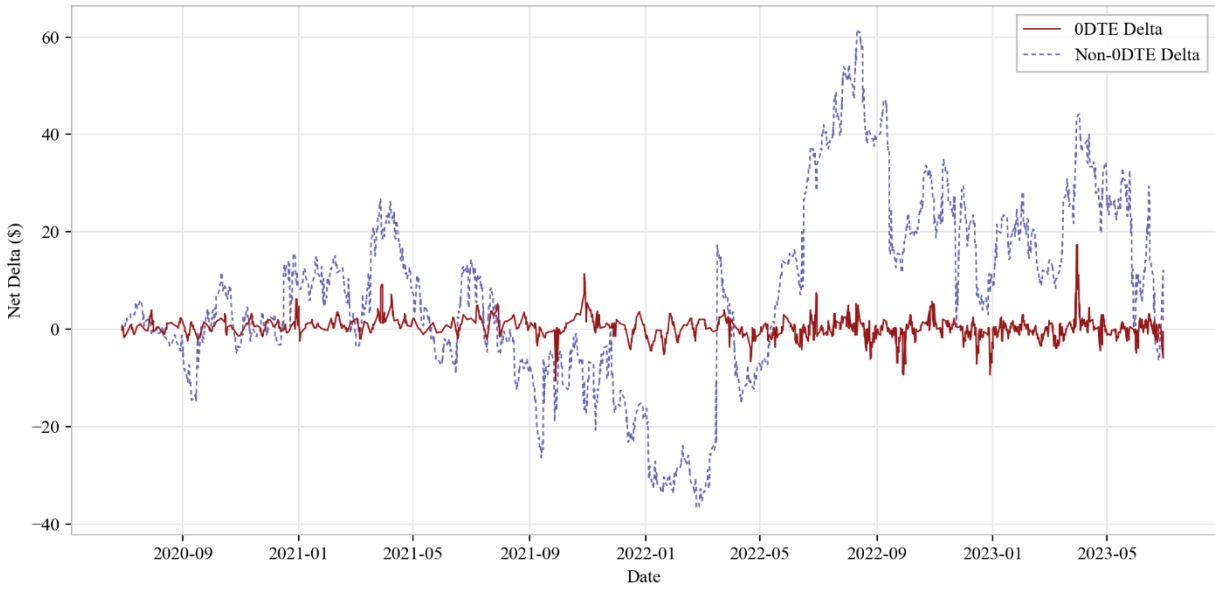
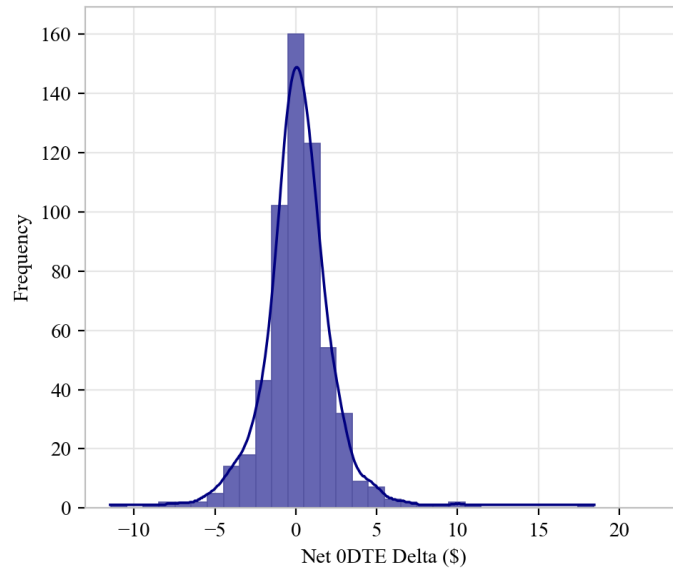


Figure 2

Deltas of the 3:30 p.m. OMM positions in 0DTE and non-0DTE S&P 500 index options

The figure plots the daily time series of the deltas of the aggregate option market maker (OMM) positions in 0DTE and non-0DTE S&P 500 index options as of 3:30 p.m. during the sample period running from July 2020 through June 2023. The computation of the deltas is described in Section 3. Deltas are expressed in billions of U.S. dollars by multiplying the usual delta, expressed in units of the underlying, by the notional value of the S&P 500 index, and then dividing by 10^9 .

Panel A. 0DTE delta at 15:30 ET



Panel B. 0DTE delta at 15:45 ET

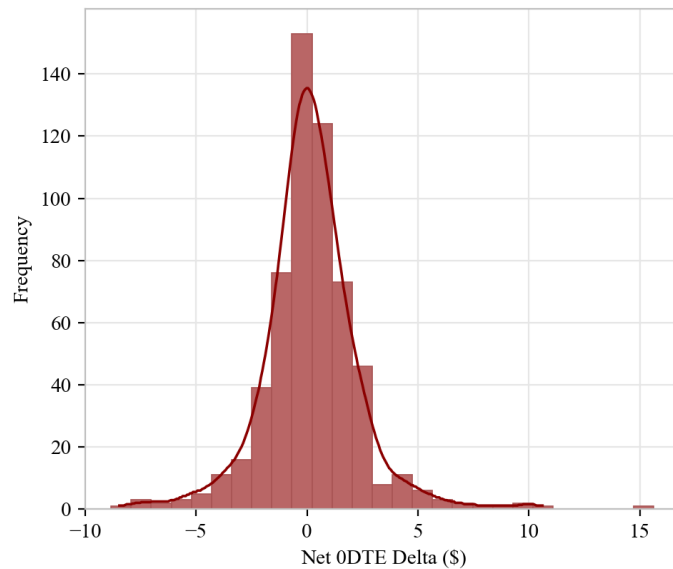
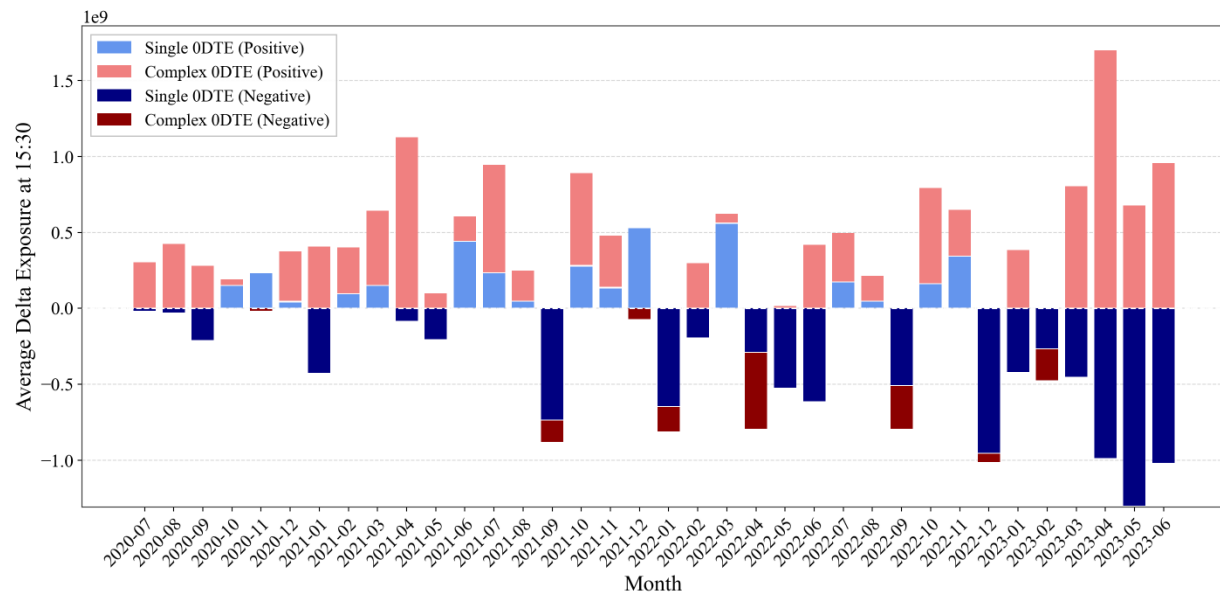


Figure 3

Distributions of the deltas of the OMM positions in 0DTE SPXW options

The two panels display histograms showing the distributions of the deltas of the aggregate option market maker (OMM) position in 0DTE SPXW options as of 3:30 p.m. (Panel A) and 3:45 p.m. (Panel B) on each trading date during the sample period running from July 2020 through June 2023. The computation of the deltas is described in Section 3. They are expressed in billions of U.S. dollars by multiplying the usual delta, expressed in units of the underlying, by the notional value of the S&P 500 index.

Panel A. 0DTE options



Panel B. Non-0DTE options

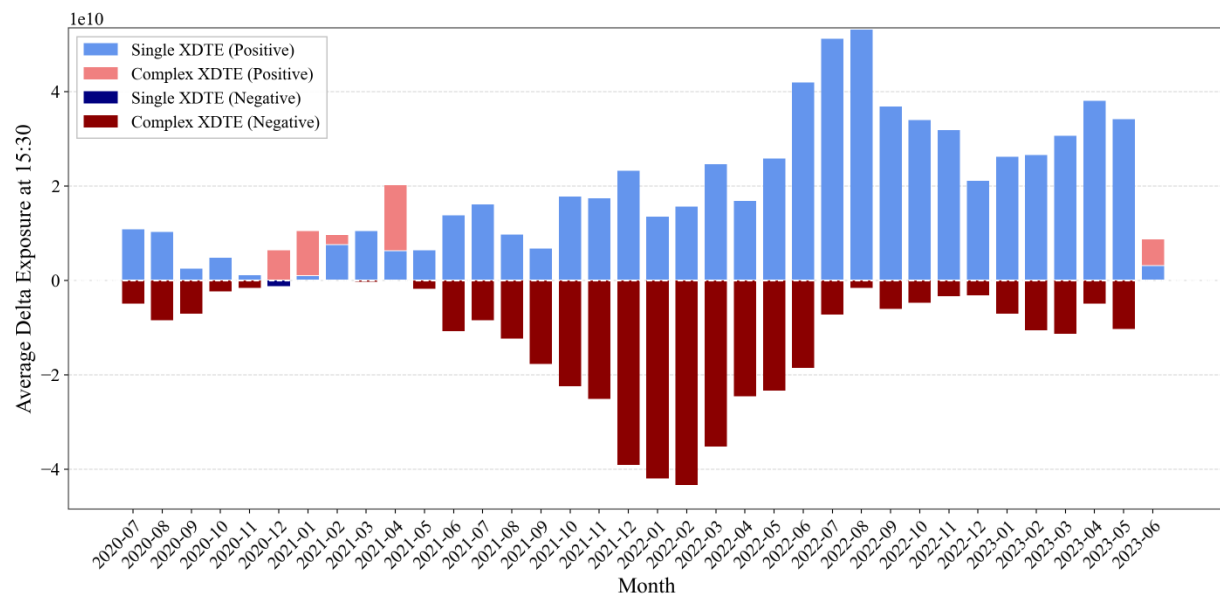
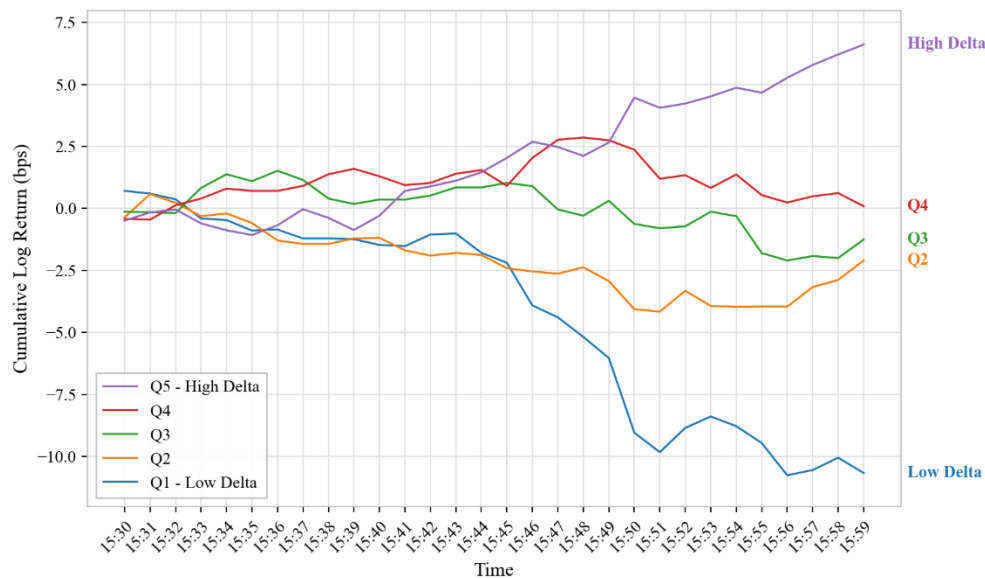


Figure 4

Deltas of OMM positions in 0DTE and non-0DTE due to single- and multi-leg trades

Panel A (B) displays for each month in the sample period the average contributions to the delta of the 3:30 p.m. 0DTE option market maker (OMM) and non-0DTE OMM positions resulting from single- and multi-leg trades. The blue bars show the net delta of the OMM positions resulting from single-leg trades, with light (dark) shading when the net delta is positive (negative). The red bars display the net delta of the OMM positions resulting from complex trades, with light (dark) shading when the net delta is positive (negative).

Panel A. Cumulative index futures return



Panel B. Cumulative order imbalance

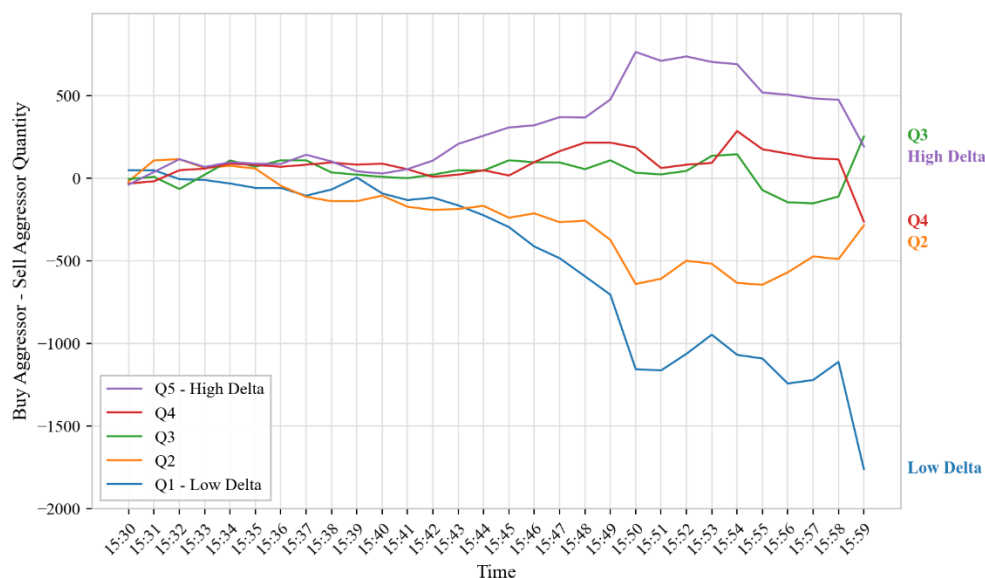


Figure 5
Cumulative index futures returns and order imbalances by OMM 0DTE delta at 3:30 p.m.
 In this figure, we first sort trading dates into five equal-sized quintiles based on the delta of the option market maker (OMM) position in expiring SPXW options as of 3:30 p.m. For each group, we compute cumulative log returns on the front-month index futures contract from 3:30 p.m. through each subsequent minute up to 4:00 p.m. using one-minute returns. Panel A plots the average cumulative log return for each quintile. Panel B plots the average cumulative order imbalance for each quintile from 3:30 p.m. through each subsequent minute up to 4:00 p.m., with trade direction (buy/sell) estimated using the Lee and Ready (1991) algorithm.

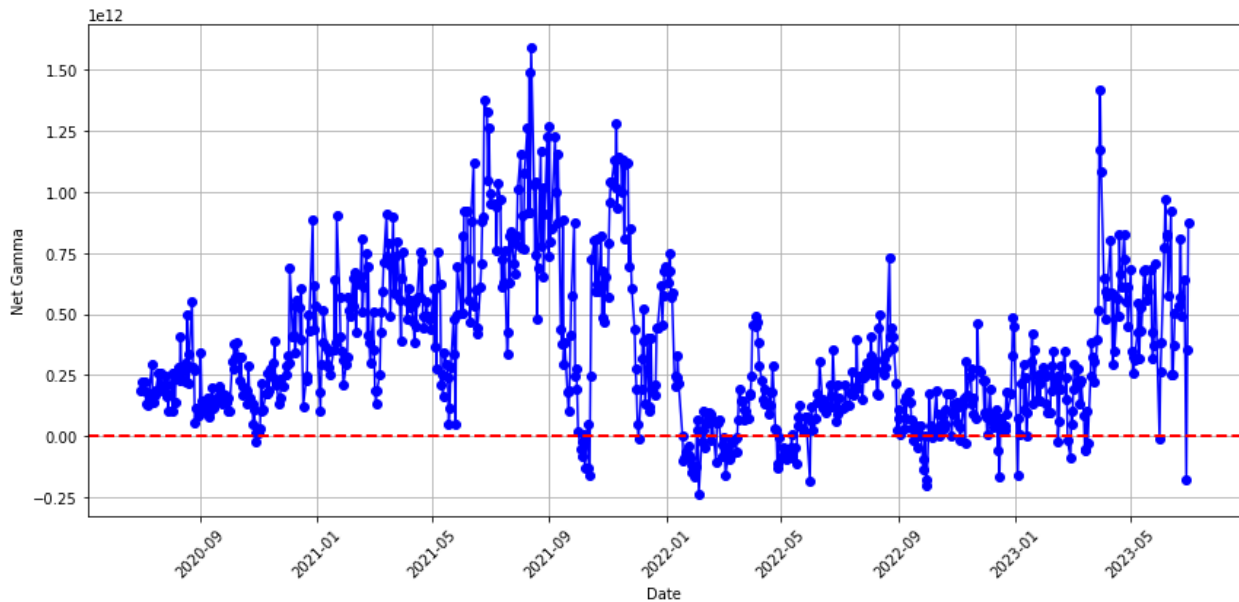


Figure 6

Time series of daily averages of gamma at one-minute frequency

For each date, we compute the average of the option market maker gammas at one-minute frequency, resulting in a single average gamma for each date. The figure plots these daily averages. The gammas are scaled by dividing by 10^{12} . The sample period runs from July 2020 through June 2023.

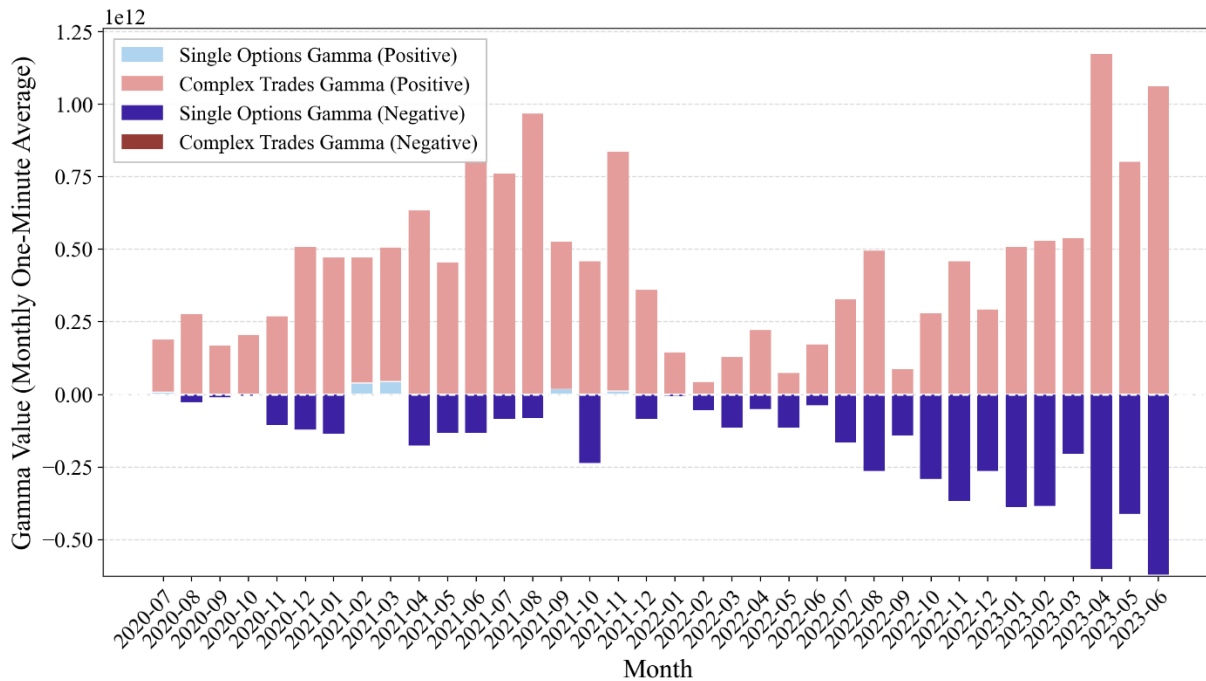
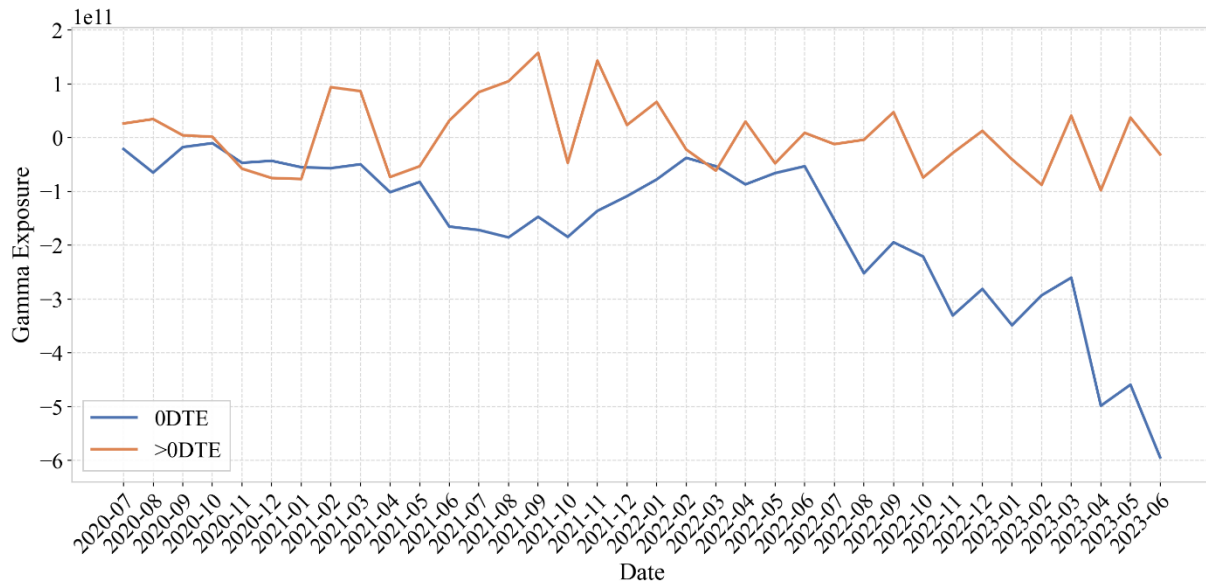


Figure 7

Contribution of single- and multi-leg trades to gamma

The figure shows the average contribution of option market maker (OMM) positions resulting from single- and multi-leg trades in SPX and SPXW options to OMM gamma during each month of the sample period. The dark blue bars in the negative region show the magnitudes of the contribution of single-leg trades when the contribution is negative; the light blue bars in the positive regions show the single-leg contributions when they are positive. The pink bars display the contributions of complex trades to OMM gamma when the contribution is positive. Complex trades do not make a negative contribution to OMM gamma in any month. The sample period runs from July 2020 through June 2023.

Panel A. Single-leg trades



Panel B. Multi-leg trades

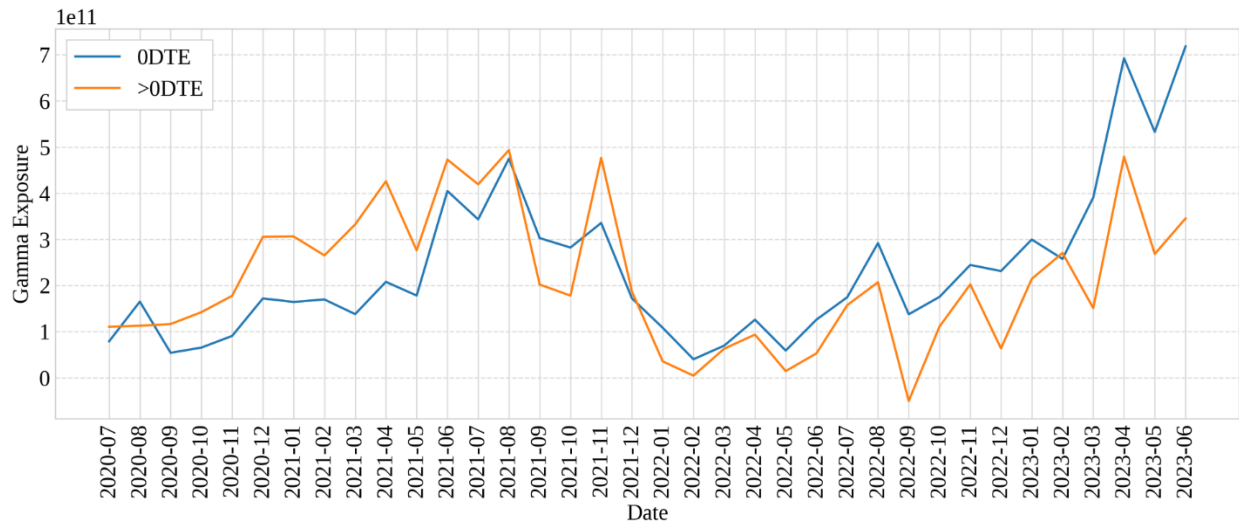


Figure 8

Contributions of 0DTE and non-0DTE option trades to OMM gamma

Panel A (B) disaggregates the gamma of the option market maker (OMM) positions resulting from single-leg (multi-leg) trades in SPX and SPXW options into that stemming from trades in options with zero days to expiration and that due to trades in options with greater than zero days to expiration. The sample period runs from July 2020 through June 2023.

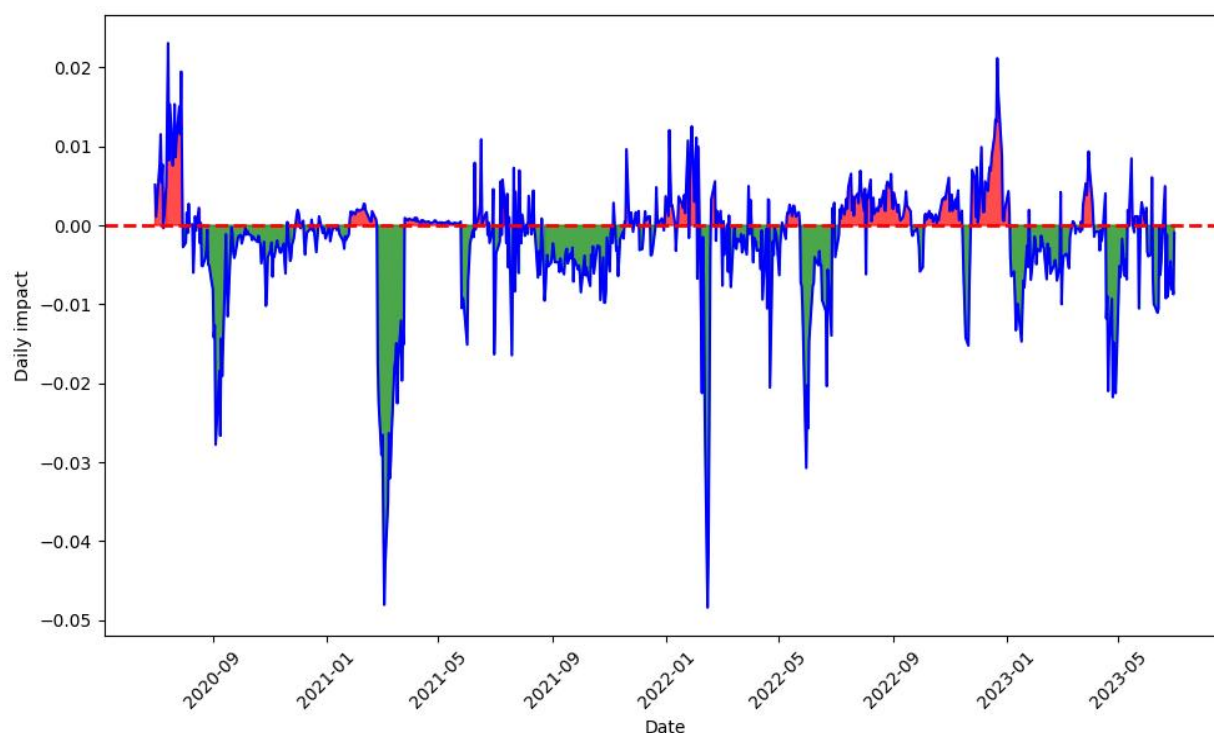


Figure 9

GARCH model estimates of gamma-induced impacts on annualized daily realized volatility

This figure plots the daily time series of impacts on the annualized daily realized volatilities. The gamma-induced impact is the difference between the annualized daily realized volatility and an estimate of what the annualized daily realized volatility would be under the counterfactual assumption that the GARCH model conditional variance is unrelated to option market maker (OMM) gamma. The GARCH model is the version with five lags of gamma, for which average coefficient estimates are reported in column (3) of Table 7. The sample period runs from July 2020 through June 2023.

Table 1**Distribution of daily trading volume by buyer and seller capacity**

This table reports the percentage of daily SPX and SPXW option trading volume attributable to each buyer–seller capacity pair. Panels A–D classify trades by days to expiration (DTE): 0DTE, 1–5DTE, 6–21DTE, and more than 21DTE, respectively. Within each panel, rows identify the capacity of the buyer, and columns identify the capacity of the seller. The final column reports the total percentage of volume purchased by each capacity, while the final row reports the total percentage sold by each capacity. Entries below 0.1% are reported as “<0.1.” Totals may differ from the sum of the displayed entries because of rounding. The sample period is January 2020 through June 2023.

		Sell side					
Trade Side	Capacity	Customer	Market maker	Firm	Professional customer	Broker-dealer	Sum
Panel A. 0DTE							
Buy	Customer	1.7	15.0	0.2	0.3	<0.1	17.2
	Market maker	14.1	1.5	0.3	0.4	0.1	16.4
	Firm	0.2	0.4	<0.1	<0.1	<0.1	0.7
	Prof. customer	<0.1	0.3	<0.1	<0.1	<0.1	0.4
	Broker-dealer	<0.1	<0.1	<0.1	<0.1	<0.1	0.1
	Sum	16.0	17.2	0.6	0.7	0.2	34.8
Panel B. 1-5DTE							
Buy	Customer	0.4	9.5	0.3	<0.1	<0.1	10.3
	Market maker	9.4	2.6	2.2	0.5	0.2	14.9
	Firm	0.4	2.0	0.3	<0.1	<0.1	2.7
	Prof. customer	<0.1	0.5	<0.1	<0.1	<0.1	0.7
	Broker-dealer	0.1	0.3	0.1	<0.1	<0.1	0.5
	Sum	10.4	15.0	2.9	0.6	0.3	29.2
Panel C. 6-21DTE							
Buy	Customer	<0.1	5.1	0.4	<0.1	<0.1	5.7
	Market maker	5.1	1.9	1.5	0.4	0.2	9.1
	Firm	0.3	1.6	0.3	<0.1	<0.1	2.3
	Prof. customer	<0.1	0.5	0.1	<0.1	<0.1	0.7
	Broker-dealer	<0.1	0.3	0.1	<0.1	<0.1	0.5
	Sum	5.6	9.4	2.4	0.5	0.4	18.3
Panel D. > 21DTE							
Buy	Customer	<0.1	5.3	1.0	<0.1	<0.1	6.4
	Market maker	5.3	3.0	3.4	1.1	0.4	13.2
	Firm	1.0	3.4	0.7	0.1	0.1	5.4
	Prof. customer	<0.1	1.1	0.2	<0.1	<0.1	1.4
	Broker-dealer	<0.1	0.4	0.1	<0.1	<0.1	0.7
	Sum	6.4	13.2	5.5	1.3	0.7	27.1

Table 2**Descriptive statistics of the deltas of OMM positions in S&P 500 index options**

This table presents statistics describing the distributions of the deltas of option market maker (OMM) positions as of 3:30 p.m. and 3:45 p.m. in S&P 500 index options (symbols SPX and SPXW). Deltas of positions in 0DTE and non-0DTE options are reported separately. The computation of the deltas is described in Section 3. They are expressed in billions of U.S. dollars by multiplying the usual delta, expressed in units of the underlying, by the notional value of the S&P 500 index.

Variable	Mean	Std. dev.	1%	25%	50%	75%	99%
$\Delta_{0DTE}(3:30 \text{ p.m.})$	0.20	2.22	-6.23	-0.75	0.14	1.23	6.27
$\Delta_{0DTE}(3:45 \text{ p.m.})$	0.17	2.20	-6.84	-0.76	0.08	1.14	6.05
$\Delta_{\text{non-0DTE}}(3:30 \text{ p.m.})$	6.99	19.05	-33.68	-4.53	5.74	19.53	53.86
$\Delta_{\text{non-0DTE}}(3:45 \text{ p.m.})$	6.99	19.09	-33.47	-4.89	5.72	19.58	53.86

Table 3**Regressions of pre-expiration futures returns on OMM delta positions**

This table displays the results of regressions that use the deltas of option market maker (OMM) positions in S&P 500 index options shortly before expiration to explain the log return on the front-month e-mini futures (symbol ES). The unit of observation is a minute. The sample consists of the minutes ending at times $t = 12:01$ p.m., ..., 4:00 p.m. during the sample period running from July 2020 through June 2023. The dependent variable is the log return R_t on the front-month ES contract during the minute ending at time t . The key explanatory variable is the interaction $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$, where τ is either 3:30 or 3:45 p.m., $\Delta_{0DTE}(\tau)$ is the delta of the OMM position in the expiring (0DTE) options at time τ , and $I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$ equals one if t (the end of the minute) is in the set $\{\tau+1, \dots, 4:00 \text{ p.m.}\}$. Thus, this indicator variable equals one for the 30 or 15 minutes before expiration. Some specifications also include the interaction $\Delta_{non-0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$, where $\Delta_{non-0DTE}(\tau)$ is the delta of the OMM position in the non-expiring options at time τ , the lagged return R_{t-1} , and minute-of-day fixed effects. For Panel A, the deltas are those of the OMM positions in S&P 500 index options (symbols SPX and SPXW). For Panel B, the deltas are those of the OMM positions in S&P 500 index and ETF (symbols SPY, VOO, and IVV) options. On days with no 0DTE options, $\Delta_{0DTE}(\tau)$ equals zero. Returns are in basis points, and deltas are divided by 10^9 so that the reported coefficients are in convenient units. t -statistics are in parentheses below the coefficient estimates.

Panel A. Using deltas of OMM positions in S&P 500 index options

Variable	$\tau = 3:30$			$\tau = 3:45$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$	0.0889 (4.09)	0.0886 (4.10)		0.1430 (4.45)	0.1427 (4.44)	
$\Delta_{non-0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$	-0.0002 (-0.10)		0.0008 (0.37)	-0.0003 (-0.10)		0.0008 (0.25)
R_{t-1}	0.0094 (2.17)	0.0094 (2.17)	0.0096 (2.22)	0.0093 (2.15)	0.0093 (2.15)	0.0096 (2.22)
Minute FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0012	0.0012	0.0010	0.0013	0.0013	0.0010
Observations	178,553	178,553	178,553	178,553	178,553	178,553

Panel B. Using deltas of OMM positions in S&P 500 index and ETF options

Variable	$\tau = 3:30$			$\tau = 3:45$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$	0.0897 (4.16)	0.0894 (4.16)		0.1437 (4.50)	0.1434 (4.49)	
$\Delta_{non-0DTE}(\tau) \times I(t \in \{\tau+1, \dots, 4:00 \text{ p.m.}\})$	-0.0003 (-0.12)		0.0008 (0.36)	-0.0004 (-0.12)		0.0008 (0.25)
$\Delta_{0DTE \text{ ETF}}(\tau) \times I(t \in \{2:01 \text{ p.m.}, \dots, 4:00 \text{ p.m.}\})$	0.0301 (0.63)	0.0298 (0.63)	0.0119 (0.24)	0.0266 (0.56)	0.0264 (0.55)	0.0122 (0.25)
$\Delta_{non-0DTE \text{ ETF}}(\tau) \times I(t \in \{2:01 \dots, 4:00 \text{ p.m.}\})$	0.0012 (0.12)	0.0012 (0.12)	0.0012 (0.12)	0.0012 (0.12)	0.0012 (0.12)	0.0011 (0.11)
R_{t-1}	0.0094 (2.17)	0.0096 (2.17)	0.0094 (2.22)	0.0093 (2.15)	0.0096 (2.15)	0.0093 (2.22)
Minute FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0012	0.0012	0.0010	0.0013	0.0013	0.0010
Observations	178,553	178,553	178,553	178,553	178,553	178,553

Table 4**Regressions of pre-expiration realized volatility on OMM delta magnitudes**

This table displays the results of regressions that use the absolute values of deltas of the option market maker (OMM) positions in S&P 500 index options shortly before expiration to explain the realized volatility of the e-mini futures (symbol ES). The unit of observation is a day, and the sample consists of all days during the sample period running from July 2020 through June 2023. The dependent variable is the annualized realized volatility of the one-minute log returns on the front-month ES contract during the period from τ to 4:00 p.m., where τ is either 3:30 p.m. or 3:45 p.m. The key explanatory variable is the absolute value $|\Delta_{0DTE}(\tau)|$, where again τ is either 3:30 or 3:45 p.m., and $\Delta_{0DTE}(\tau)$ is the delta of the OMM position in the expiring (0DTE) options at time τ . The specifications also include the absolute value $|\Delta_{non-0DTE}(\tau)|$, where $\Delta_{non-0DTE}(\tau)$ is the delta of the OMM position in the non-expiring options at time τ , year and week fixed effects (that is, a fixed effect for each week in the sample period), and day-of-week fixed effects. For Panel A, the deltas are those of the OMM positions in S&P 500 index options (symbols SPX and SPXW). For Panel B, the deltas are those of the OMM positions in S&P 500 index and ETF (symbols SPY, VOO, and IVV) options. On days with no 0DTE options, $\Delta_{0DTE}(\tau)$ equals zero. $\Gamma_{0DTE}(\tau)$ and $\Gamma_{non-0DTE}(\tau)$ are OMM gammas in S&P 500 index and ETF options. Realized volatility is annualized by multiplying the realized variance during the 30-minute period from 3:30 to 4:00 p.m. (15-minute period from 3:45 to 4:00 p.m.) by 13×252 (26×252) and taking the square root. Deltas are multiplied by 10^{-12} so that the coefficients are in convenient units. t -statistics are in parentheses below the coefficient estimates.

Panel A. Using deltas of OMM positions in S&P 500 index options

Variable	$\tau = 3:30$				$\tau = 3:45$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ \Delta_{0DTE}(\tau) $	34.98 (2.35)		36.74 (2.49)	30.88 (1.97)	24.63 (1.63)		25.90 (1.73)	25.21 (1.56)
$ \Delta_{non-0DTE}(\tau) $		-10.54 (-1.61)	-11.63 (-1.76)	-7.87 (-1.21)		-10.94 (-1.68)	-11.47 (-1.73)	-9.09 (-1.40)
$\Gamma_{0DTE}(\tau)$				-0.33 (-3.92)				-0.16 (-2.33)
$\Gamma_{non-0DTE}(\tau)$				-0.84 (-4.42)				-0.66 (-3.29)
Year + week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.416	0.414	0.417	0.434	0.379	0.379	0.380	0.389
Observations	769	769	769	769	769	769	769	769

Panel B. Using deltas of OMM positions in S&P 500 index and ETF options

Variable	$\tau = 3:30$				$\tau = 3:45$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ \Delta_{0DTE}(\tau) $	40.84 (2.75)		42.03 (2.90)	35.77 (2.31)	31.36 (2.11)		32.20 (2.23)	31.71 (2.00)
$ \Delta_{non-0DTE}(\tau) $		-9.21 (-1.44)	-10.17 (-1.57)	-6.73 (-1.05)		-11.65 (-1.79)	-12.05 (-1.83)	-9.95 (-1.54)
$\Gamma_{0DTE}(\tau)$				-0.33 (-3.99)				-0.17 (-2.48)
$\Gamma_{non-0DTE}(\tau)$				-0.82 (-4.36)				-0.65 (-3.21)
Year + week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.417	0.413	0.418	0.434	0.380	0.379	0.382	0.391
Observations	769	769	769	769	769	769	769	769

Table 5**Distribution of daily summary statistics for aggregate OMM gamma**

This table displays statistics describing the variation in the gamma of the aggregate option market maker (OMM) options position that we compute at one-minute frequency for each trading date. For each trading date, we compute the mean, median, standard deviation, maximum, and minimum of the gammas on that date. We then compute the statistics describing the distribution (across dates) of the daily statistics. The units are billions. Panel A presents the statistics for the entire sample running from July 2020 through June 2023. Panels B and C display statistics for subsamples ending in April 2022 and starting in May 2022, respectively.

Panel A. July 2020 - June 2023

Statistic	Mean	Std. dev.	Min.	1%	5%	10%	25%	Median	75%	90%	95%	99%	Max.
Daily mean	343.3	321.6	-235.8	-158.0	-60.3	4.8	110.4	254.2	539.8	813.3	959.5	1,267.8	1,592.6
Daily median	342.4	319.9	-227.8	-143.5	-66.2	5.2	108.8	256.5	538.3	805.6	947.8	1,277.9	1,621.0
Daily std.dev.	86.1	91.5	3.6	7.2	14.8	22.1	37.3	62.3	108.8	159.6	208.5	499.1	956.9
Daily max	739.4	1,176.5	-147.4	-46.2	61.1	134.5	276.1	488.9	881.3	1,392.6	1,899.0	4,075.6	16,743.4
Daily min	71.7	411.3	-3,548.2	-1,343.1	-409.5	-271.8	-92.5	81.0	260.6	489.3	674.7	860.0	1,068.3

Panel B. July 2020 - April 2022

Statistic	Mean	Std. dev.	Min.	1%	5%	10%	25%	Median	75%	90%	95%	99%	Max.
Daily mean	411.1	341.1	-235.8	-130.1	-59.5	27.3	158.0	331.7	625.4	906.3	1,039.2	1,281.7	1,592.6
Daily median	412.8	343.0	-227.8	-133.8	-45.6	24.1	157.4	335.6	636.6	909.1	1,048.8	1,307.5	1,621.0
Daily std.dev.	73.9	72.4	4.3	7.1	11.6	17.8	31.4	52.8	93.8	142.4	183.6	324.6	633.5
Daily max	711.3	805.8	-114.2	-42.8	53.3	136.0	296.4	535.4	908.6	1,375.5	1,840.0	3,082.9	11,424.7
Daily min	186.1	328.6	-1,949.0	-605.3	-269.8	-139.1	21.2	151.9	391.5	589.4	748.7	887.0	939.7

Panel C. May 2022 - June 2023

Statistic	Mean	Std. dev.	Min.	1%	5%	10%	25%	Median	75%	90%	95%	99%	Max.
Daily mean	235.9	253.9	-202.4	-178.6	-62.3	-17.4	64.2	174.8	337.8	603.3	724.7	984.6	1,456.6
Daily median	230.8	240.8	-197.8	-164.7	-70.4	-10.9	64.2	181.2	343.6	573.0	704.5	873.7	1,456.9
Daily std.dev.	105.5	112.9	3.6	19.6	28.0	33.9	48.8	78.3	126.8	187.7	233.5	722.1	956.9
Daily max	783.9	1,597.2	-147.4	-63.5	74.1	134.3	257.2	430.8	794.5	1,437.7	2,118.7	7,280.8	16,743.4
Daily min	-109.6	461.5	-3,548.2	-2,314.7	-655.6	-390.0	-196.9	-44.3	76.7	240.9	372.5	655.5	1,068.3

Table 6**OMM gamma by trading strategy and underlying**

This table displays the daily average option market maker (OMM) gamma, in billions, due to positions created by single-leg trades, vertical call spreads, vertical put spreads, and other complex trades. We report vertical call and put spreads separately because they are the most common multi-leg trades. We first aggregate OMM trades within each strategy category to obtain the net OMM position created by each type of trade. We then compute the gamma of these net positions at the one-minute frequency and average the resulting gamma across the trade category. The first four columns report the average gamma associated with positions in S&P 500 index options (symbols SPX and SPXW), SPY, IVV, and VOO options, respectively. The final column reports the total gamma across all four underlying securities, while the last row reports the sum of average gamma across all trade categories. The sample period is July 2020 through June 2023.

Trade category	SPX/SPXW	SPY	IVV	VOO	Total
Single-leg trades	-106.64	-54.85	0.02	0.12	-161.35
Vertical call spreads	93.11	1.66	0.00	0.01	94.78
Vertical put spreads	50.75	-7.59	-0.01	0.00	43.15
Other complex trades	305.37	5.86	0.04	0.04	311.31
Total	342.59	-54.92	0.05	0.17	287.89

Table 7**GARCH estimates of the effect of OMM gamma on intraday e-mini futures volatility**

This table presents estimation results for intraday GARCH models of the variance of one-minute returns on the S&P 500 e-mini futures contract (symbol ES) described in equations (11)-(15). The models include either 1, 5, or 30 lags of option market maker (OMM) gamma (Γ_t) as indicated by the presence of the parameters ϕ_j , except that only selected ϕ_j are presented for model (8). The parameters α , β , m , and γ are the parameters in equations (12) and (13). The symbols ϕ_j denote the weights on the OMM gamma at time $t - j$, where j is the lag in minutes. Models (1)-(4) use the gammas of the OMMs' positions in SPX and SPXW options. Model (5) replaces Γ_{t-1} with an estimate of the expected OMM gamma at $t + 10$, as described in the text. Model (6) is like Model (3) except that it adds the gammas of the positions in ETF options (SPY, IVV, and VOO) resulting from trades on the Cboe exchanges. Model (7) scales the ETF positions resulting from trades on the Cboe exchanges to obtain an estimate of the positions in these options resulting from trades on all exchanges. Model (8) is the same as model (3) except that it uses 30 instead of five lags of gamma. All models except (4) estimate the initial variance for each day in the optimization of the log likelihood; model (4) uses the sample variance of the day's standardized returns as the estimate of the initial variance. The models are estimated using data from each sample month from July 2020 through June 2023, and the reported values are the average across months. The standard errors shown in parentheses below each parameter estimate are computed from the 36 monthly parameter estimates. The final row presents average values of the likelihood ratio test (LRT) statistics for the joint null that all parameters except α and β equal zero. No LRT statistic is reported for model (4), which is not nested in model (1), or for model (8), which requires a different sample.

Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	0.045 (0.002)	0.044 (0.002)	0.044 (0.002)	0.053 (0.003)	0.044 (0.002)	0.044 (0.002)	0.044 (0.002)	0.045 (0.003)
β	0.922 (0.007)	0.923 (0.007)	0.923 (0.007)	0.906 (0.009)	0.922 (0.007)	0.923 (0.007)	0.922 (0.007)	0.919 (0.008)
m		0.125 (0.022)	0.145 (0.027)	0.149 (0.022)	0.138 (0.026)	0.110 (0.023)	0.058 (0.030)	0.136 (0.023)
γ		-0.499 (0.096)	-0.516 (0.099)	-0.468 (0.092)	-0.510 (0.103)	-0.532 (0.101)	-0.495 (0.095)	-0.492 (0.102)
ϕ_1			0.488 (0.048)	0.381 (0.045)	0.475 (0.043)	0.461 (0.044)	0.436 (0.044)	0.466 (0.057)
ϕ_2			0.140 (0.008)	0.140 (0.009)	0.154 (0.009)	0.148 (0.007)	0.147 (0.008)	0.087 (0.008)
ϕ_3			0.097 (0.009)	0.119 (0.009)	0.109 (0.009)	0.107 (0.008)	0.109 (0.008)	0.044 (0.005)
ϕ_4			0.099 (0.011)	0.134 (0.010)	0.105 (0.011)	0.109 (0.011)	0.115 (0.011)	0.029 (0.004)
ϕ_5			0.175 (0.031)	0.226 (0.022)	0.157 (0.024)	0.175 (0.025)	0.192 (0.027)	0.022 (0.004)
ϕ_{10}								0.010 (0.002)
ϕ_{20}								0.007 (0.001)
ϕ_{30}								0.093 (0.030)
Init. var. est.	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
LRT ($\gamma = 0$)		8.62	8.85		8.52	8.82	8.45	

Table 8**GARCH estimates for initial and new OMM gamma**

This table presents estimation results for intraday GARCH models of the variance of one-minute returns on the S&P 500 e-mini futures contract in which the gammas of option market makers' (OMM) initial and new options positions are included separately, as in equation (16). Each day, the initial position consists of the options held by OMMs at the beginning of regular trading hours (9:30 am). The new position at time t is the position resulting from the accumulation of the day's trades up through time t . The parameters α , β , m , γ_{initial} and γ_{new} are the coefficients in the variance equation (16), where γ_{initial} and γ_{new} are the coefficients on the gammas of initial and new positions, respectively. Models (2) and (3) include one lag of the gammas; they differ in that model (2) includes the SPX and SPXW options in the computation of the gammas, while model (3) also includes the positions in ETF options (SPY, IVV, and VOO) resulting from trades on the Cboe exchanges. Models (4) and (5) use five and 30 lags of the gammas, and include only the SPX and SPXW options in the computation of the gammas. All models estimate the initial variance for each day in the optimization of the log likelihood. The models are estimated using data from each sample month from July 2020 through June 2023, and the reported values are the average across months. The standard errors shown in parentheses below each parameter estimate are computed from the 36 monthly parameter estimates. The final row of the table presents the average values of the likelihood ratio test (LRT) statistics, testing the null hypothesis that all parameters except α and β are jointly zero.

Parameter	(1)	(2)	(3)	(4)	(5)
α	0.045 (0.002)	0.044 (0.002)	0.044 (0.002)	0.044 (0.002)	0.045 (0.003)
β	0.922 (0.007)	0.923 (0.007)	0.923 (0.007)	0.922 (0.007)	0.919 (0.008)
m		0.121 (0.024)	0.098 (0.024)	0.116 (0.030)	0.113 (0.027)
γ_{initial}		-0.381 (0.092)	-0.390 (0.093)	-0.416 (0.094)	-0.372 (0.094)
γ_{new}		-0.767 (0.127)	-0.777 (0.132)	-0.872 (0.133)	-0.557 (0.208)
Init. var. estim.	Yes	Yes	Yes	Yes	Yes
LRT ($\gamma = 0$)		10.62	10.76	11.56	

Table 9**GARCH-Implied Changes and Distributions of Daily and 30-Minute Realized Volatility**

This table reports summary statistics for annualized realized volatility (RV) and changes in annualized realized volatility. Panel A presents the estimated impact of option market maker (OMM) gamma on daily and 30-minute realized volatility based on the GARCH model. The change in annualized daily realized volatility is computed using equations (17) to (19), and the corresponding change in annualized 30-minute realized volatility is computed analogously. Panels B and C report the distributions of the levels and changes in annualized realized volatility at the daily and 30-minute frequencies, respectively. The sample period extends from July 2020 through June 2023.

Panel A. GARCH model changes in daily and 30-minute realized volatilities

Statistic	Mean	Std. dev.	Min.	1%	5%	10%	25%	Median	75%	90%	95%	99%	Max.
Change in daily RV	-0.21%	0.76%	-4.84%	-3.03%	-1.52%	-0.95%	-0.46%	-0.08%	0.16%	0.44%	0.72%	1.39%	2.31%
Change in 30-min RV	-0.19%	0.80%	-7.37%	-3.28%	-1.56%	-0.95%	-0.41%	-0.06%	0.15%	0.44%	0.72%	1.55%	5.86%

Panel B. Annualized daily realized volatility

Statistic	Mean	Std. dev.	Min.	1%	5%	10%	25%	Median	75%	90%	95%	99%	Max.
Realized volatility	12.7%	6.1%	3.5%	3.9%	5.0%	6.0%	8.1%	11.4%	16.0%	20.9%	24.1%	33.0%	36.9%
Change in RV	0.0%	4.5%	-16.0%	-13.3%	-7.5%	-5.2%	-2.2%	0.0%	2.2%	5.1%	7.5%	12.2%	18.3%

Panel C. Annualized 30-minute realized volatility

Statistic	Mean	Std. dev.	Min.	1%	5%	10%	25%	Median	75%	90%	95%	99%	Max.
Realized volatility	12.0%	7.3%	1.7%	2.6%	3.8%	4.8%	6.9%	10.4%	15.2%	21.5%	26.0%	36.3%	94.5%
Change in RV	0.0%	4.6%	-52.2%	-11.6%	-6.2%	-4.3%	-2.0%	-0.1%	1.7%	4.3%	6.5%	14.2%	63.4%

Internet Appendix to

The Price Impact of Hedging Expiring Index Options

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Internet Appendix A. The Cboe Trade Data and the Identification of Complex Trades

This appendix describes the proprietary trade data provided by Cboe Global Markets, explains how we use the data in the various analyses in the paper, and describes how we identify complex trades in the data and classify them into the strategy categories used in the paper.

A.1 Description of the Cboe trade data

The data consist of records of executions in S&P 500 index options (symbols SPX and SPXW) and, for some analyses, options on the S&P 500 ETFs with symbols SPY, IVV, and VOO, during the period running from January 2020 through June 2023. The records of trades in the index options are from the Cboe Options Exchange (C1), on which all SPX and SPXW trading takes place. The ETF options records are from the four Cboe exchanges: the Cboe Options Exchange (C1), the Cboe C2 Options Exchange, the Cboe EDGX Options Exchange, and the Cboe BZX Options Exchange. A limitation of the ETF options data, discussed in Section 3.2, is that they do not include trades executed on non-Cboe exchanges.

The unit of observation is a trade record. Each single-leg trade, and each leg of each complex trade, appears as at least two trade records, one for the buy side and one for the sell side of the execution. A trade or trade leg appears as more than two records when the passive side of the execution is shared among two or more traders. Table IAA1 lists the fields included in each trade record. Three identifiers link the records. The field EXEC_ID identifies the execution, so that the buyer and seller records of the same execution (or leg) share the same EXEC_ID. The field COMPLEX_EXEC_ID identifies the complex execution: the records for all legs of a multi-leg execution share the same COMPLEX_EXEC_ID, and the field is null for trades executed in the simple (single-leg) book. Finally, the field ORDER_ID identifies the order submitted by each trader, so that all legs of a trader's complex order carry the trader's ORDER_ID. A single complex order that executes against multiple counterparties, or in multiple partial executions, gives rise to multiple complex executions that share the same ORDER_ID on the side of the order submitter.

Each record also reports the trading capacity of the trader (field CAPACITY). We group the capacities provided in the Cboe data into the broader categories of customer, market maker, professional customer, firm, and broker-dealer used in the paper. For the SPX and SPXW options, market maker trades carry the capacity code M. For the ETF options, which trade on multiple exchanges, we treat both the codes M and N, where N denotes a market maker on an

away exchange, as market maker trades. For the non-market maker capacities, the field OPEN_CLOSE indicates whether the trade opened a new position or closed an existing position. The field SIM_COM indicates whether the execution occurred in the simple book or resulted from a complex order, and the field CHANNEL reports the execution mechanism, for example the complex order book (COB), the complex order auction (COA), the automated improvement mechanism (AIM), or open outcry. We use the records of executions during regular trading hours, and exclude FLEX options.

A.2 Use of the data in the analyses

The trade records are used in three main ways. First, they are the input to the computation of the volume shares by trading capacity reported in Table 1. Because each execution appears as at least one buy record and at least one sell record, summing the field SIZE across records double counts contract volume; whenever we compute volumes or position changes we therefore divide the summed sizes by two, or equivalently sign the records using the field SIDE and net buys against sells.

Second, the records are the input to the computation of the aggregate option market maker (OMM) net positions described in Section 3.3. For each option series, we select the records with a market maker capacity, sign each record's size as positive for a buy (SIDE = B) and negative for a sell (SIDE = S), and cumulate the signed sizes from the inception of trading in the series. The result, for each series, is a time series of the aggregate OMM net position at one-minute frequency from 9:30 a.m. to 4:00 p.m. on each trade date. For the ETF options the cumulation is carried out across the records from the four Cboe exchanges. The 0DTE positions used in the hedge unwinding analysis of Section 4 are obtained by restricting the position series to options for which the trade date equals the expiration date. Decomposing the expiring positions by option type (field CALL_PUT_FLAG) and the sign of the cumulated net position yields the long call, short call, long put, and short put components of the expiring OMM inventory. These minute-frequency positions, combined with the minute-frequency deltas and gammas described in Section 3.4, produce the deltas of the 3:30 p.m. and 3:45 p.m. OMM positions in expiring options used in Section 4 and the minute-frequency OMM gammas used in the GARCH analyses of Sections 5 and 6.

Third, the records are used to decompose the OMM positions, and their deltas and gammas, into components attributable to single-leg and complex trades (Figures 4 and 8 and

Table 6), and to compute the monthly volumes of the various categories of complex trades (Internet Appendix Figure IAB4). The field SIM_COM identifies whether each record resulted from a single-leg or complex order, and the classification of complex trades into strategy categories is described next.

A.3 Identification and classification of complex trades

A complex trade is submitted to the exchange as a single order specifying two or more legs, and the Cboe data preserve the linkage among the legs. We reconstruct each complex trade by collecting, for each trade date, the records with SIM_COM = COMPLEX and grouping them by the field ORDER_ID. Grouping by ORDER_ID rather than COMPLEX_EXEC_ID reassembles the entire order as submitted by the trader: a large complex order that executes against several counterparties, or in several partial executions, generates several complex executions with distinct COMPLEX_EXEC_IDs, and grouping on the complex execution identifier alone would fragment such an order into multiple smaller trades, and in some cases into apparent one-leg trades. Within each order, we aggregate the executed sizes by option series, that is, by the combination of option root, call/put flag, strike price, and expiration date, so that partial executions of the same leg are combined. The result is, for each complex order, the set of its legs and the number of contracts executed in each leg.

We then classify each complex order into a strategy category using the characteristics of its legs. An order with exactly two legs of the same expiration is classified as a vertical spread if both legs are calls, or both are puts, with two distinct strikes and equal sizes in the two legs; it is a vertical ratio spread if the leg sizes differ. A two-leg order consisting of one call and one put with the same expiration and equal sizes is classified as in Fu et al. (2026). An order in which the two legs are the same option type and strike but different roots (SPX and SPXW), and thus different settlement conventions, is classified as an a.m./p.m. trade. All remaining orders are classified by their number of legs, that is, as other one-, two-, three-, or four-leg complex trades, or other complex trades. In the SPX and SPXW data, an apparent one-leg complex trade typically arises when the counterparties to the legs of a complex order differ; for the ETF options, a one-leg complex trade can also arise when the order is a buy-write (covered call), because the stock leg of the order does not appear in the options trade data. For the monthly volume figure (Internet Appendix Figure IAB4), the categories vertical spreads (combining call and put vertical spreads), other two-leg trades (combining ratio spreads, straddles, strangles, and

other two-leg orders), and one-, three-, and four-leg and other complex trades are obtained by aggregating the total order sizes, that is, the sum of the executed sizes across the order's legs, by trade date and category, and then summing within each month.

An example from the data illustrates the construction. On September 20, 2022, a customer order executed three legs in SPXW options expiring March 31, 2023: buy two of the 3,450-strike puts, buy two of the 2,600-strike puts, and sell four of the 3,175-strike puts, a (broken-wing) put butterfly. The order appears in the data as six records: three buy-side and sell-side records for the customer's three legs, all carrying the customer's ORDER_ID, and three matching records for the market maker on the other side, all carrying the market maker's ORDER_ID. The six records share a single COMPLEX_EXEC_ID linking the legs of the execution, and each leg's pair of records shares an EXEC_ID. Grouping the customer's records by ORDER_ID and aggregating by option series recovers the three legs and their sizes, and the classification rules above place the order in the three-leg category. The same records, signed by the field SIDE and restricted to the market maker capacity, contribute a position of short two 3,450 puts, short two 2,600 puts, and long four 3,175 puts to the aggregate OMM position in the corresponding series.

Table IAA1
Fields included in each Cboe trade record

Field	Description
TRADE_DATE	The trade date.
TRANSACT_TIME	The timestamp of the execution, reported to sub-millisecond precision, Eastern time.
UNDERLYING	The underlying asset (e.g., SPX, SPY).
OSI_ROOT	The OSI option root symbol. For the index options this distinguishes the a.m.-settled SPX options from the p.m.-settled SPXW options; for the ETF options it identifies the ETF (SPY, IVV, or VOO).
EXPIRE_DATE	The expiration date of the option series.
CALL_PUT_FLAG	C for a call, P for a put.
STRIKE_PRICE	The strike price of the option series.
DURATION_TYPE	The listing cycle of the series (e.g., W for weekly, M for standard monthly).
FLEX	Indicator equal to TRUE for FLEX options. We exclude FLEX options from the analysis.
ORDER_ID	Identifier of the order submitted by the trader. All legs of a complex order carry the same ORDER_ID.
EXEC_ID	Identifier of the execution. The buyer and seller records of the same execution share the same EXEC_ID.
COMPLEX_EXEC_ID	Identifier of the complex (multi-leg) execution. The records for all legs of a complex execution share the same COMPLEX_EXEC_ID. The field is null for single-leg trades.
OPEN_CLOSE	O if the trade opened a new position and C if it closed an existing position. The field is populated for the non-market maker capacities.
CAPACITY	The trading capacity of the trader, e.g., customer (C), market maker (M), away market maker (N), professional customer (U), firm (F), and broker-dealer (B).
SIZE	The number of contracts of the execution or leg.
GTH	Indicator equal to Y if the trade was executed during the global (extended) trading hours session.
SIM_COM	Equal to SIMPLE if the execution occurred in the simple (single-leg) book, and COMPLEX if it resulted from a complex order.
CHANNEL	The execution mechanism, e.g., the complex order book (COB), the complex order auction (COA), the automated improvement mechanism (AIM and AIM Complex), and open outcry.
MODIFICATION_SEQ	Sequence number of the record within the execution.
PREM_PRICE	The premium (price) of the option, per contract, in index or ETF points.
SIDE	B if the record is the buy side of the execution and S if it is the sell side.

Internet Appendix B. Additional Results

Figure IAB1 plots the deltas of the OMM positions in the 0DTE and non-0DTE options as of 3:45 p.m. during the sample period running from July 2020 through June 2023. It resembles Figure 2 in the main text, which plots the deltas of the OMM positions as of 3:30 p.m. The solid red and dashed purple lines display the deltas of the aggregate OMM position in the expiring (0DTE) and other (non-0DTE) SPXW options. The deltas are expressed in billions of U.S. dollars; they are computed by taking the usual delta, expressed in numbers of index futures contracts, converting to dollars by multiplying by the notional value of one index futures contract, and then dividing by 10^9 .

Figure IAB2 plots average cumulative log index futures returns and order imbalances from 3:45 p.m. to 4:00 p.m. Trading dates are sorted into five equal-sized groups based on the delta of the OMM position in expiring SPXW options as of 3:45 p.m. The top panel plots average cumulative log returns on the front-month index futures, and the bottom panel plots average cumulative order imbalances, where trade direction is estimated using the Lee and Ready (1991) algorithm.

Figure IAB3 illustrates the intraday variation in OMM gamma. This figure consists of seven panels, each of which displays the time-series of gamma at one-minute frequency on a selected day. As in Figure 6, the gammas are scaled by dividing by 10^{12} . The seven days are chosen to be representative of the possible variation in OMM gamma. Specifically, they are the days with the standard deviation of the one-minute gammas closest to the 1st, 5th, 25th, 50th, 75th, 95th, and 99th percentiles of the distributions of daily standard deviations.

Figure IAB4 shows the monthly volume of vertical spreads, other two-leg complex trades (for example, calendar, diagonal, and ratio spreads), three-leg complex trades, four-leg complex trades, and other complex trades, during our sample period.

Figure IAB5 displays histograms of the GARCH model estimates of gamma-induced changes in annualized daily and 30-minute realized volatility. Panels A and B report results for daily and 30-minute realized volatility, respectively. The estimates are based on the model with five lags of gamma reported in column (3) of Table 7.

Figure IAB6 displays analogous histograms based on the linear regression model. Panels A and B report results for annualized daily and 30-minute realized volatility, respectively. The estimates are based on the model with five lags of gamma reported in column (6) of Table IAB2.

Figure IAB7 displays histograms of changes in annualized daily and 30-minute realized volatility due to all causes. Panels A and B report results for daily and 30-minute realized volatility, respectively.

Table IAB1 reports the results of placebo regressions that show that the delta of the OMM position in expiring options does not explain index futures returns during periods other than the 30 minutes prior to expiration.

Table IAB2 reports the results of linear regression models in which squared one-minute index futures returns are regressed on lagged OMM gamma and lagged squared returns. Similar to the GARCH model, in the linear model, lagged gamma $\Gamma_{t-1,d}$ impacts r_t^2 directly through the coefficient γ_1 . Then r_t^2 impacts r_{t+1}^2 through the coefficient on r_t^2 , and r_{t+1}^2 in turn impacts r_{t+2}^2 , which in turn impacts r_{t+3}^2 , and so forth. Again, the process continues until the impact of $\Gamma_{t-1,d}$ on squared returns eventually decays. The models include up to five lags of gamma and fixed effects for hour, date, hour interacted with year, and hour interacted with day of the week.

Table IAB3 reports summary statistics describing the distributions of gamma-induced changes in annualized daily and 30-minute realized volatility estimated using the linear regression model. We first recover estimates of the residual $e_{t,d}$ using the relation

$$\begin{aligned} \hat{e}_{t,d} = r_{t,d}^2 - \hat{\omega} - \sum_{l=1}^5 \hat{\alpha}_l r_{t-l,d}^2 - \sum_{l=1}^L \hat{\gamma}_l \Gamma_{t-l,d} - \hat{\delta}_d - \sum_{h=1}^7 \hat{\theta}_h I(t \in A_h) w_j \\ - \sum_{h=1}^7 \hat{\vartheta}_h I(t \in A_h) Y_x + e_{t,d}, \end{aligned} \quad (20)$$

where parameters with “hats,” for example, $\hat{\omega}$, are estimates. We then set the coefficients on the lagged market maker gammas, γ_1 through γ_5 , to zero, and use equation (20) and the recovered innovations $\hat{e}_{t,d}$ to simulate the squared return $\hat{r}_{t,d}^2$. This process allows us to remove the influence of gamma on the squared returns, thereby yielding estimated gamma-free squared returns. We then use the simulated return and equation (18) to compute a gamma-free realized variance. The impact of gamma on S&P 500 index volatility is calculated using equation (19) at daily and 30-minute frequencies.

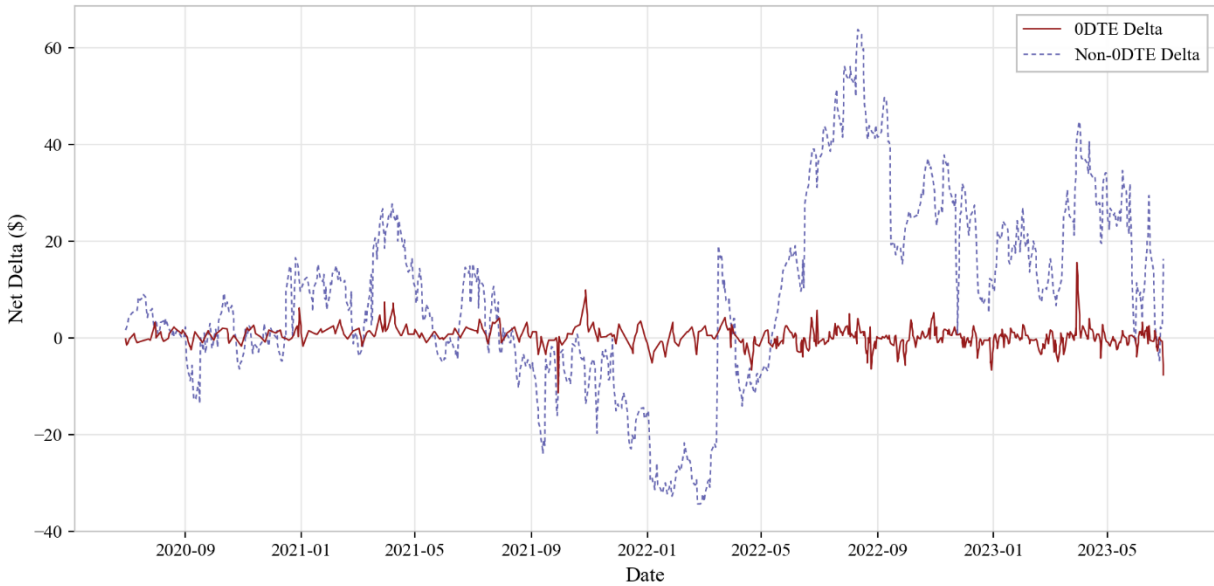
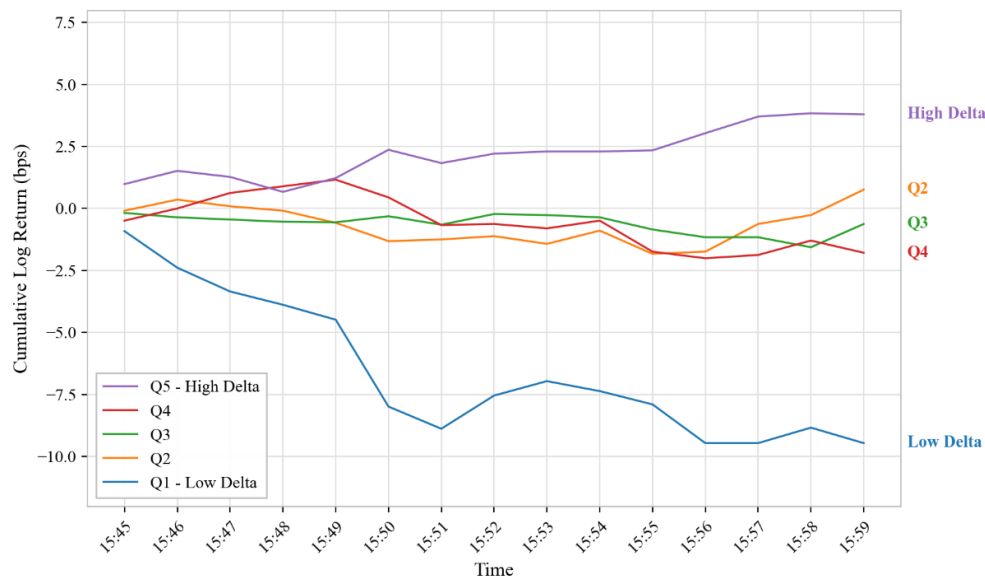


Figure IAB1

Deltas of the 3:45 p.m. OMM positions in 0DTE and non-0DTE S&P 500 index options

The figure plots the daily time series of the deltas of the aggregate option market maker (OMM) positions in 0DTE and non-0DTE S&P 500 index options as of 3:45 p.m. during the sample period running from July 2020 through June 2023. The computation of the deltas is described in Section 3. They are expressed in billions of U.S. dollars by multiplying the usual delta, expressed in units of the underlying, by the notional value of the S&P 500 index, and then dividing by 10^9 .

Panel A. Cumulative index futures return



Panel B. Cumulative order imbalance

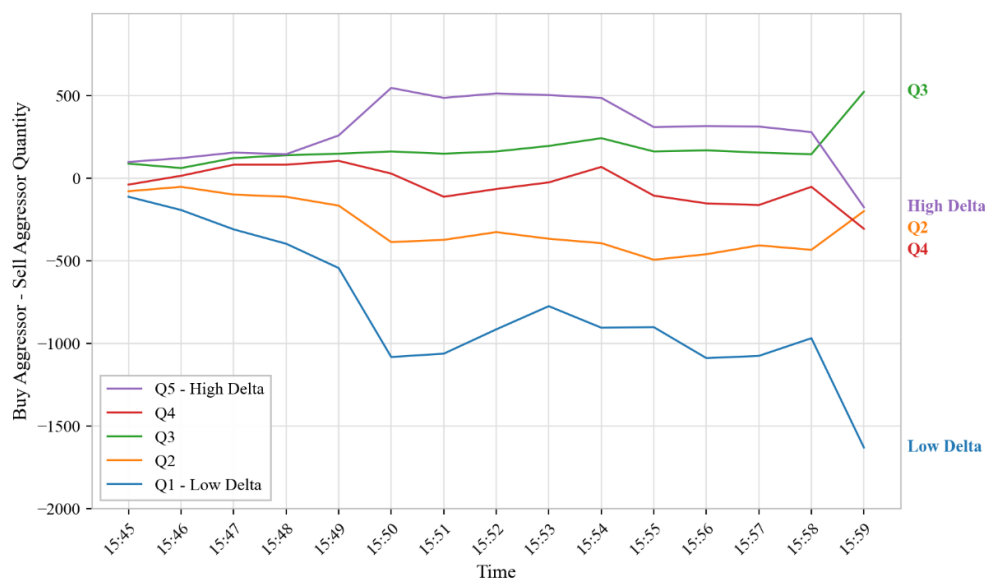


Figure IAB2

Cumulative index futures returns and order imbalances by OMM 0DTE delta at 3:45 p.m.

In this figure, we first sort trading dates into five equal-sized quintiles based on the delta of the option market maker (OMM) position in expiring SPXW options as of 3:45 p.m. For each group, we compute cumulative log returns on the front-month index futures contract from 3:45 p.m. through each subsequent minute up to 4:00 p.m. using one-minute returns. Panel A plots the average cumulative log return for each quintile. Panel B plots for quintile the average cumulative order imbalance from 3:45 p.m. through each subsequent minute up to 4:00 p.m., with trade direction (buy/sell) estimated using the Lee and Ready (1991) algorithm.

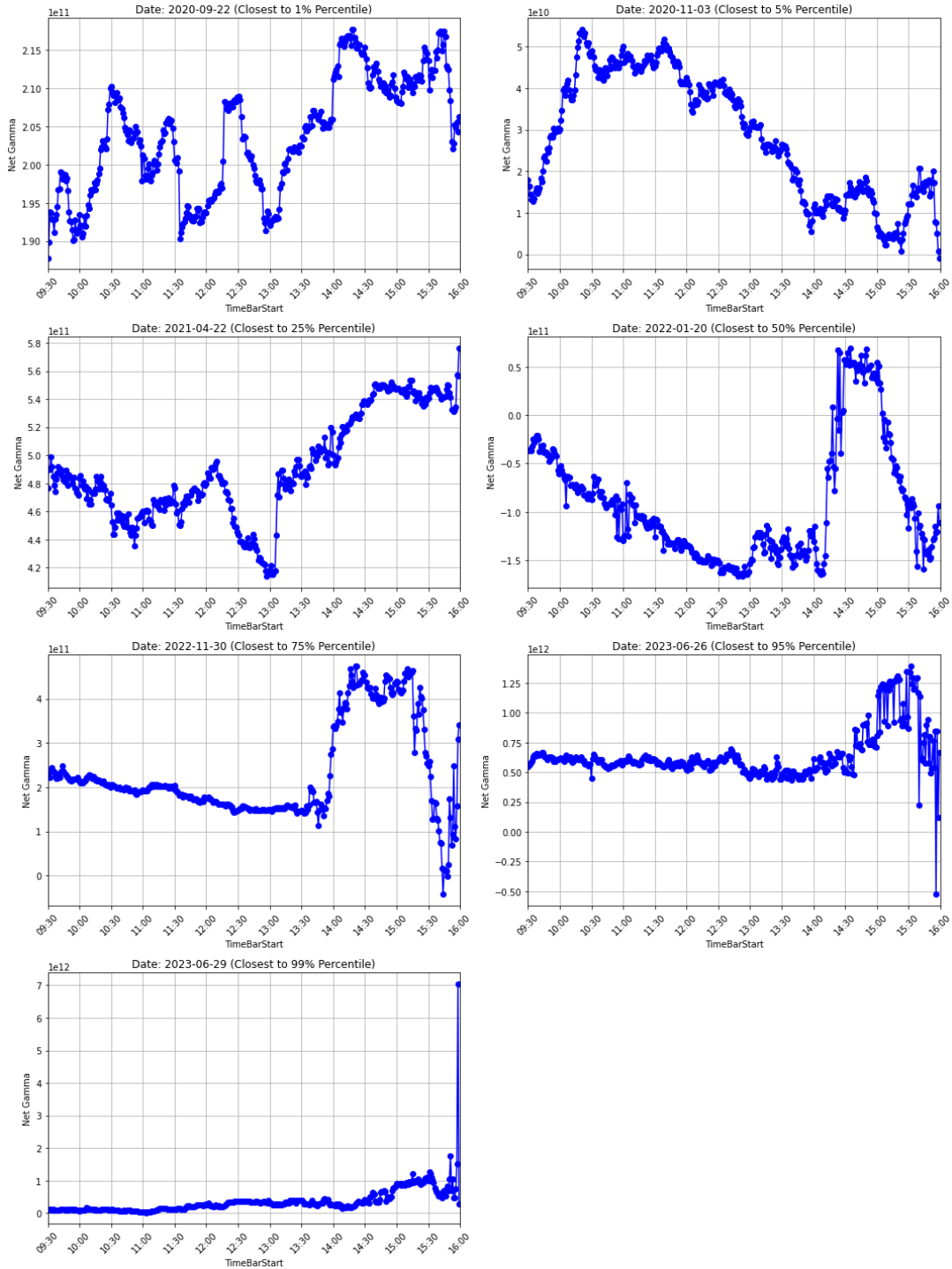
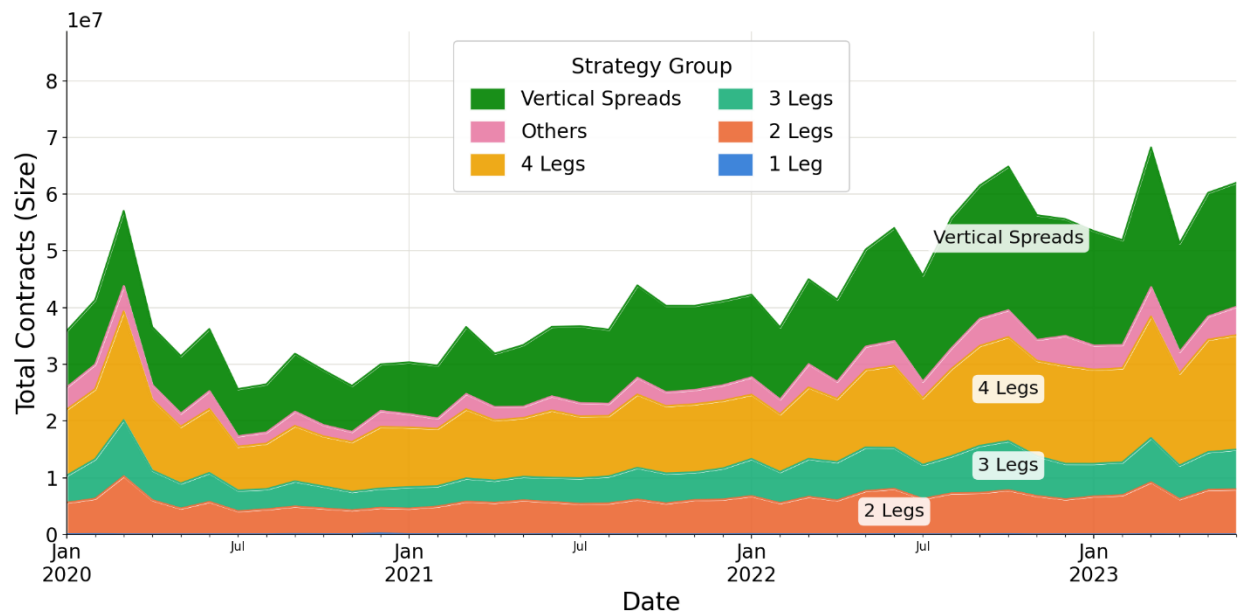


Figure IAB3

Time series of gammas at one-minute frequency for representative days

This figure displays the time-series of option market maker gammas at one-minute frequency for seven representative days. The seven days are those with the standard deviation of the one-minute gammas closest to the 1st, 5th, 25th, 50th, 75th, 95th, and 99th percentiles of the distributions of daily standard deviations. The gammas are scaled by dividing by 10^{12} .

Panel A. S&P 500 index options (SPX and SPXW)



Panel B. S&P 500 ETF options (SPY, VOO, and IVV)

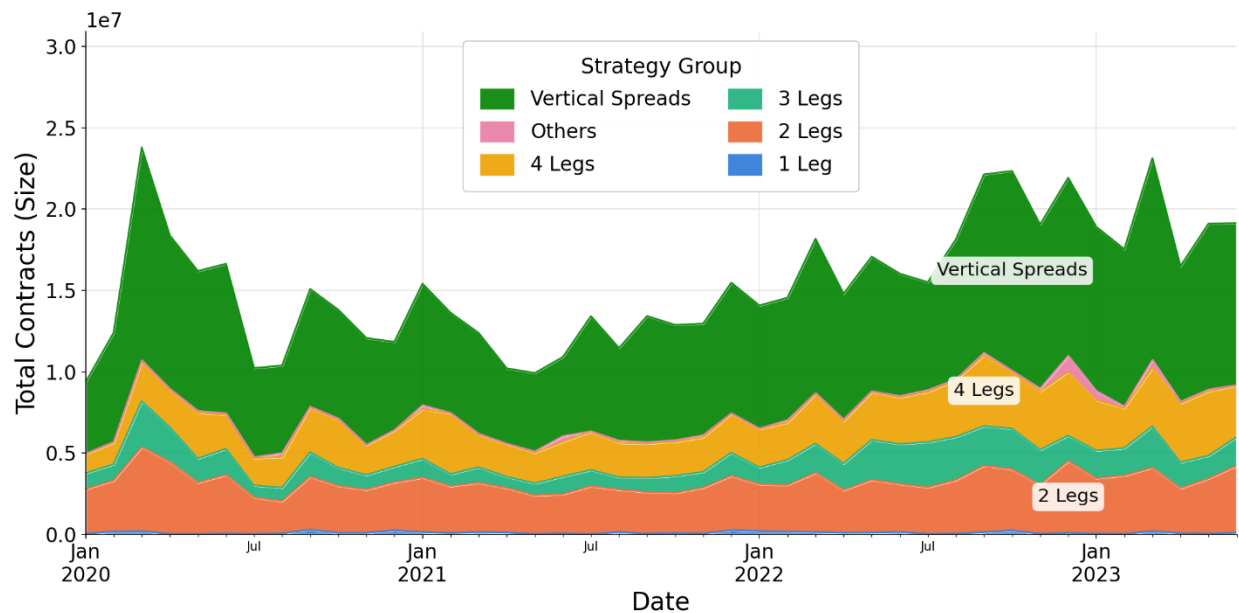
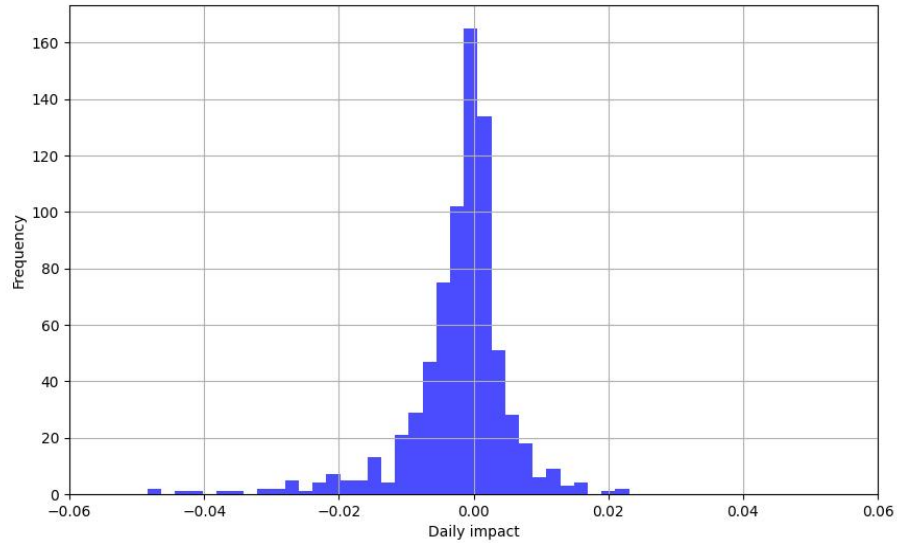


Figure IAB4

Monthly volume of complex trades by type of complex trade

The figure shows the monthly volumes of various categories of complex trades in S&P 500 index options (SPX and SPXW) and S&P 500 ETF options. The categories are vertical spreads, other complex trades with two legs, complex trades with 3 or 4 legs, and other complex trades. Panel A displays results for trades in SPX and SPXW options, and Panel B displays the results for S&P 500 ETF options.

Panel A. Gamma-induced impacts on annualized daily realized volatility



Panel B. Gamma-induced impacts on annualized 30-minute realized volatility

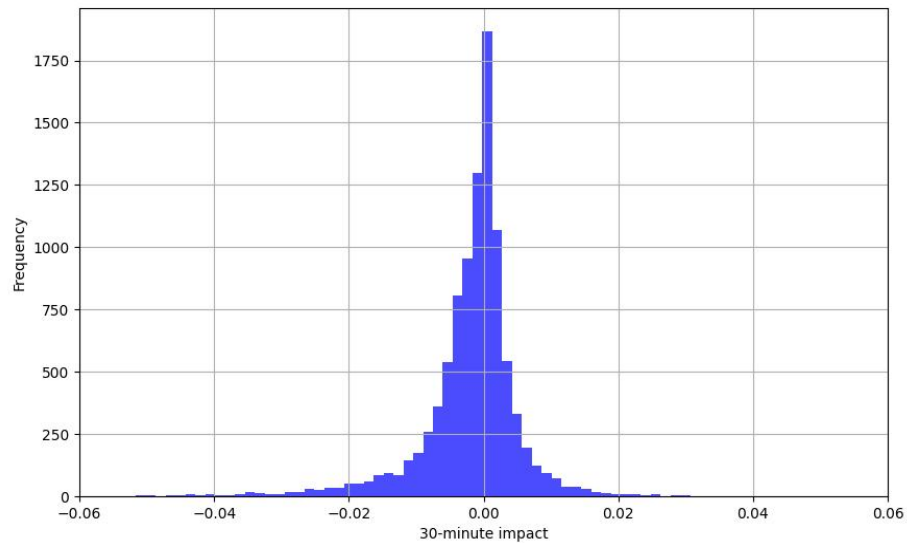
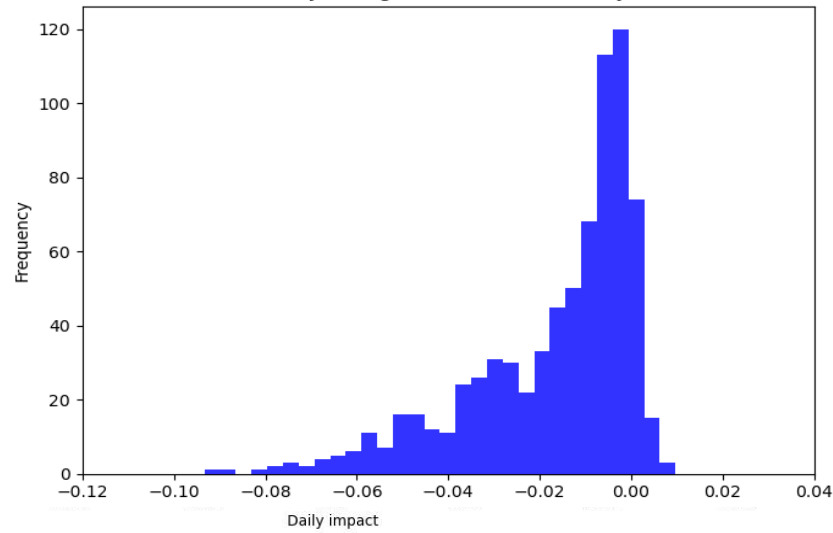


Figure IAB5

Histograms of GARCH model estimates of gamma-induced impacts on realized volatilities

Panels A and B display histograms representing the distributions of the gamma-induced impacts on annualized daily (Panel A) and 30-minute (Panel B) realized volatilities. The gamma-induced impact is the difference between the annualized daily or 30-minute realized volatility and an estimate of what the realized volatility would be under the counterfactual assumption that variance is unrelated to gamma. The GARCH model is the version with five lags of gamma, for which average coefficient estimates are reported in column (3) of Table 7. The sample period is July 2020 through June 2023.

Panel A. Gamma-induced impacts on annualized daily realized volatility



Panel B. Gamma-induced impacts on annualized 30-minute realized volatility

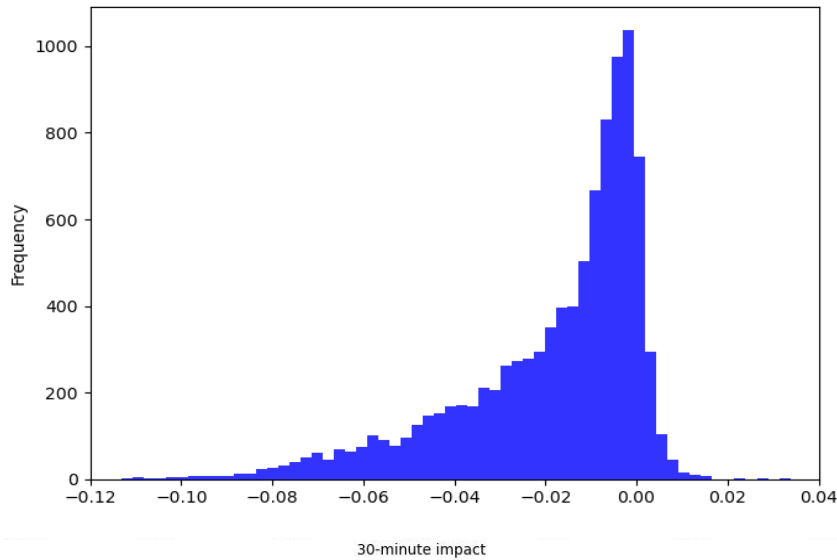
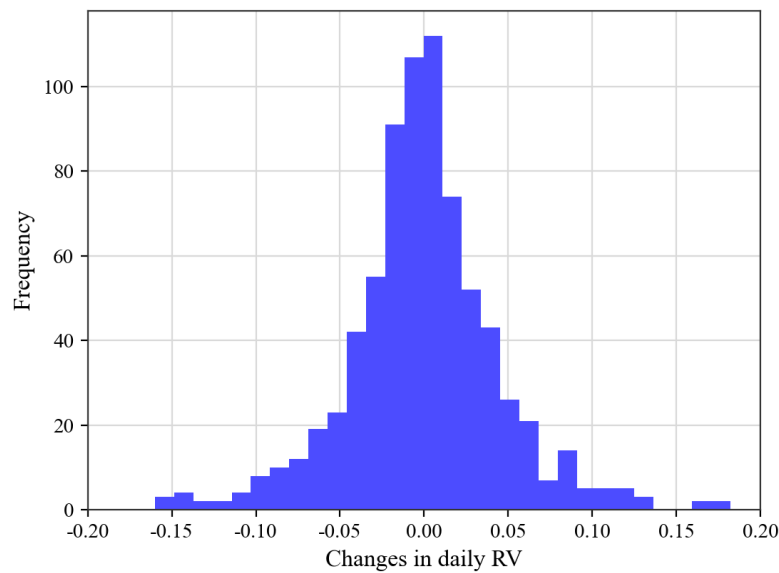


Figure IAB6

Histograms of linear model estimates of gamma-induced impacts on realized volatilities

Panels A and B display histograms representing the distributions of the gamma-induced impacts on annualized daily (Panel A) and 30-minute (Panel B) realized volatilities. The gamma-induced impact is the difference between the annualized daily or 30-minute realized volatility and an estimate of what the realized volatility would be under the counterfactual assumption that variance is unrelated to gamma. The model is the version with five lags of gamma, for which average coefficient estimates are reported in column (6) of Table IAB2. The sample period is July 2020 through June 2023.

Panel A. Daily changes in realized volatility



Panel B. Changes in 30-minute realized volatility

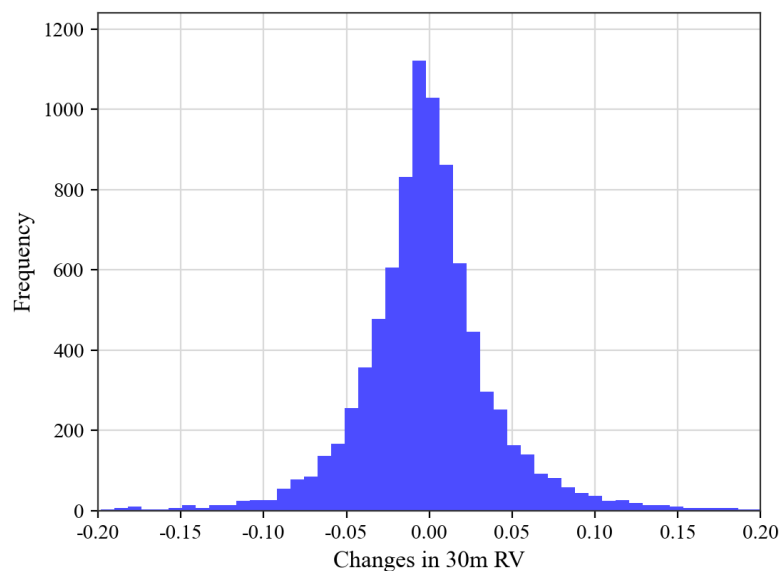


Figure IAB7

Histograms of changes in annualized daily and annualized 30-minute realized volatility

Panels A and B display histograms representing the distributions of changes in annualized daily and annualized 30-minute realized volatility, respectively. The realized volatilities are computed using log returns on the futures contract with highest trading volume on each date. The sample period runs from July 2020 through June 2023.

Table IAB1**Placebo tests of the impact of OMM delta on e-mini futures returns**

This table displays the results of placebo regressions that explore whether the deltas of option market maker (OMM) positions in S&P 500 index options at times well before expiration when OMMs are not systematically unwinding hedges explain the log return on the e-mini futures (symbol ES). The unit of observation is a minute. The sample consists of the minutes ending at times $t = 12:01$ p.m., ..., 4:00 p.m. during the sample period running from July 2020 through June 2023. The dependent variable is the log return R_t on the front-month ES contract during the minute ending at time t . The key explanatory variable is the interaction $\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, \nu\})$, where $(\tau, \nu) = (1:30 \text{ p.m.}, 2:00 \text{ p.m.})$ or $(\tau, \nu) = (2:30 \text{ p.m.}, 3:30 \text{ p.m.})$, $\Delta_{0DTE}(\tau)$ is the delta of the OMM position in the expiring (0DTE) options at time τ , and $I(t \in \{\tau+1, \dots, \nu\})$ equals one if t (the end of the minute) is in the set $\{\tau+1, \dots, \nu\}$. Some specifications also include the interaction $\Delta_{\text{non-0DTE}}(\tau) \times I(t \in \{\tau+1, \dots, \nu\})$, where $\Delta_{\text{non-0DTE}}(\tau)$ is the delta of the OMM position in the non-expiring options at time τ , the lagged return R_{t-1} , and minute-of-day fixed effects. The deltas are computed from the OMM positions in S&P 500 index options (symbols SPX and SPXW). On days with no 0DTE options, $\Delta_{0DTE}(\tau)$ equals zero. Returns are in basis points, and deltas are divided by 10^{-9} so that the reported coefficients are in convenient units. t -statistics are in parentheses below the coefficient estimates.

Variable	$\tau = 1:30, \nu = 2:00$			$\tau = 2:30, \nu = 3:30$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{0DTE}(\tau) \times I(t \in \{\tau+1, \dots, \nu\})$	-0.0003 (-0.03)		-0.0003 (-0.02)	0.0081 (0.74)		0.0067 (0.62)
$\Delta_{\text{non-0DTE}}(\tau) \times I(t \in \{\tau+1, \dots, \nu\})$	0.0000 (0.02)	0.0000 (0.02)		-0.0011 (-0.75)	-0.0010 (-0.67)	
R_{t-1}	0.0096 (2.22)	0.0096 (2.22)	0.0096 (2.22)	0.0096 (2.22)	0.0096 (2.22)	0.0096 (2.22)
Minute FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.001	0.001	0.001	0.001	0.001	0.001
Observations	178,553	178,553	178,553	178,553	178,553	178,553

Table IAB2**Linear regression estimates of the effect of OMM gamma on intraday e-mini futures volatility**

This table displays the results of linear regression models in which the squared one-minute return (r_t^2) on the S&P 500 e-mini futures contract is regressed on lagged gammas and lagged squared returns. The variables $\Gamma_{t-l,d}$ and $r_{t-l,d}$ are the gamma of the aggregate option market maker (OMM) net position and the return at time $t - l$ of day d , respectively. All models include fixed effects for hour, date, day of the week (DOW), and year. The last row reports the values of F-statistics for tests of whether the coefficients on the additional gamma-lag variables in each model are jointly equal to zero relative to the previous specification. The sample period is July 2020 through June 2023.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
$\Gamma_{t-1,d}$		-7.84 (1.26)	-4.70 (2.09)	-4.28 (2.19)	-3.52 (2.14)	-3.25 (2.09)
$\Gamma_{t-2,d}$			-4.18 (1.80)	-3.34 (1.84)	-2.64 (1.64)	-2.12 (1.55)
$\Gamma_{t-3,d}$				-1.52 (2.09)	0.18 (2.18)	0.64 (2.09)
$\Gamma_{t-4,d}$					-3.65 (1.70)	-2.28 (1.62)
$\Gamma_{t-5,d}$						-2.92 (1.61)
r_{t-1}^2	0.09 (0.02)	0.09 (0.02)	0.09 (0.02)	0.09 (0.02)	0.09 (0.02)	0.09 (0.02)
r_{t-2}^2	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)
r_{t-3}^2	0.06 (0.02)	0.06 (0.02)	0.06 (0.02)	0.06 (0.02)	0.06 (0.02)	0.06 (0.02)
r_{t-4}^2	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)
r_{t-5}^2	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)	0.05 (0.01)
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour $\times$ year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour $\times$ DOW FE	Yes	Yes	Yes	Yes	Yes	Yes
F-stat. (γ vs prev.)		52.7	5.5	0.6	2.4	1.4

Table IAB3**Linear regression-implied changes in daily and 30-minute realized volatility**

This table displays summary statistics describing the distribution of the impacts of option market maker (OMM) gamma on annualized daily volatility and annualized 30-minute volatility. The impact on annualized daily realized volatility (RV) is computed using equations (17)-(19), and the impact on annualized 30-minute realized volatility is computed similarly. These are the results of the linear model. The sample period is July 2020 through June 2023.

Measure	Mean	Std. dev.	Min.	1%	5%	10%	25%	Median	75%	90%	95%	99%	Max.
Daily RV	-1.68%	1.81%	-9.33%	-7.21%	-5.45%	-4.49%	-2.73%	-0.98%	-0.35%	-0.01%	0.14%	0.45%	0.97%
30-min. RV	-1.83%	2.04%	-11.31%	-8.14%	-6.16%	-4.85%	-2.82%	-1.09%	-0.34%	0.02%	0.19%	0.61%	3.38%