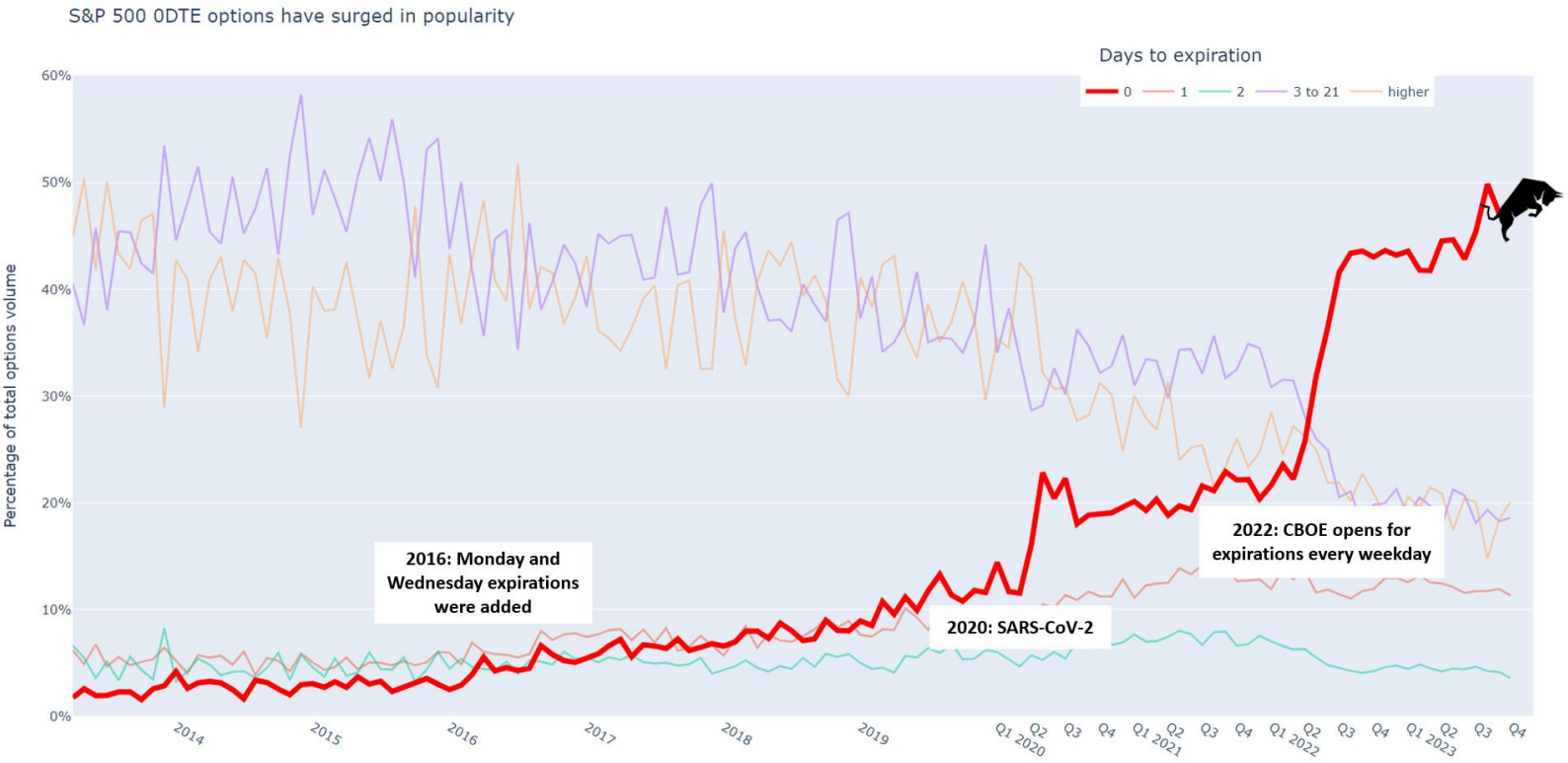
THE RISE AND IMPACTS OF ZERO DAYS-TO-EXPIRATION OPTIONS



FIN11 – Trading and Market Microstructure

The Norwegian School of Economics

Final Term Paper

Candidates: 133, 135, 179, and 198

Abstract

The trading volume of zero days-to-expiration (0DTE) options has seen a significant increase in recent years. However, these financial derivatives are underexplored. This paper aims to fill the gap by investigating the relationship between 0DTE options and the S&P 500. In doing so, we use a combination of theory and historical data. Our Python code to process and analyze data is available in the Appendix.

The results show that the increased trading in 0DTE options is associated with volatility and sudden price movements. We also find that puts correlate with a decline in the SPX, whereas calls correlate with an increase in the underlying. The paper argues that market makers' hedging activities are one of the explanations. We also acknowledge the limitations and weaknesses of our analysis and discuss these throughout the text.

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1 Introduction

In Berkshire Hathaway's 2002 annual report, Warren Buffet warned: "derivatives are financial weapons of mass destruction, carrying dangers that, while now latent, are potentially lethal" (Buffett, 2002). Derivatives contracts are financial instruments whose value is tied to the value of an underlying asset or instrument (Harris, 2003, s. 41). Within a few years after Buffet's statement, the world witnessed the devastating financial crisis of 2008. While multiple factors contributed to this crisis, there is little doubt that derivatives were one of them (Somanathan & Nageswaran, 2015).

Despite regulations and new standards in response to this, global derivatives markets kept growing. The notional value of outstanding derivatives rose to $632 trillion in 2022 (BIS, 2022). Comparably, the value of the global stock market was $98.5 trillion the same year (Statista Research Department, 2023).

One well established type of derivative is options. However, in the last couple of years, a new sub-category of options has surged in popularity, and it is only in the past few months that it has garnered some attention from niche media sources. In 2016, Zero Days-to-Expiration (0DTE) options accounted for only 5% of the total S&P 500 options volume. Today, they comprise over 50% (Zaionz, The Rise Of SPX & 0DTE Options, 2023).

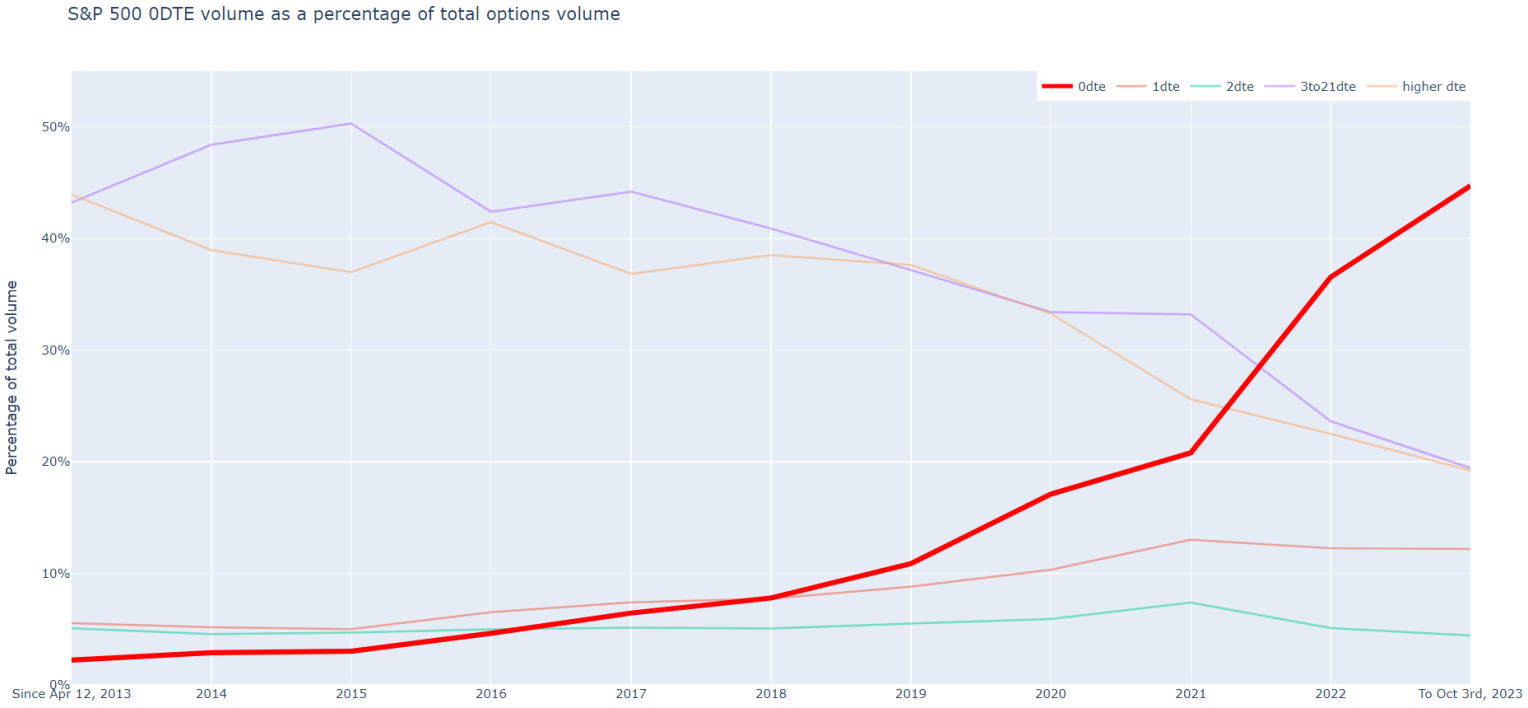


FIGURE 1

The emergence of these instruments, seemingly out of nowhere, reminds us of the cautionary wisdom shared by Warren Buffett. Thus, this term paper seeks to explore the following research question:

"What are the spillover effects from the trading in zero days-to-expiration options on the underlying?"

To answer this, we continue by providing essential background information and theoretical foundations. Following this, we delve into a discussion of our methodology and introduce the dataset underpinning our research. Further on, we will analyze and examine the data, leading to a conclusion.

2 Options

2.1 Theoretical framework

An option is a contract giving the owner the right to buy or sell the underlying security, at a fixed price, at some point in the future. The underlying can include stocks, indexes, commodities, ETFs, and currencies (Ahmed, The rise of 0DTE stock options and how they could be a risk to markets, 2023). An option contract requires an upfront payment in exchange for the possibility to carry out the transaction. This is referred to as the option premium (Varadarajan & Schenk-Hoppé, 2023). There are two types of options: calls and puts. A call option gives you the right to buy the underlying asset. A put option gives you the right to sell it. The fixed price at which you're allowed to transact at in the future is called the strike price. And the date at which you may transact is called the expiration date.

The buyer of a call option receives a payoff if the price of the underlying is higher than the strike price on the expiration date. Consider buying call options on index A with a strike price of $100 and a premium of $2. Then the price of the underlying index increases to $120. The options are "in the money" (ITM). Exercising the contract will give a 20% return, minus the $2 premium. Usually, the seller of the options will pay the investor the difference between the index price and the strike price as a cash settlement on expiration (Varadarajan & Schenk-Hoppé, 2023). Compared to individual stocks where investors get ownership of the underlying. Conversely, if the price of index A ends up below the strike price, there will be no reason to exercise the option. The call option is "out of the money" (OTM). With put options, however, investors stand to profit if the price of the underlying drops below the specified strike price.

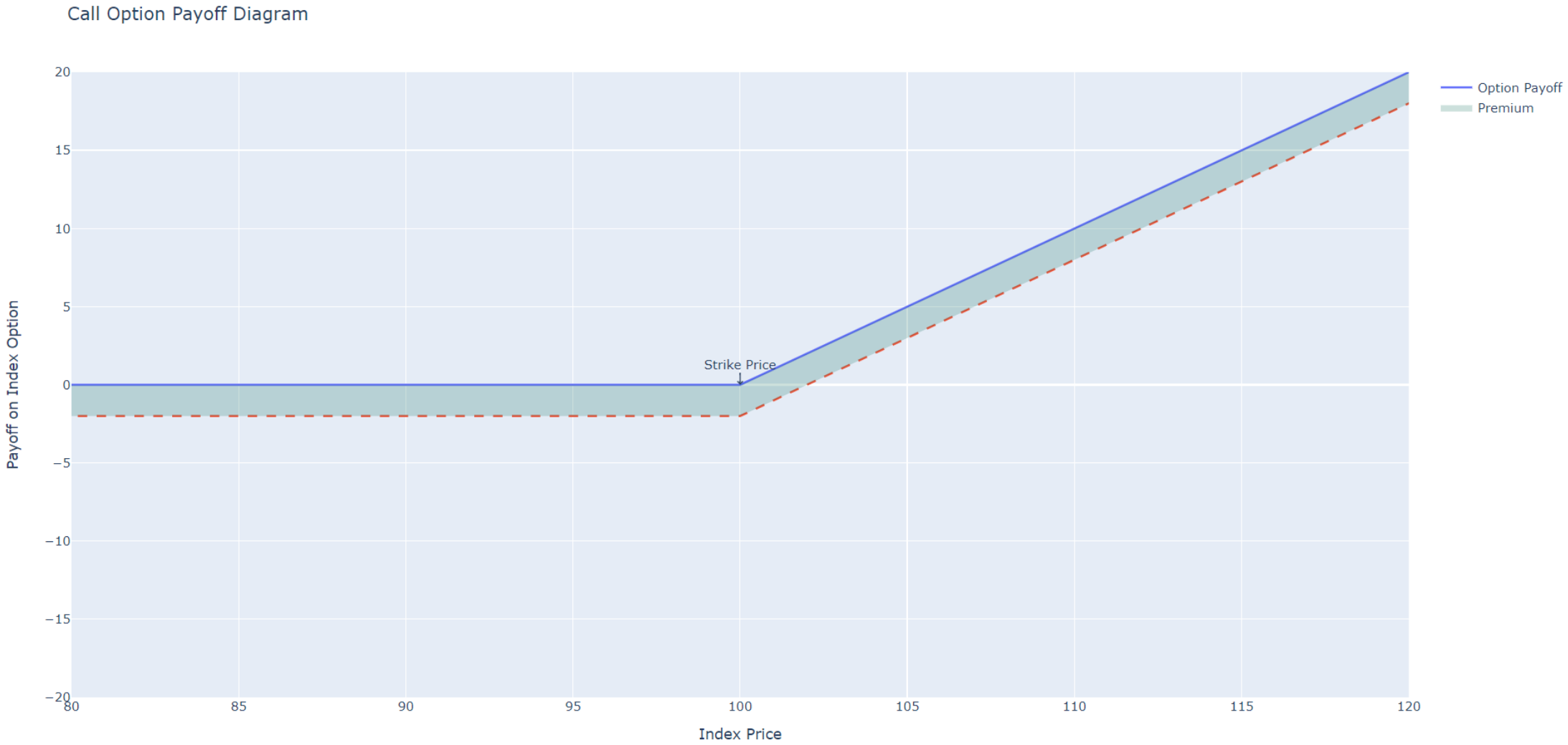

Call Option Payoff Diagram
Payoff on Index Option
Index Price
Strike Price
Option Payoff
Premium
20
15
10
5
0
−5
−10
−15
−20
80
85
90
95
100
105
110
115
120

FIGURE 2

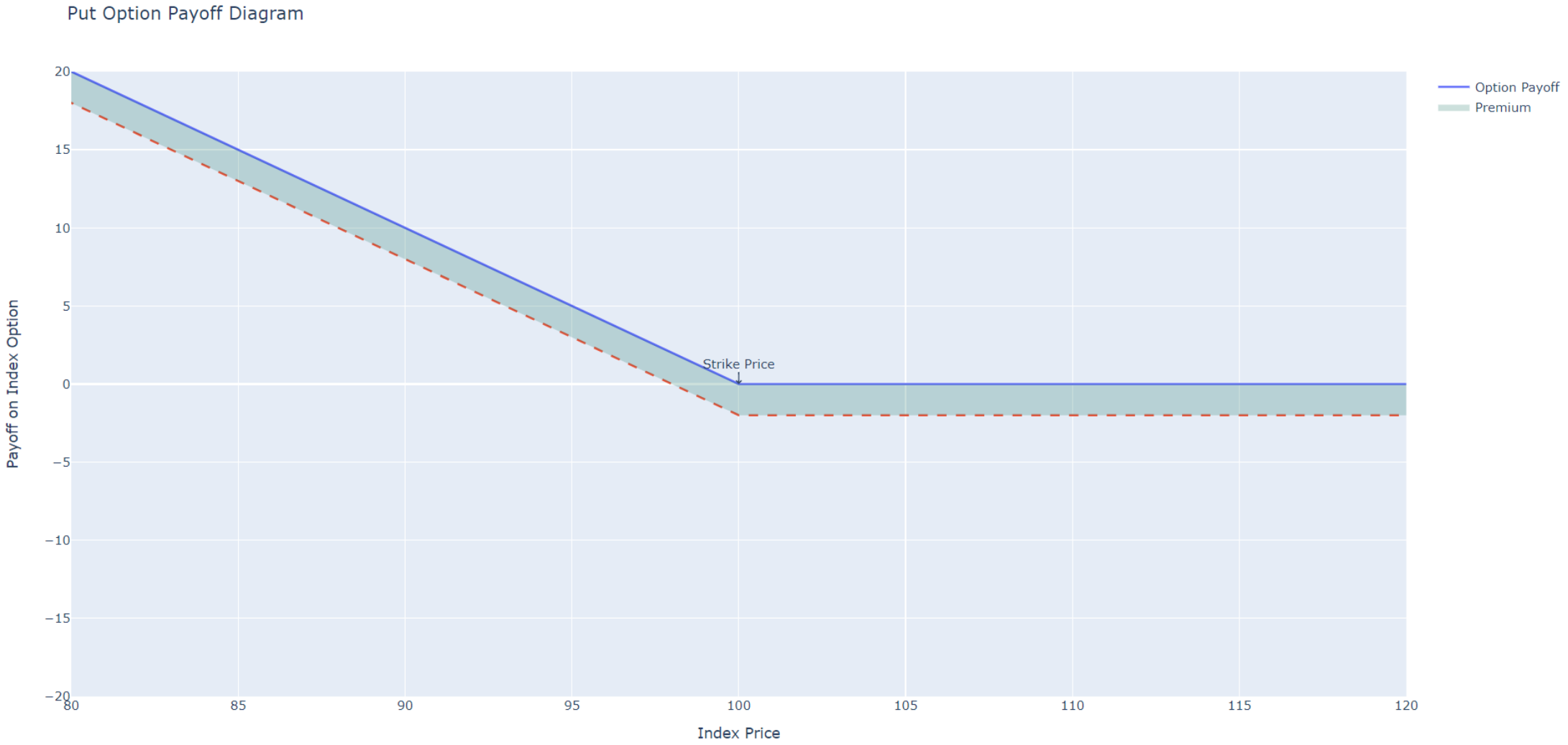

Put Option Payoff Diagram
Option Payoff
Premium
Strike Price
Payoff on Index Option
Index Price
20
15
10
5
0
−5
−10
−15
−20
80
85
90
95
100
105
110
115
120

FIGURE 3

2.2 Time Decay of Options

In 1973, Fischer Black and Myron Scholes published "The Pricing of Options and Corporate Liabilities". The researchers showed how the price of an option could be determined from 1) the price of the underlying, 2) the volatility, 3) the exercise price, 4) the maturity, and 5) the risk-free rate (Black & Scholes, 1973). Relevant for this paper, is how the model demonstrates that the value of an option decreases as time to expiry nears.

$$d_1 = \frac{ln\left(\frac{S_0}{X}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = \frac{ln\left(\frac{S_0}{X}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$C_0 = S_0N(d_1) - Xe^{-rT}N(d_2)$$

S_0 = Stock price

X = Exercise price

r = Risk-free interest rate

T = Time to expiration

σ = Standard deviation of log returns (volatility)

Options' Greeks is another important topic, with this paper focusing on delta and theta. Delta measures how much an option's price moves for every $1 change in the price of the underlying. Theta measures the loss in value that options experience as time passes. The Time Decay of Options. Depreciation accelerates as the option approaches its expiration. Consider two call options on the same stock, both currently trading at $100. Option A is a 30-day call with a strike price of $105. Option B is a 180-day call with the same strike. Assume equal implied volatility, and that all other factors are constant. For option A (30DTE), the theta might be -0.03. This means that Option A loses approximately $0.03 in value per day as time passes. For option B (180DTE), the theta might be -0.01. This example illustrates that shorter-term options tend to experience more significant time decay compared to longer-term options, ceteris paribus (Schwab, 2002).

δ

Delta

θ

Theta

When the options' value decreases the closer it gets to expiry, how is it then, that zero days-to-expiration options have become so popular?

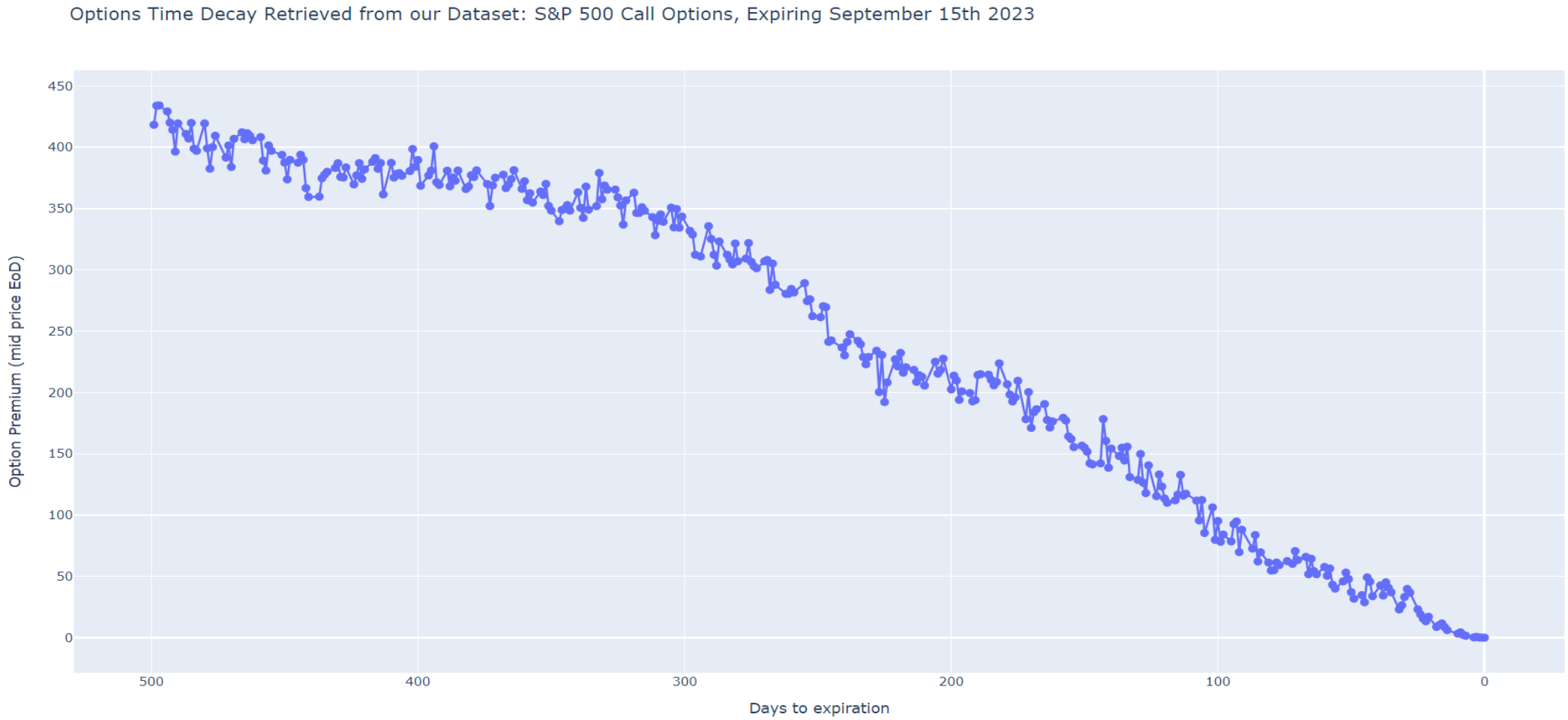

Options Time Decay Retrieved from our Dataset: S&P 500 Call Options, Expiring September 15th 2023
Option Premium (mid price EoD)
450
400
350
300
250
200
150
100
50
0
500
400
300
200
100
0
Days to expiration

FIGURE 4

2.3 The rise of 0DTE options

Zero days-to-expiration options are contracts with less than a day before expiring. They can be used to bet on market moves, but also to protect against them – a hedging strategy. Traders convinced that a stock is going to decline, can purchase put options as a direct investment. One of the advantages is that the trader is not exposed to overnight risk. Investors who want to go long a stock they think will increase in value, can buy puts as a hedge against price decline. The possibility to sell the stock by exercising the put with a higher strike price balances out the losses on the stock. So why hedge an investment with 0DTEs instead of just "plain vanilla" options? Because they're cheaper. Ref. the Theta Decay (Schaeffer, 2023).

2.3.1 Why Market Makers like 0DTEs

A market maker may sell a call option with a strike price 3% above where the market for the underlying is trading. As long as the market does not rally more than 3% during the day, the value of that contract will go to zero, allowing the seller to pocket the premium. Studies from the University of Muenster shows that over the past few years, retail traders may have incurred daily losses amounting to a staggering $358 000 by investing in what the researchers describes as "lottery-like assets" (Lu Wang, Day Traders Lose $358,000 Per Day Gambling on Zero-Day Options , 2023). It is easy to understand why market makers are drawn to writing 0DTE options. Moreover, financial institutions use these derivatives to delta hedge. The Chicago Board Options Exchange is seeing a trend where market makers increasingly turn to options instead of futures to reduce the directional risk associated with price movements in the underlying asset (Doar, 2023). This will be discussed more in detail.

2.3.2 Why traders like 0DTEs

Options have traditionally been the domain of Wall Street professionals. But retail investors plunged in during SARS-CoV-2. 0DTEs were discovered by retail investors as a way of gambling during the meme-stock era in 2021. Tech stocks like Tesla soared, and (far) out-of-the-money call options gained in popularity, due to the inexpensive way to ride the bullish market. The use of 0DTEs have gained further traction since May 2022 after Chicago Board Options Exchange added Tuesday and Thursday expirations, now covering each weekday (Lu Wang, What are Zero-Day Stock Options? Why Do They Matter?, 2023). Generally, a contract close to its expiration with a strike price near the money will be very sensitive to price changes in the underlying. That makes 0DTEs attractive to traders looking for short-term profits from price

movements and volatility. They offer a high leverage effect; a small amount of money can give large exposure to the underlying asset. The extent of retail investors' participation in 0DTE trades remains a subject of uncertainty. According to JPMorgan, retail investors account for only 5% of these trades, with the majority of activity likely driven by computer-powered institutional players. In contrast, the CBOE estimates that retail investors are a significant driving force behind as much as 40% of all 0DTE trades (Lu Wang, Retail Traders Are Driving Up to 40% of Zero-Day Options Boom, 2023).

Option Alpha, an automated trading platform, conducted an analysis of 230 000 trades from the preceding year. Their findings revealed that S&P 500-linked options constituted over 80% of all 0DTE trades made through them (Cernera, Plessis, Henry, & Grosse, 2023). Given that these are among the most actively traded, this paper will employ SPX 0DTEs as the benchmark. They are classified as European-style, allowing them to be exercised at expiration only. This mitigates the risk of early assignment, associated with American-style options (Zaionz, The Rise Of SPX & 0DTE Options, 2023). The CBOE currently accounts for approximately 35% of all options trading volume in the United States, making it the largest options exchange (Cboe, 2023). Therefore, we will focus our analysis on trades made here.

3 Data

When trying to address the research question: *"What are the spillover effects from the trading in zero days-to-expiration options on the underlying?"*, we started with finding data[1]. After contacting the CBOE directly, we eventually acquired two critical datasets: 1) an EoD Summary of all option trades made on their exchange in the last ten years, and 2) intraday data from the 15th of August this year. This specific day was chosen due to its high volume. In total, the data amounted to over 5GB. Bloomberg was used to retrieve 30-minute price interval data for the S&P 500 the last decade. Additionally, we obtained one-minute price interval data on August 15th. To make sense of this, Python was employed. The code can be found in the Appendix. We refined our analysis by excluding non-trading days to accurately calculate days to expiry.

[1] NHH's Bloomberg and Eikon subscriptions offered very limited historical derivatives data. Prompting us to explore OptionMetrics, a source commonly used by researchers. However, the vendor sold exclusively to institutional clients, and our NHH representative deemed their services too costly.

Dataset	Data	Number of Observation
April 2013 to May 2022 EoD data	nDTE%, Option Volume	1083
May 2022 to October 2023 EoD data	nDTE%, Option Volume	349
August 15th, 2023, 1-minute data	Put/Call Ratio, nDTE%, Option Volume	390
SPX 30-min price data: April 2013 - October 2023	Price, volatility	2640
SPX 1-min price data: August 15th, 2023	Price, volatility	390

TABLE 1

4 Analysis

4.1 Volatility

In the early weeks of 2018, what had previously been a period of calm market volatility abruptly transformed into Volmageddon. Complex financial products linked to the volatility index (VIX) played a pivotal role. The high volatility triggered a wave of selling in American stocks, causing the S&P to slip 4%, its worst month in over two years (McGeever, 2018). JPMorgan strategist Marko Kolanovic warned earlier in 2023 that the popularity of 0DTE trades could potentially pave the way for 'Volmageddon 2.0' (Ahmed, Rise of near-term options trading carries risk of Volmageddon 2.0 -JPM's Kolanovic, 2023).

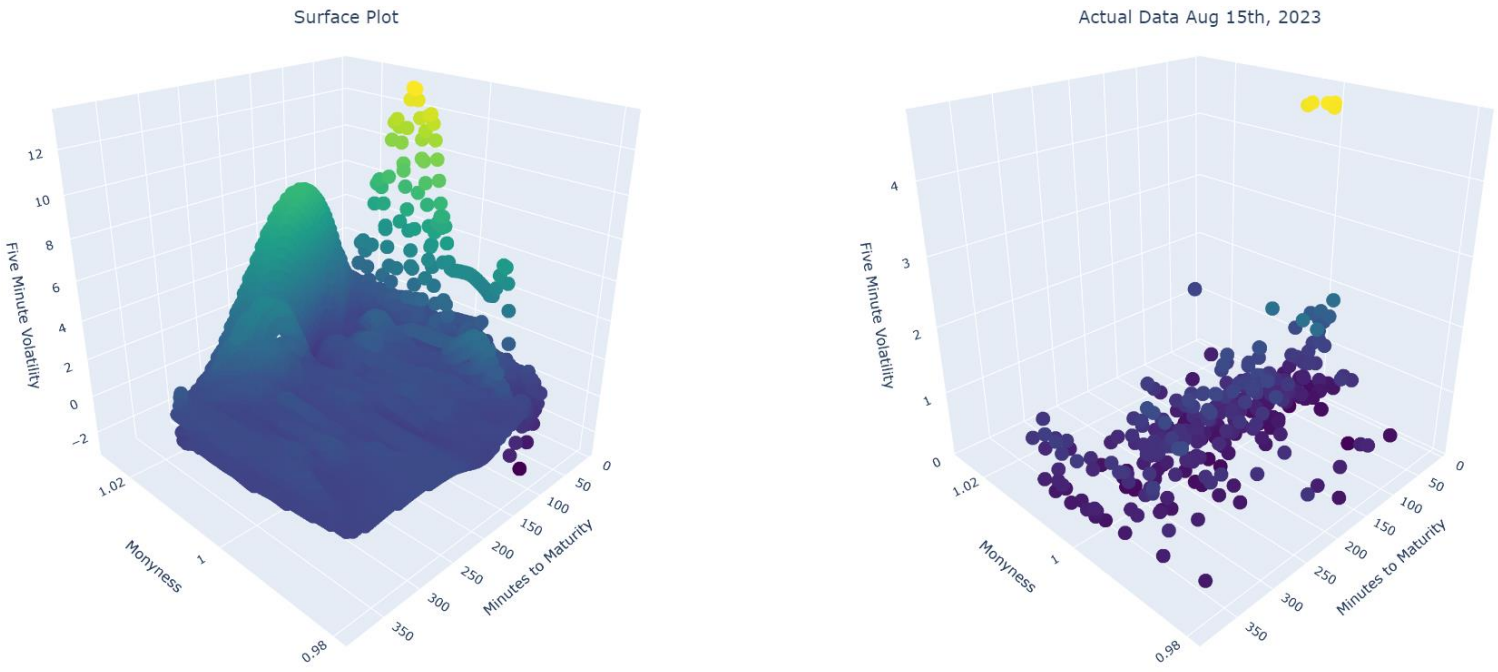


FIGURE 5: MONEYNESS = STRIKE / S&P 500

In Figure 5, we used the intraday data to plot a three-dimensional volatility surface. Showing implied volatilities against moneyness and time to maturity. It shows that the options experience higher volatility the closer they get to maturity.

When researching 0DTE options' impact on the volatility of the underlying, we started by calculating the percentage of 0DTE volume in relation to the total options volume (i.e., 0DTE%) for each day. Then, we calculated the realized 30-minute volatility of SPX by assessing price changes every half hour and determining the standard deviation. The dependent variable in our analysis is intraday volatility, while 0DTE% is the primary independent. We also incorporated control variables such as historical volatility and same-day returns. The results with the control variables can be found in the Appendix. Subsequently, we performed an Ordinary Least Squares (OLS) regression analysis to explore the relationships within the dataset. Both over a ten-year period and intraday. This study adds to the literature by analyzing the most recent data.

4.1.1 Results: 2013 - 2022

Our analysis illustrated below, suggests that there has indeed been a positive correlation between the 0DTE% and SPX volatility in the years 2013 to 2022. The explanatory power (R^2) is 11%, with a coefficient of 0.052 and the p-value is approximately zero. Moreover, when looking at the correlation between volatility and options with a longer time to expiration, our analyses show that 0DTE% has the greatest explanatory power of all the different maturities. A coefficient of 0.052 means that an increase in the 0DTE% of 4.3 percentage points (one standard deviation in the period January to October 2023) from one day to another, is correlated with a 0.0023 higher 30-minute volatility the second day compared to the first (0.052*0.043=0.0023).

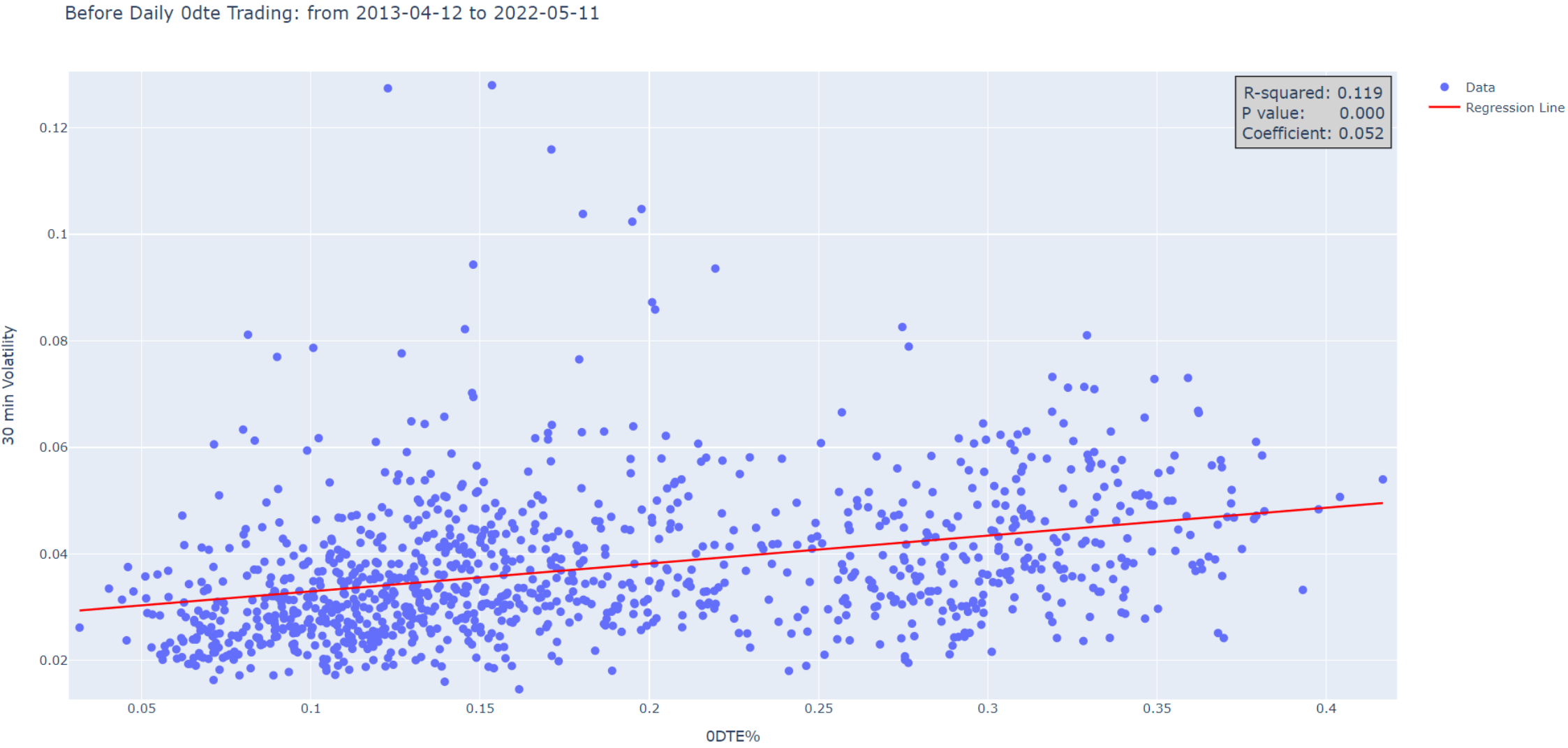

Before Daily 0dte Trading: from 2013-04-12 to 2022-05-11
R-squared: 0.119
P value: 0.000
Coefficient: 0.052
Data
Regression Line
30 min Volatility
0DTE%
0.12
0.1
0.08
0.06
0.04
0.02
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4

FIGURE 6

OLS Regressions Results

Volatility and 0DTE% in each year from 2013

Variable	Coefficient	R-squared	P-value
0dte_pct	0.052	0.119	0.000
1dte_pct	0.035	0.005	0.148
2dte_pct	0.015	0.003	0.143
3dte_pct	-0.035	0.007	0.035
4dte_pct	-0.020	0.008	0.048
5to21dte_pct	-0.020	0.029	0.000
22to43dte_pct	-0.031	0.040	0.000
44to64dte_pct	0.005	0.000	0.557
higher_dte_pct	0.053	0.019	0.000
lagged_0dte_avg_pct	0.045	0.079	0.000

TABLE 2

4.1.2 Results: Intraday

In addition to looking at this correlation over time, we wanted to examine the intraday relationship between zero-day options and volatility. The difference here is that we have used 0DTE volume and not percentage. We looked at volatility and volume within the same 5-minute periods. The results are fairly similar to the ten-year analysis, but even more convincing, as the coefficient is steeper. This can be seen in Figure 7 below.

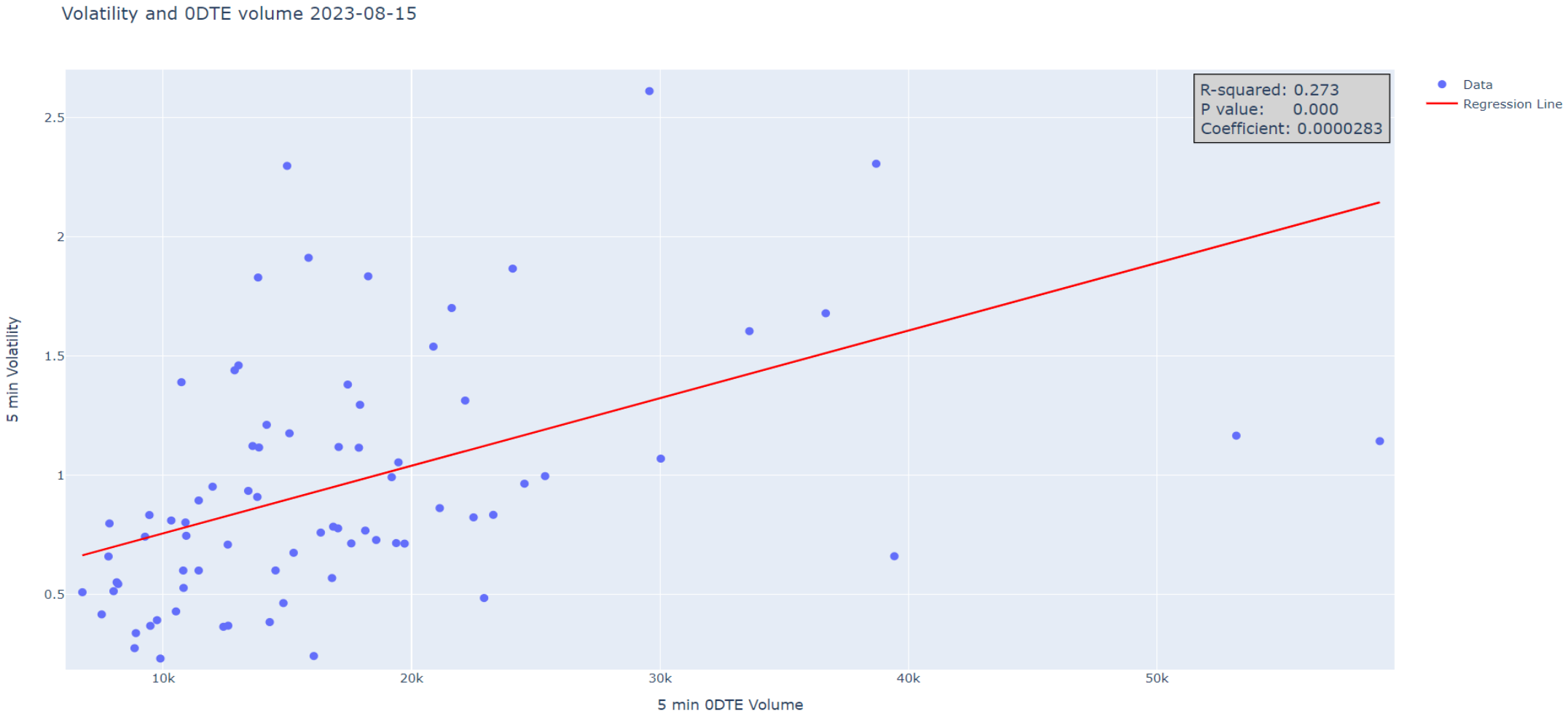

Volatility and 0DTE volume 2023-08-15
R-squared: 0.273
P value: 0.000
Coefficient: 0.0000283
Data
Regression Line
5 min Volatility
2.5
2
1.5
1
0.5
10k
20k
30k
40k
50k
5 min 0DTE Volume

FIGURE 7

4.1.3 Interpretation

Numerous factors can contribute to the heightened volatility associated with 0DTE options. Some argue that it is not the 0DTE trades per se that increases the volatility, but rather the associated hedging from market makers (Lu Wang, What are Zero-Day Stock Options? Why Do They Matter?, 2023). To put it simply, options writers, who take the other side of transactions, must buy and sell the underlying to keep a market-neutral stance. For example, when you purchase a call option with the expectation that a stock's price will rise, the options dealer who sold you that contract stands to make a loss if it increases. To mitigate its risk, the market maker will acquire some of the underlying stock, and as the stock's price moves closer to the option's strike price, the market maker will increase its stock holdings. This process can magnify minor price movements into significant fluctuations or trigger abrupt reversals in the market (Lu Wang, What are Zero-Day Stock Options? Why Do They Matter?, 2023).

4.1.4 High Explanatory Power

However, it is highly probable that our OLS regression analyses yield biased coefficients. One concern is that the explanatory power is unreasonably high. The notion that 0DTE options, a derivative type relatively undiscovered before the pandemic, could account for 11% of the volatility in the 500 largest American public companies over the past decade, seems unrealistic. A high R^2 value might occur because there exists a two-way causality between the two variables. This means that while 0DTE options may indeed contribute to increased volatility in the underlying assets, the reverse could also be true – heightened volatility in the underlying assets could be a driver for the rise in 0DTE trading. The reasoning here is that trading 0DTE options is more likely to be profitable when volatility is high; volatility attracts 0DTE traders. Hence, the regression analysis itself only says something about the correlation, not the causality.

Moreover, a high R^2 may also arise due to its ability to capture variations stemming from an external third variable that concurrently impacts both the dependent and the independent variable. There can be several such confounding variables. For instance, consider the surge in retail traders as an example. Research indicates a connection between retail traders and increased market volatility (Baig, Blau, Butt, & Yasin, 2022). At the same time, retail traders have contributed to the surge in 0DTEs. Hence this could be a third variable affecting both volatility and 0DTE%.

4.1.5 Negative Coefficient from May 2022

One discovery that amazed us was the surprising shift in correlation in May 2022. See Figure 8. Upon conducting the same OLS regression analysis now spanning from May 2022 to October 2023, zero-day options now exhibited a negative correlation with volatility. Despite a substantial increase in the volume of 0DTE options during this period, there has been a reduction in overall volatility (Ciolli, 2023). Additionally, splitting the dataset into one-year periods shows that the coefficient has actually been negative in some of the more recent years. This negative correlation raises the argument that 0DTE may not wield significant influence over the volatility in the underlying.

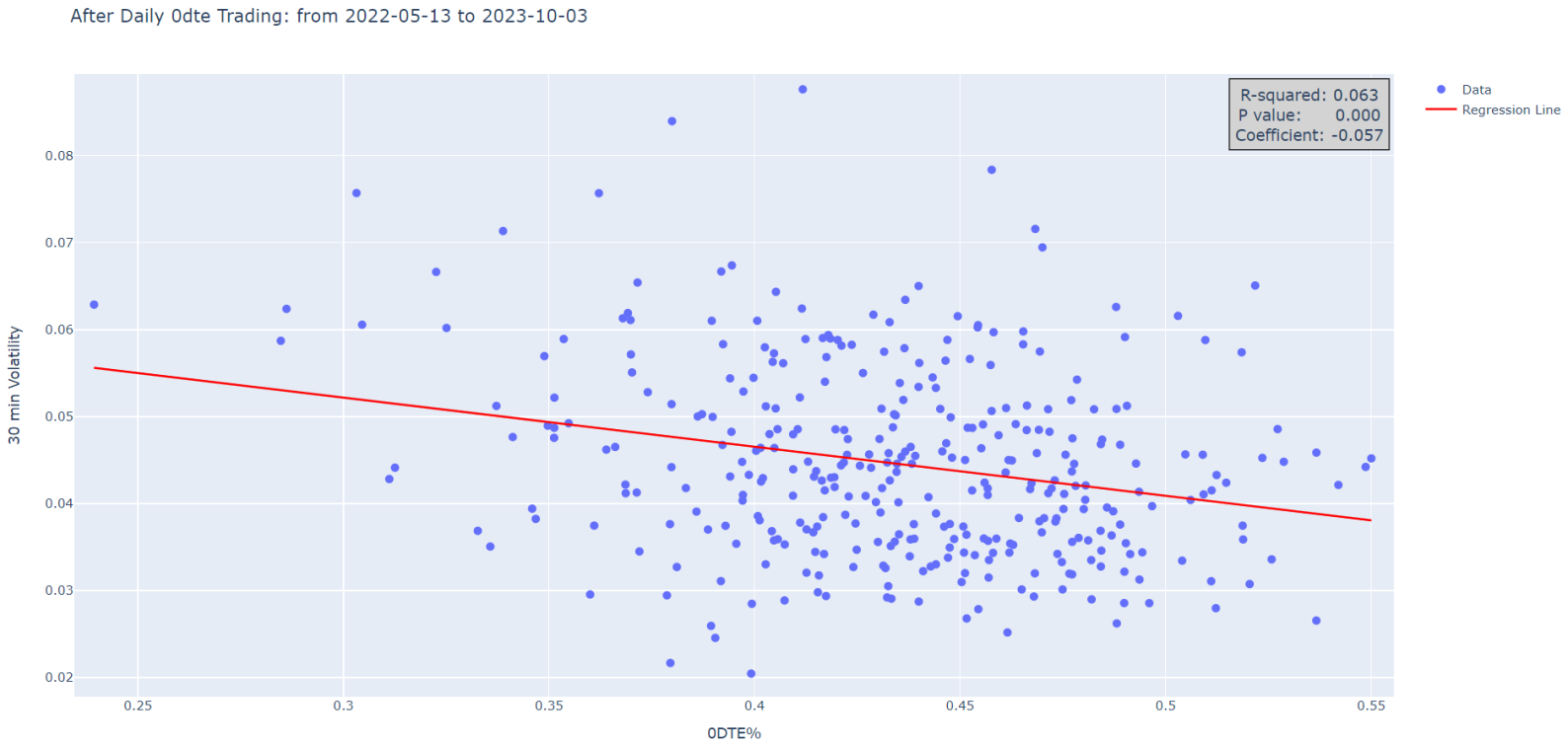


FIGURE 8

OLS Regressions Results

Volatility and 0DTE% in each year from 2013

Year	Coefficient	R-squared	P-value
2013	0.096	0.143	0.036
2014	0.146	0.255	0.000
2015	-0.003	0.000	0.953
2016	0.060	0.089	0.002
2017	0.093	0.162	0.000
2018	0.104	0.066	0.001
2019	0.093	0.131	0.000
2020	-0.072	0.047	0.006
2021	0.088	0.103	0.000
2022	-0.019	0.011	0.121
2023	-0.032	0.026	0.027

TABLE 3

Analyzing one year at a time, the results were less significant in 2022, judging by the p-value. This is most likely due to the shift in correlation mid-year, after the introduction of every-day expiry in May.

In summary, we have highlighted the general connection between 0DTE options and volatility. It is, though, likely to be a two-way causality. 0DTE options can drive volatility because of the associated hedging, and volatility can attract options traders. The correlation can also be attributed to a third variable.

4.2 Effects on Price Movements in The Underlying

4.2.1 Intraday: 15.08.2023

On the 15th of August this year, there was notably large volumes in SPX 4440-strike puts, a level close to where the market was trading at that time. Trading in those puts added up to almost 100 000 contracts during the day. There was a sell-off in the underlying from 3pm to 3:30pm where the index fell. Ultimately leading to a sharp drop in prices (Lu Wang, BofA Disputes Goldman Logic on Zero-Day Option Threat to Stocks , 2023). Looking at the graph below, the decline seems to align well with the high put volume.

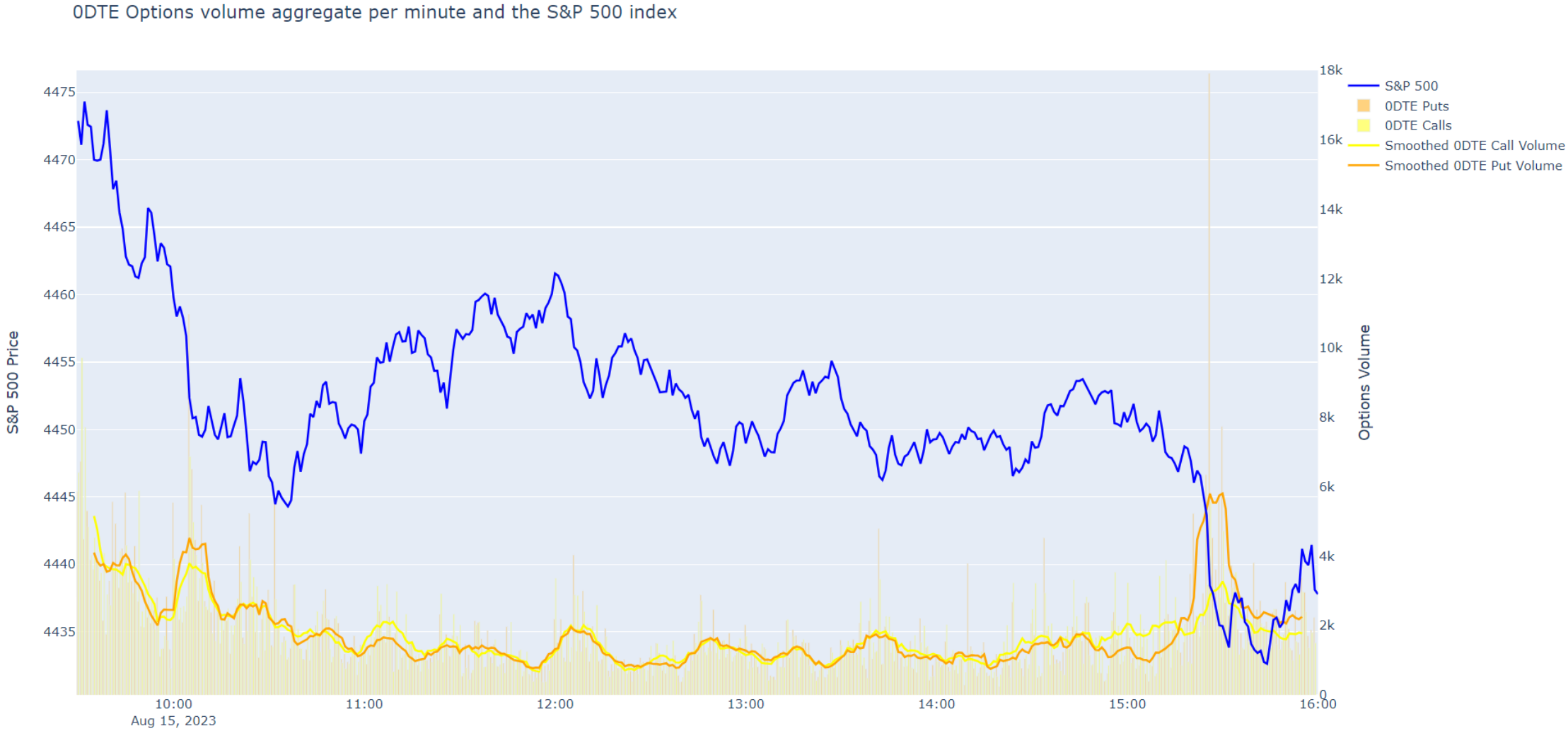

0DTE Options volume aggregate per minute and the S&P 500 index
S&P 500 Price
Options Volume
4475
4470
4465
4460
4455
4450
4445
4440
4435
18k
16k
14k
12k
10k
8k
6k
4k
2k
0
10:00
Aug 15, 2023
11:00
12:00
13:00
14:00
15:00
16:00
S&P 500
0DTE Puts
0DTE Calls
Smoothed 0DTE Call Volume
Smoothed 0DTE Put Volume

FIGURE 9

Figure 10 below, depicts the price movement of the SPX alongside the put/call ratio (PC). A put/call ratio greater than 1 means that market participants are trading and purchasing more put options than call options. Around 3:30 pm, this ratio spiked significantly. Investors were acquiring nearly four times as many puts as calls, essentially betting on a decline in the S&P 500. Interestingly, shortly after this surge in put options, the SPX did in fact experience a decline.

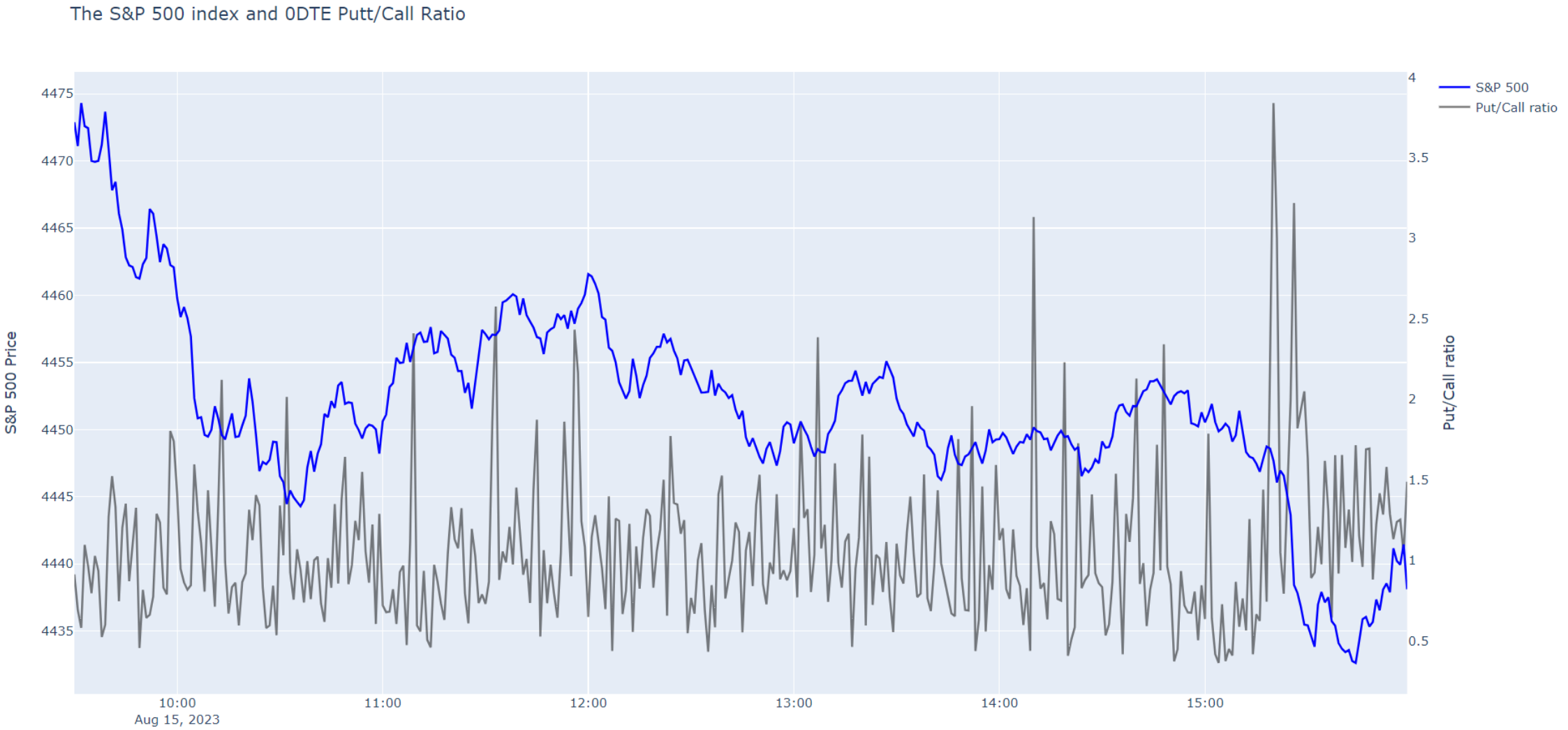

The S&P 500 index and 0DTE Putt/Call Ratio
S&P 500 Price
Put/Call ratio
S&P 500
Put/Call ratio
4475
4470
4465
4460
4455
4450
4445
4440
4435
4
3.5
3
2.5
2
1.5
1
0.5
10:00
Aug 15, 2023
11:00
12:00
13:00
14:00
15:00

FIGURE 10

4.2.2 Approach

One question that emerged during our initial research was how to assess these derivatives' potential of influencing price movements. To explore this, one experimental scenario could be envisioned as follows: Imagine the price of the underlying asset moving in a particular direction, and then, assume that investors engage in significant 0DTE trading. Would the initial price movements persist in the same direction, but with greater momentum? If this is the case, it could potentially be attributed to the impact of the options. However, it's important to acknowledge the complexity of such an analysis. To draw robust conclusions, a comprehensive examination would require a substantial amount of historical intraday data, far beyond what we have access to.



FIGURE 11

Thus, we rather opted to conduct a preliminary, non-representative assessment of this hypothesis, using the intraday data we possess from the 15th of August. Our objective is also to provide a demonstration of how a more extensive research effort could be undertaken in the future.

4.2.3 Results

We did an OLS regression analysis of this trading day, filtering the data to only include minutes where the put/call ratio was larger than 1.22 or less than 0.82. This corresponds to a put/call ratio that is not in balance. The 0DTE volumes can be very high, but if the PC ratio = 1, our hypothesis is that the high volumes shouldn't have any effect on the underlying as the puts and calls cancel each other out.

From the results in Table 4, it can be observed that puts are associated with a subsequent decline in the SPX the following minute, whereas calls are linked to an increase. Regarding the cause-and-effect relationship, the time order of the variables strengthens our findings, as price changes in the future cannot affect the current options trading volume. It is relevant to look at the effects on the underlying relatively quickly after the option has been written, since hedging nowadays moves swiftly. Causality is strongly linked to time order.

```
======================
OLS Regression Results
======================
Data: periods of unbalanced 0dte put/call ratios
Dep. Variable: pct_change_next_1min
R-squared:  0.016
p value puts:   0.0648532028
p value calls:  0.4007644763
coefficient puts:  -0.0000000240
coefficient calls:  0.0000000156
```

TABLE 4

```
============================================================
One-Minute S&P 500 Price Variations on 8/15/2023 (% change)
============================================================
Largest rally:        0.00117
Largest decline:     -0.00082
Mean of abs values:   0.00019
Median of abs values: 0.00015
```

TABLE 5

In this OLS analysis, multicollinearity is a problem, resulting in a large p-value for one of the independent variables. While the coefficients may seem modest, it is essential to bear in mind that the analysis is examining percentage price changes and how options volumes affect these within one-minute intervals. Table 5 shows that the minute where the SPX experienced the biggest price change, involved an increase of 0.117%. With the coefficient from our regression analysis, a net volume of 2410 0DTE puts (one standard deviation) would result in a decline in the SPX of - 0.0058% the following minute (2410 * - 0.0000000240 = - 0.000058 = - 0.0058%). This compares to about one third of the mean and median percentage price change. The average traded put volume was 4112. Taking this trade into consideration, a net volume of 4112 put options equals to a percentage chance in the underlying of - 0.01% (4112 * - 0.0000000240 = - 0.0000987 = - 0.01%). This is substantial because the coefficients only explain price changes that stem from 0DTE options, as opposed to the mean and median values that picks up everything that might move the index. However, note that the R-squared is very low. This means that the OLS analysis most likely just picked up noise.

Because of the large p-value due to multicollinearity and the low R-squared, we did a similar analysis, now limiting the data to minutes where the volume of puts or calls exceeded 3000, under the assumption that larger orders are the ones that make a real impact. The coefficients here are fairly similar to the first analysis, but now the results are significant on a 90% confidence interval. The R-squared is also substantially higher than the previous one. The p-values are close to 10% which is likely a result of a limited sample size. Filtering out all minutes where the 0DTE put or call volume was less than 3000 leaves us with only 65 data points.

```
======================
OLS Regression Results
======================
Data: periods of large 0dte put or call volumes
Dep. Variable: pct_change_next_1min
R-squared:  0.063
p value puts:   0.0844607277
p value calls:  0.0983493348
coefficient puts:  -0.0000000301
coefficient calls:  0.0000000492
```

TABLE 6

4.2.4 Interpretation

Continuing the discussions surrounding the 15th of August: how can the results be interpreted and what can explain the decline in the SPX following the significant accumulation of 0DTE put options? Consider a scenario where a retail trader decides to sell (short) a SPX put option with a strike price set 3% below the current market price. Subsequently, if the underlying asset starts falling towards that strike level, the retail trader would need to repurchase the put option at a higher price. Because the value of the put option increases as it gets closer to the strike price. When multiple traders simultaneously attempt to repurchase these options (buying puts), it can drive the put option prices even higher. Triggering a response from the market makers, typically large banks or financial institutions, who seek to hedge their risk associated with writing the contracts. In our example, this involves shorting the index, thereby exerting further downward pressure on the SPX. This sequence of actions can potentially initiate a self-perpetuating cycle. Some analysts express concerns that such one-directional trading can exacerbate intraday market fluctuations, especially during periods of low liquidity (Ahmed, The rise of 0DTE stock options and how they could be a risk to markets, 2023).

An alternative explanation for the decline in the SPX following the surge in put volume (see Figure 12) could of course be that the 0DTE traders had accurately gauged bearish sentiment and responded accordingly. And that their anticipation of negative market sentiment turned out to be correct. Nonetheless, what remains noteworthy is the rapidity with which the SPX falls after the surge in put options.


0DTE Options volume and the S&P 500 index
S&P 500 Price
Options Volume
S&P 500
0DTE Puts
0DTE Calls
4450
4445
4440
4435
18k
16k
14k
12k
10k
8k
6k
4k
2k
0
15:00
Aug 15, 2023
15:10
15:20
15:30
15:40
15:50
16:00

FIGURE 12

4.2.5 Summary of Intraday Insights

This second part of the analysis is closely interconnected with the first one. Zero-day options' potential of affecting price movements is inherently tied to their potential of increasing market volatility. Our analyses suggest that zero-day options can lead to price changes in the underlying if the traded volumes are significant. However, it is important to recognize that August 15th may not provide a representative sample. Our 'findings', naturally, do not establish conclusive proof of any phenomenon. But it does serve to illustrate the hypothesis and the dynamics at play. The PC-ratio on the other hand, had too low explanatory power to draw any conclusions from it. Peter Tchir at Academy Securities commented that the current 0DTE frenzy from risk-hungry investors somewhat resembles the excitement around horse racing. He noted that it is likely to draw regulatory scrutiny should the activity fuel an equity selloff (Lu Wang, What are Zero-Day Stock Options? Why Do They Matter?, 2023).

4.3 Predictive Power

The last thing we wanted to look at when analyzing how 0DTE options affect the underlying index, was their predictive power. According to Marko Kolanovic, the JPMorgan strategist cited earlier in this paper, zero-day options can have a disproportionate influence on the overall equity market (Lu Wang, What are Zero-Day Stock Options? Why Do They Matter?, 2023). This phenomenon is known as the tail wagging the dog, where a less important part influences the major or more significant part (Merriam-Webster, 2023). To test this hypothesis, we introduced two new variables: 0DTE put% and 0DTE call% of the total volume during the day. One can argue that this is an even better metric than the PC ratio because the variables also say something about the 0DTE volume relative to the total option volume. When conducting the regression analysis, we used 0DTE put% and 0DTE call% as our independent variables and the same-day return of the SPX as the dependent variable.

4.3.1 Results

The results in Table 7 show that over the past 2640 trading days, puts have in general correlated with a decline in the SPX, whereas calls have correlated with an increase in the underlying. The coefficients from the regression analysis show that an increase in 0DTE put% of 2.55 percentage points from one day to another (one standard deviation, in the period January to October 2023), correlates with an index decline of -0.4% (-0.1602*0.0255 = - 0.004 = - 0.4%). This is when the 0DTE call% is held unchanged.

```
======================
OLS Regression Results
======================
Data: Aggregate data per day from 2013 to 2023
Dep. Variable: EoD return
R-squared:  0.18
p value put%:   0.00
p value call%:  0.00
coefficient puts:  -0.16
coefficient calls:  0.16
```

TABLE 7

This does not in itself prove causality one way or another. For instance, if the index has a downward momentum, it may incentivize traders to buy more put options. As noted earlier, the high

R-squared is an argument for a two-way causality. However, when combined with our intraday analysis looking at the effect the subsequent minute (see Table 6), it makes a more convincing argument. Table 6 did indeed show the temporal order of events: puts/calls were *followed* by a corresponding decline/increase in the index the *next* minute. Thus, we can argue that it is the 0DTEs causing price changes, and not the other way around. At least not to the same extent.

5 Future Research

This paper has explored various aspects of zero days-to-expiration options, yet it leaves some questions unanswered and there are still ideas waiting to be explored.

5.1 Market manipulation

If it holds true that 0DTEs and options in general can influence the price of the underlying asset, this could create opportunities for profiting from market manipulation. Consider a hedge fund with vast resources that decides to buy substantial quantities of put options, targeting the underlying asset with the smallest market capitalization. The market makers that offer these put options, will hedge their position by selling the underlying asset, which, in turn, exerts downward pressure on the asset's price. This hedging activity might potentially drive the option into-the-money. Essentially, by acquiring these put options, the hedge fund contributes to a decline in the underlying asset's price, creating a self-fulfilling prophecy.

However, it is essential to note that market makers will not engage in writing such options if it guarantees losses for them. The hedge fund buying the put options would need to distribute their purchases across multiple market makers at the same time, typically banks, to execute this strategy effectively. For the sake of clarification: Sections 9 and 10 of the Securities and Exchange Act of 1934 prohibit the manipulation of security prices (Blokhina, 2019).

Monitoring how banks in practice hedge the 0DTEs they have written would give the chance to discern the cause-and-effect relationships at play, when comparing the hedging activity to the price movements in the underlying. In doing so, the research could possibly conclude whether the potential for market manipulation exists.

5.2 Expand the Intraday Dataset

The intraday analysis conducted in this paper was limited to one single trading day. Expanding the dataset to include multiple days would enable us to assess whether the observed effects persist. Such an extension would significantly enhance the robustness of our findings.

Regarding intraday events, some have expressed concerns about the potential for a "black swan" connected to 0DTE options, drawing parallels to the Flash Crash in 2010 (Campbell, 2023). On May 6th, 2010, the Dow experienced heightened nervousness, characterized by high volatility and a prevailing negative sentiment. The crash was triggered by a program selling over $4 billion worth of E-mini futures, which prompted other traders to react by also selling. This selling pressure in the futures market subsequently spread to stocks, and automated trading programs responded to the rapid decline by shutting down (Cornell University, 2012). Earlier this year, the founder of SpotGamma highlighted the potential for zero-day options to trigger a similar flash crash. According to him, this risk arises due to the hedging requirements imposed on market makers. Such incidents could become particularly dangerous when coupled with un-expected news (Ahmed, Rise of near-term options trading carries risk of Volmageddon 2.0 - JPM's Kolanovic, 2023). Thus, a study looking more closely into trading days where a high 0DTE volume is combined with unforeseen events or bearish news, could uncover whether there is reason to fear the same dynamics as in 2010.

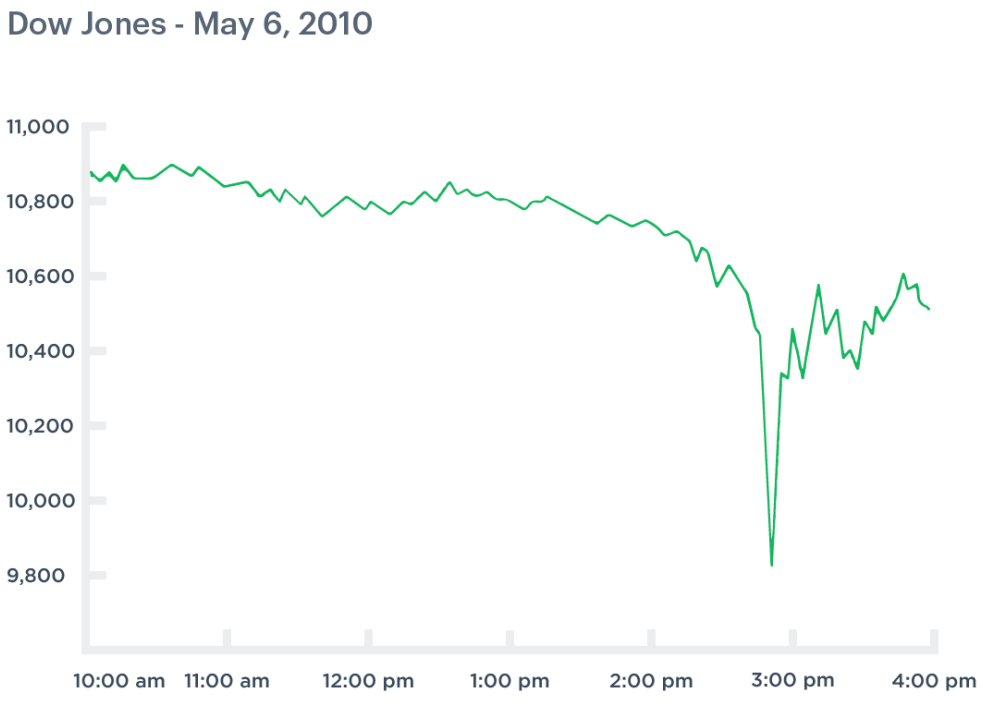


FIGURE 13: RETRIEVED FROM OPTION ALPHA

5.3 Retail-to-Institution Ratio

In part 2.3.2, the paper mentioned the ongoing debate regarding the estimates of the proportion of trading volume assigned to retail traders. This debate exists because some observers attribute the prevalence of smaller transactions as being associated with retail traders, while others, like

JPMorgan, argues that small orders are more likely the result of institutions fragmenting larger orders to cloak their strategies (Lu Wang, Retail Traders Are Driving Up to 40% of Zero-Day Options Boom, 2023).

It would be interesting to further examine the retail-to-institution ratio and the potential distinct effects these two groups have on the underlying market. There may be differences between how retail traders and institutions apply 0DTE options. Suppose that retail traders predominantly employ 0DTE options to speculate on market direction, while institutions primarily utilize them for hedging existing positions. In a market characterized by positive sentiment, the retail trader would purchase SPX call options. On the other hand, an institution that acquires stocks, driven by the same bullish sentiment, may employ SPX put options to hedge their portfolio. Assuming all other factors remain constant, the retail trader's actions will exert upward pressure on the S&P, while the institution's strategy serves to dampen the overall bullish sentiment. This example underscores the relevance in researching the actual retail-to-institution ratio and whether there is a systematic difference in behavior between the two.

6 Limitations

Before concluding, we want to acknowledge the limitations of our research, by summarizing the most important ones. There are four main issues to consider, which have also been commented on earlier in the text. First, some of our regression analyses have yielded p-values greater than 5%, which means that the results are not statistically significant at the 95% confidence level. However, the large p-values could be due to factors such as the sample size. Therefore, a high p-value does not necessarily imply that there is no correlation.

Second, we cannot make any causal claims based on our data. Even though the paper examined the 0DTE volumes and the price movements in the next minute, there is no way to be completely sure that the options are causing these price changes. Similarly, no causal relationship between 0DTE% and volatility over the ten-year period can be inferred.

Third, our data is prone to substantial noise due to the multitude of factors influencing financial markets. Not only the intraday data, but also the EoD summaries, where both the daily and overnight noise is aggregated. Consequently, our term paper sometimes exhibits low R-squared values as a result of this.

Lastly, a potential pitfall of our research is that we have used intraday data from one single trading day. 15.08.2023 may not be representative for a typical day, and it may exhibit more or less extreme points than usual. On the other hand, such days can be every more relevant for our research question than the average days. Mandy Xu, who is the Head of Derivatives Market Intelligence at The Chicago Board Options Exchange, has argued that there is no noticeable market impact from the trading of 0DTE options. She argues that volatility and price patterns for the SPX align with historical averages, claiming that this is “due to the balanced nature of 0DTE trading” (Mandy Xu, 2023). However, sceptics seem to be more concerned about the intraday effects of these short-term options, rather than the long-term averages.

7 Conclusion

In this paper, we sought to answer the question: *"What are the spillover effects from the trading in zero days-to-expiration options on the underlying?"*. More specifically, we have looked at how 0DTEs may affect the S&P 500. These options are in general positively correlated with increased volatility both intraday and over time. As most experts have suggested, this is likely due to the associated delta hedging from market makers. Furthermore, our intraday data showed that high volumes of puts or calls were followed up by price movements. Finally, over the past decade, one could make a case for the predictive power of puts and calls in relation to the performance of the S&P.

The concern that might stay with readers after reading this term paper is the intraday potential of self-reinforcing spirals unsettling the market. This occurs when a substantial portion of investors are trading in unison, and the hedging activities of market makers further amplify the momentum in the same direction. Such dynamics can give rise to events similar to Volmageddon in 2018 or the Flash Crash in 2010. As Karl Johan Molnes wrote in Finansavisen in August: "All financial innovations come to an end, the day one side of the trade suffers a huge loss" (Molnes, 2023).

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Zaionz, J. (2023). *The Rise Of SPX & 0DTE Options*. Retrieved from Cboe: https://go.cboe.com/l/77532/2023-08-11/ffh41m/77532/1691776633zvMs4Hml/The_Rise_of_SPX___0DTE_Options_WP_v1.0.4__Final.pdf

9 Appendix

9.1 OSL Regression with Control Variables

Before the introduction of every-day 0DTE options expiry.

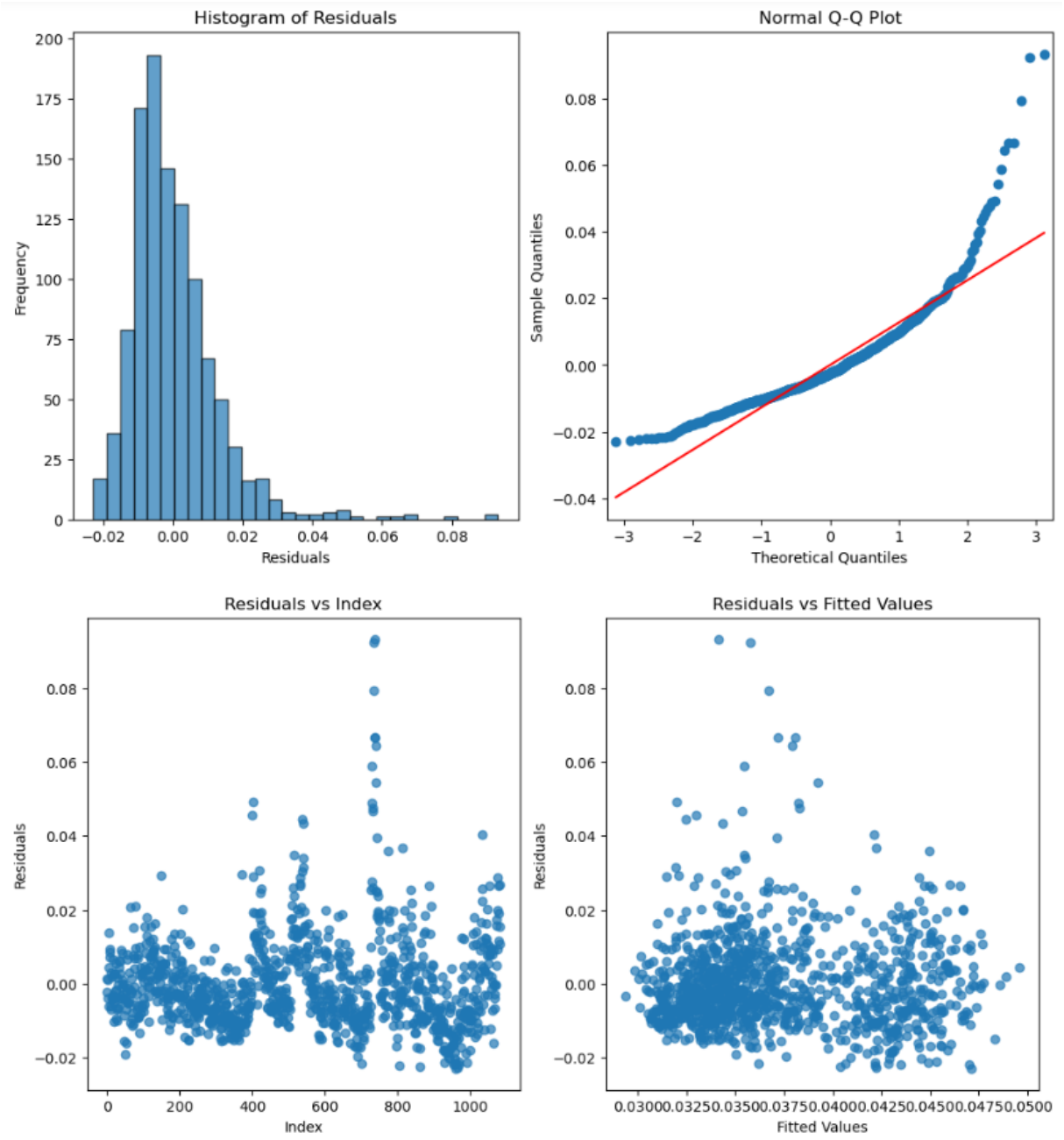
```
======================
OLS Regression Results
======================
Data: Aggregate data per day from 2013 to May 2022
Dep. Variable: volatility
R-squared: 0.60
p value 0DTE%:                      0.00
p value same-day return:            0.00
p value past average volatility: 0.00
coefficient 0DTE%:                     0.02
coefficient same-day return:         -0.24
coefficient past average volatility: 0.71
```

After the introduction of every-day 0DTE options expiry.

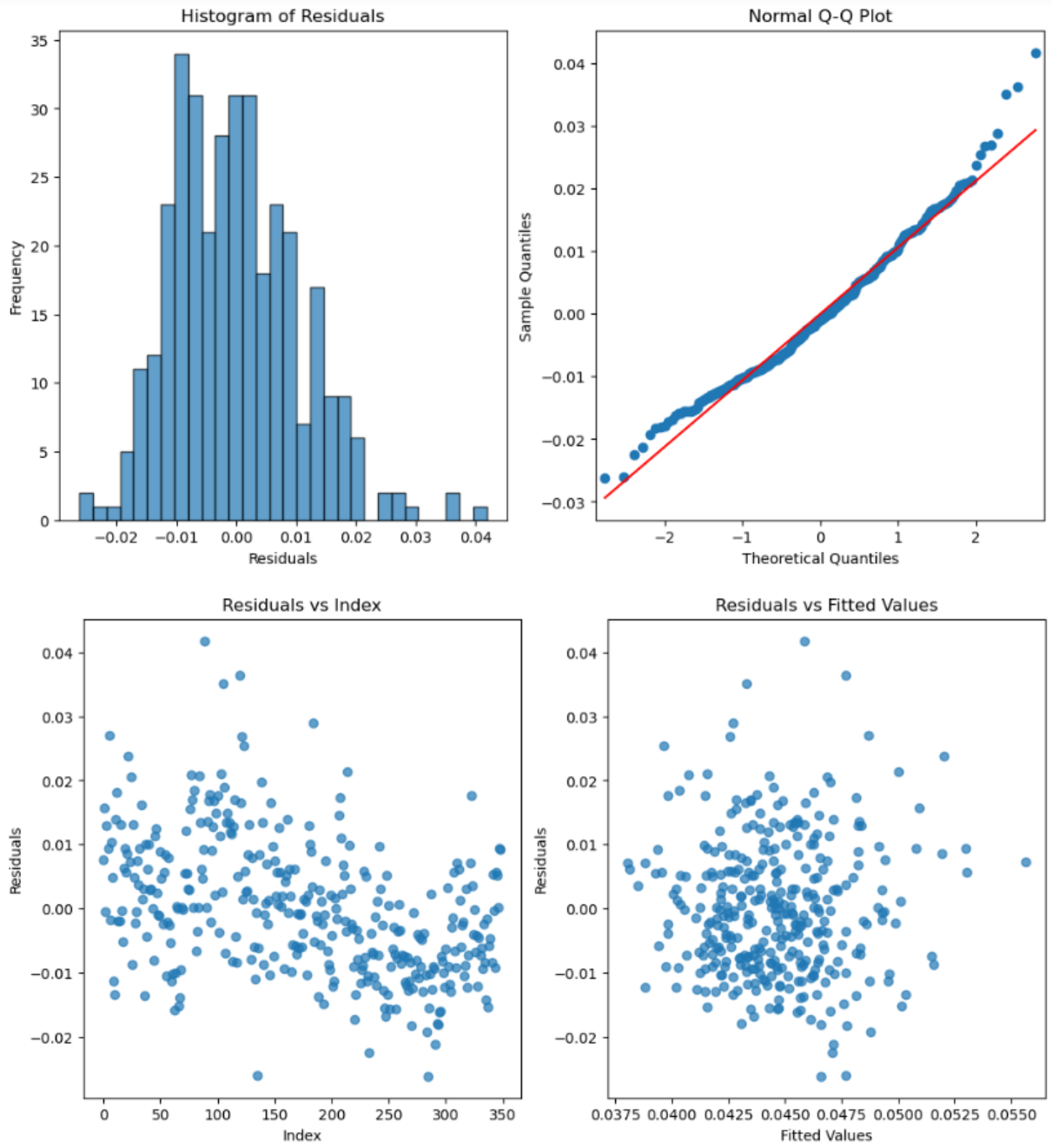
```
======================
OLS Regression Results
======================
Data: Aggregate data per day from May 2022 to October 2023
Dep. Variable: volatility
R-squared: 0.30
p value 0DTE%:                   0.02
p value same-day return:         0.00
p value yesterday's volatility: 0.00
coefficient 0DTE%:                  -0.03
coefficient same-day return:        -0.18
coefficient yesterday's volatility: 0.49
```

9.2 Diagnosis Plots

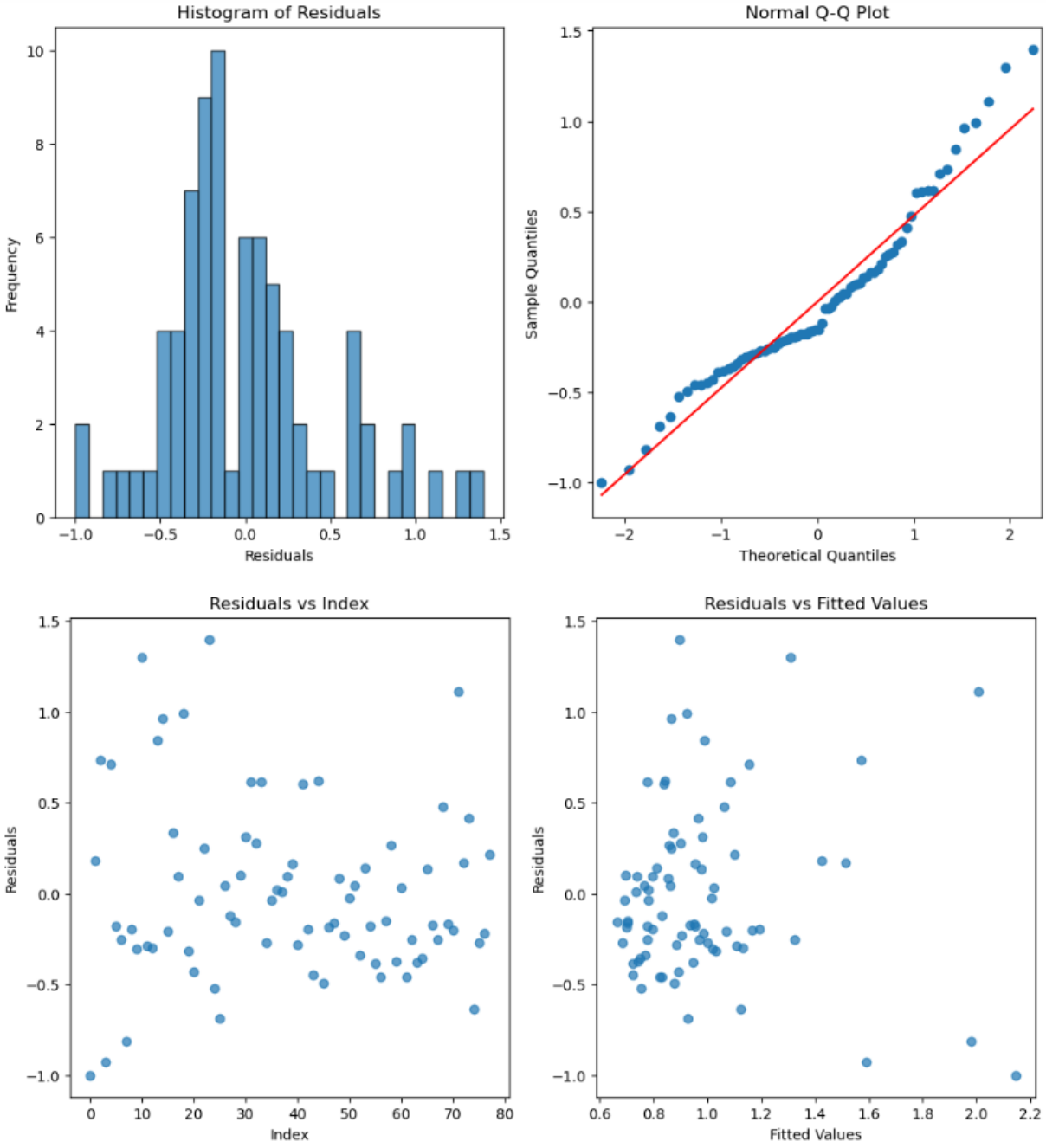
The diagnosis plots to the regression analysis in Figure 6 titled “Before Daily 0DTE Trading: from 2013-04-12 to 2022-05-11”.



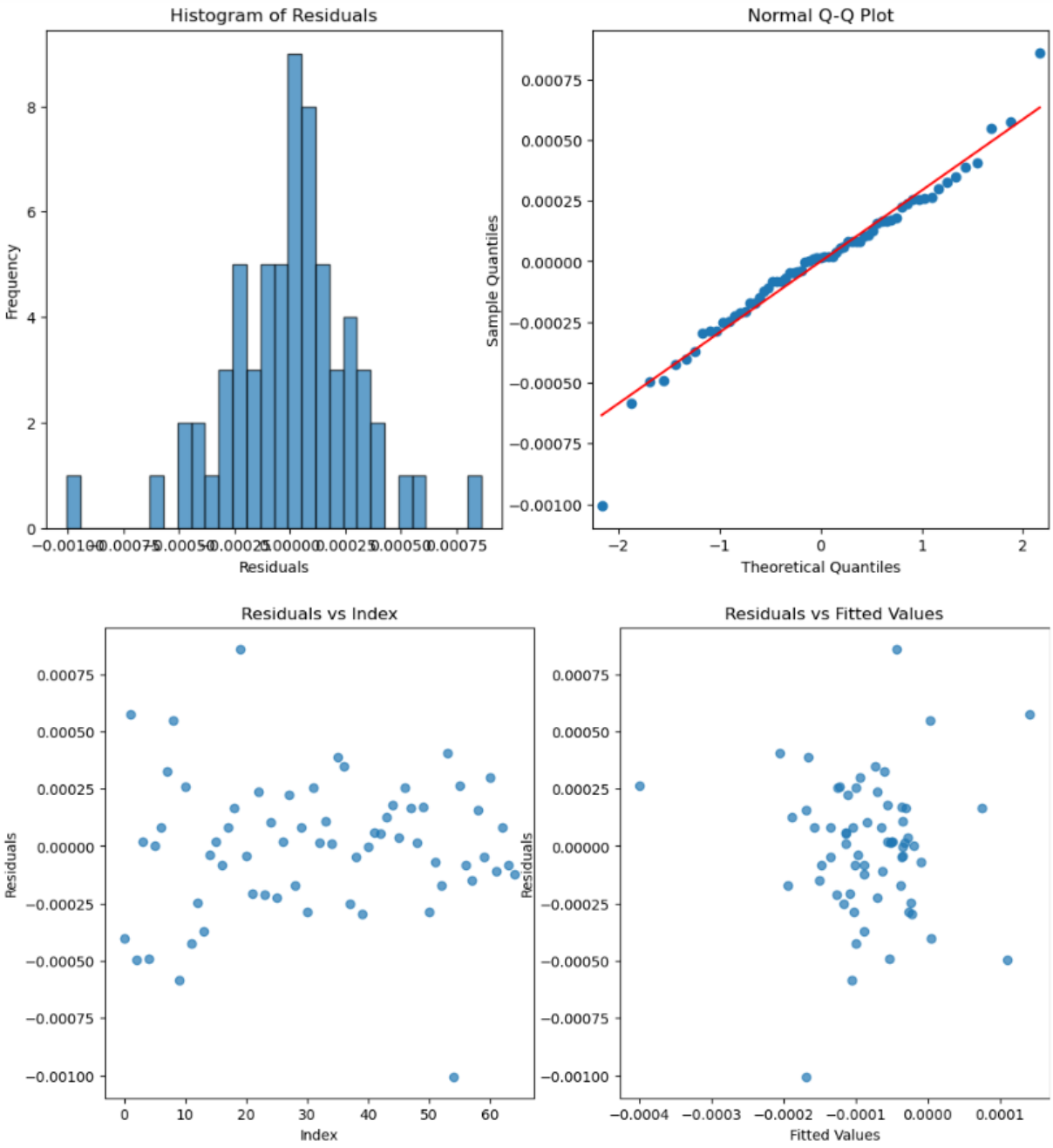
The diagnosis plots to the regression analysis in Figure 8 titled “After Daily 0dte Trading: from 2022-05-13 to 2023-10-03”.



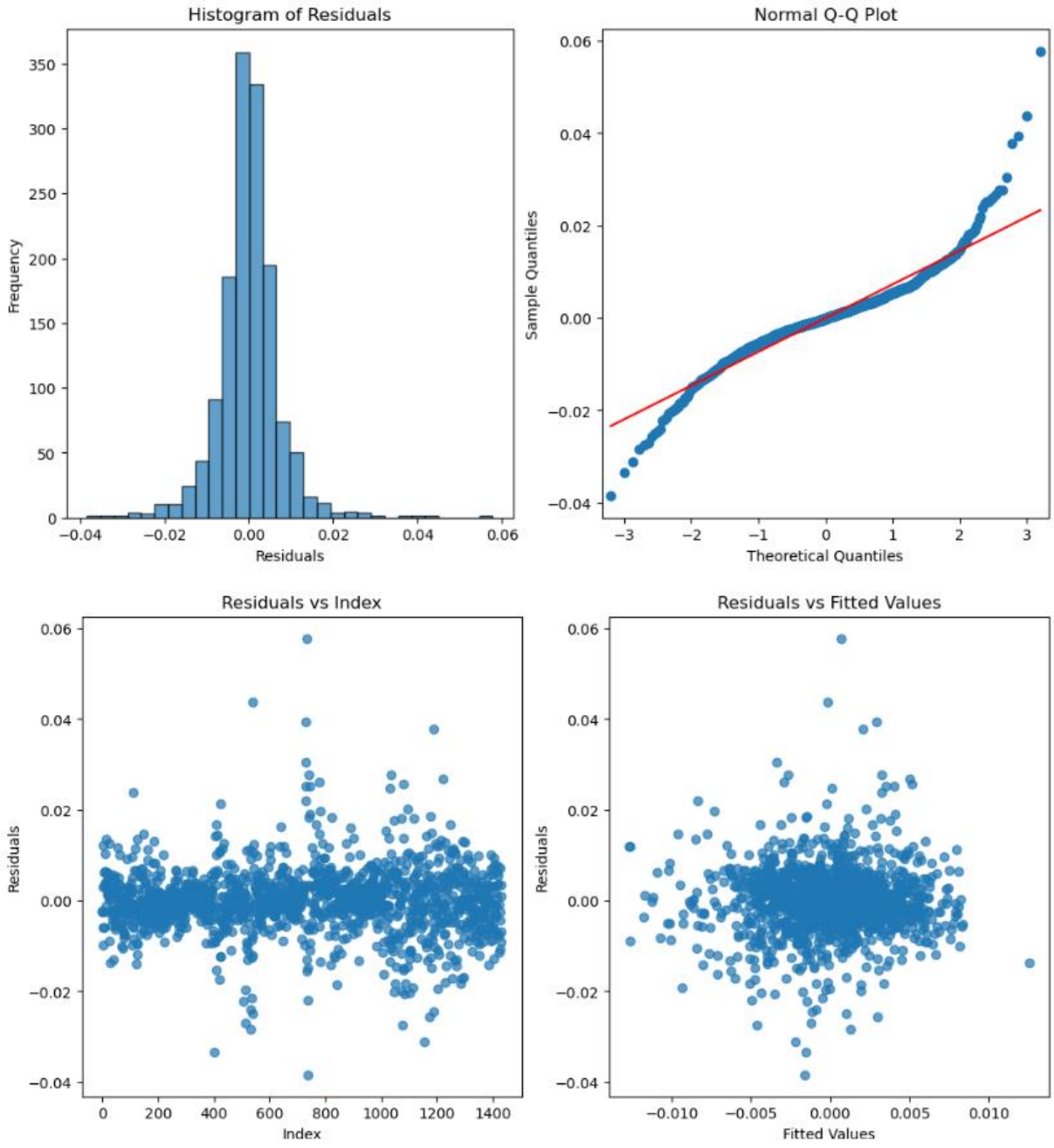
The diagnosis plots to the regression analysis in Figure 7 titled “Volatility and 0DTE volume 2023-08-15”.



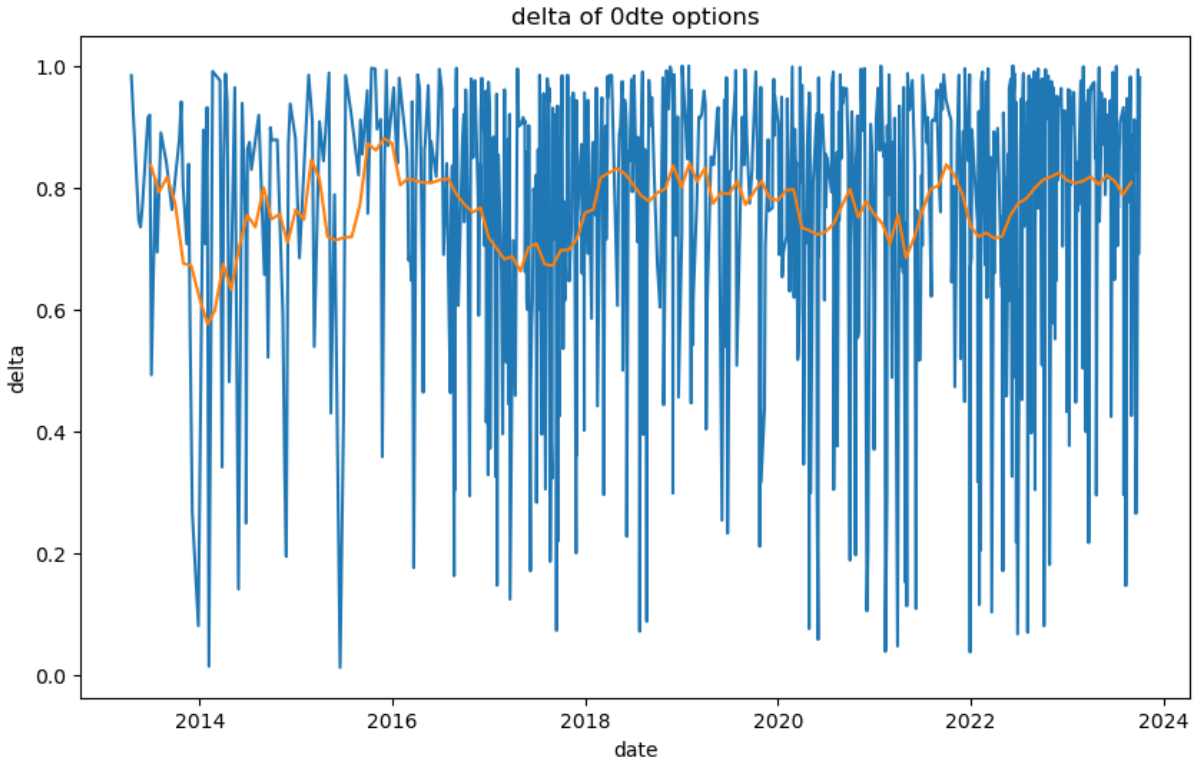
The diagnosis plots to the regression analysis in Table 6 with the data “Periods of large 0DTE put or call volume”.



The diagnosis plots to the regression analysis in Table 7 with the data “0DTE Put% and Call% from 2013 to 2023”.



9.3 0DTE Option's Delta over the Last Decade



9.4 Python Code for Processing of Raw Data

In [1]:
```
#!pip install pandas_market_calendars
import pandas as pd
from datetime import datetime, timedelta
import pandas_market_calendars as mcal
import os
import math



datasetPath = "C:\\Users\\bendi\\Desktop\\dataset"

tradingDaysFolders = os.listdir(os.path.join(datasetPath, "aggregatePerDay"))

csvFilePaths = [os.path.join(datasetPath, "aggregatePerDay", folderName, folderName+".csv")
                for folderName in tradingDaysFolders]

csvFilePaths.reverse()
```

In [2]:
```
calendar = mcal.get_calendar("CBOE_Index_Options")
tradingDays = calendar.schedule(
    datetime(2013, 4, 10),
    datetime(2030, 1, 1)).index

def countTradingDays(start_date, end_date):
    filtered_days = tradingDays[(tradingDays >= start_date) & (tradingDays <= end_date)]
    return len(filtered_days) - 1
```

Calculate nDTE%

For each day: "0dte_cnt", "1dte_cnt", "2dte_cnt", "3dte_cnt", "4dte_cnt", "5to21dte_cnt", "22to43dte_cnt", "44to64dte_cnt", "higher_dte_cnt"

In [3]:
```
print(datetime.now())

# One row per trading day: Will store the number of Ndte options traded and their percentage of the total options trading volume
dailyNdteOptionsVolume = pd.DataFrame(columns=["0dte_put_cnt",
                                               "1dte_put_cnt",
                                               "2dte_put_cnt",
                                               "3dte_put_cnt",
                                               "4dte_put_cnt",
                                               "5to21dte_put_cnt",
                                               "22to43dte_put_cnt",
                                               "44to64dte_put_cnt",
                                               "higher_dte_put_cnt",

                                               "0dte_call_cnt",
                                               "1dte_call_cnt",
                                               "2dte_call_cnt",
                                               "3dte_call_cnt",
                                               "4dte_call_cnt",
                                               "5to21dte_call_cnt",
                                               "22to43dte_call_cnt",
                                               "44to64dte_call_cnt",
                                               "higher_dte_call_cnt"])

# for each trading day in the dataset (one csv file per day)
for n, path in enumerate(csvFilePaths):
    df = pd.read_csv(path)

    #count Ndte trades
    day = {"0dte_put_cnt": 0,
           "1dte_put_cnt": 0,
           "2dte_put_cnt": 0,
           "3dte_put_cnt": 0,
           "4dte_put_cnt": 0,
           "5to21dte_put_cnt": 0,
           "22to43dte_put_cnt": 0,
           "44to64dte_put_cnt": 0,
           "higher_dte_put_cnt": 0,

           "0dte_call_cnt": 0,
           "1dte_call_cnt": 0,
           "2dte_call_cnt": 0,
           "3dte_call_cnt": 0,
           "4dte_call_cnt": 0,
           "5to21dte_call_cnt": 0,
           "22to43dte_call_cnt": 0,
           "44to64dte_call_cnt": 0,
           "higher_dte_call_cnt": 0}

    for index, row in df.iterrows():
        volume = row['trade_volume']

        quote_datestr = row['quote_date']
        expirationstr = row['expiration']

        quote_date = datetime.strptime(quote_datestr, "%Y-%m-%d")
        expiration = datetime.strptime(expirationstr, "%Y-%m-%d")

        ndte = countTradingDays(quote_date, expiration)

        option_type = "put" if row['option_type']=="P" else "call"

        if ndte <= 4:    # equivalent of 0-7 including weekends
            day[f"{ndte}dte_{option_type}_cnt"] += volume
        elif ndte <= 21: # equivalent of 30 including weekends
            day[f"5to21dte_{option_type}_cnt"] += volume
        elif ndte <= 43: # equivalent of 60 including weekends
            day[f"22to43dte_{option_type}_cnt"] += volume
        elif ndte <= 64: # equivalent of 90 including weekends
            day[f"44to64dte_{option_type}_cnt"] += volume
        else:
            day[f"higher_dte_{option_type}_cnt"] += volume

    # add this trading day's data to the master dataframe
    row = pd.DataFrame([day])
    row.index = [quote_date]

    dailyNdteOptionsVolume = pd.concat([dailyNdteOptionsVolume, row])

    #save to file every 100
    if n%100 == 0:
        print(n)
        dailyNdteOptionsVolume = dailyNdteOptionsVolume.rename_axis("date")
        dailyNdteOptionsVolume.to_csv("backup.csv")

print(datetime.now())
```

```
2023-10-23 22:15:40.179081
```

```
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300
1400
1500
1600
1700
1800
1900
2000
2100
2200
2300
2400
2500
2600
2023-10-24 00:17:23.073767
```

Zero trades: 2018-03-12
Zero trades: 2017-11-24
Zero trades: 2017-11-21

Write to csv

In [4]:
```
# Giving a name to the index
dailyNdteOptionsVolume = dailyNdteOptionsVolume.rename_axis("date")
# Save the DataFrame to a CSV file
dailyNdteOptionsVolume.to_csv("output.csv")
```

SPX Volatility

In [12]:
```
# exclude the closing price of the previous day in the calculation of tha daily volatility?
intraday = True

# Read CSV into a DataFrame
dailyNdteOptionsVolume = pd.read_csv("dailyNdteOptionsVolume.csv", parse_dates=['date'], dayfirst=True, index_col='date')

# Read Historic price data into a DataFrame
path = os.path.join(datasetPath, "spx.xlsx")
spx30minPrice = pd.read_excel(path, sheet_name="spx30min", parse_dates=['date'], index_col='date')
# reverse the dataframe, such that it goes from 2013 to 2023 (important for calculation)
spx30minPrice = spx30minPrice.iloc[::-1]



# calculate volatility for each day in our options dataset
calendar = mcal.get_calendar("CBOE_Index_Options")
optionsTradingDays = calendar.schedule(
    datetime(2013,4,10), # max and min from dataset
    datetime(2023,10,3)).index

spxIntradayVolatility = pd.DataFrame(columns=["volatility", "return"])

for n,day in enumerate(optionsTradingDays):
    # Extract data for the current day. Does not inlcude prev day's closing price. We want to stuy the impact on intraday vol.
    day_data = spx30minPrice[spx30minPrice.index.date == day.date()]

    # add prev day close price
    if n!=0 and not intraday:
        day_data = pd.concat([prevDayClose, day_data])

    # Calculate intraday volatility
    intraday_volatility = math.sqrt( day_data['last_price'].pct_change().std() )

    # Calculate intraday return
    if not day_data.empty:
        opening_price = day_data.iloc[0]['last_price']
        closing_price = day_data.iloc[-1]['last_price']
        intraday_return = (closing_price - opening_price) / opening_price
    else:
        intraday_return = 0

    # add this trading day's data to the master dataframe
    row = pd.DataFrame([{"volatility": intraday_volatility, "return": intraday_return}])
    row.index = [day.date()]

    spxIntradayVolatility = pd.concat([spxIntradayVolatility, row])

    # save close
    if not intraday: # dette blir ikke riktig hvis annen tidssjone use .iloc[0]['last_price']
        prevDayClose = day_data[(day_data.index.hour == 22)].tail(1)

# Giving a name to the index and reverse again so that the dataframe goes from 2023 to 2013
spxIntradayVolatility = spxIntradayVolatility.rename_axis("date")[::-1]
```

Write to CSV

In [13]:
```
# Save the DataFrame to a CSV file
spxIntradayVolatility.to_csv(f"spx{'Intraday' if intraday else ''}Volatility.csv")
```

Intraday 0DTE%

Calculate nDTE_cnt for every 1 min aggregate volume

Separate put and call options

In [15]:
```
path = os.path.join(datasetPath, "UnderlyingOptionsTradesCalcs_2023-08-15", "UnderlyingOptionsTradesCalcs_2023-08-15.csv")
data = pd.read_csv(path, parse_dates=['quote_datetime', 'expiration'])
```

In [16]:
```
# sort trades after quote_datetime
data = data.sort_values(by='quote_datetime')
# filter out pre trading
data = data[data["quote_datetime"] >= datetime(2023, 8, 15, 9, 30)]
```

In [17]:
```
data
```

Out[17]:

	underlying_symbol	quote_datetime	sequence_number	root	expiration	strike	option_type	exchange_id	trade_size	trade_price	...	trade_iv	trade_delta	underlying_bid	underlying_ask	number_of_exchanges	(exchange	t
7866	^SPX	2023-08-15 09:30:02.156	1389257	SPX	2023-09-15	2400.0	P	5	1	0.15	...	0.6883	-0.0006	4473.1475	4473.1475	0	NaN	
22914	^SPX	2023-08-15 09:30:02.305	1438065	SPX	2024-01-19	3500.0	P	5	1	22.20	...	0.2755	-0.0609	4473.1475	4473.1475	0	NaN	
531771	^SPX	2023-08-15 09:30:02.343	1446980	SPXW	2023-08-18	4480.0	P	5	1	28.90	...	0.1509	-0.5374	4473.1475	4473.1475	0	NaN	
531525	^SPX	2023-08-15 09:30:02.343	1446920	SPXW	2023-08-18	4480.0	C	5	1	21.90	...	0.1480	0.4618	4473.1475	4473.1475	0	NaN	
17530	^SPX	2023-08-15 09:30:02.392	1458174	SPX	2023-10-20	4200.0	P	5	1	34.74	...	0.1864	-0.1771	4473.1475	4473.1475	0	NaN	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
457323	^SPX	2023-08-15 16:59:39.805	2981751029	SPXW	2023-08-16	4405.0	P	5	50	4.23	...	0.1687	-0.1990	4437.2651	4437.2651	0	NaN	
585326	^SPX	2023-08-15 16:59:44.320	2981757785	SPXW	2023-10-20	4100.0	C	5	1	399.89	...	0.2045	0.8515	4437.2651	4437.2651	0	NaN	
585712	^SPX	2023-08-15 16:59:44.320	2981757786	SPXW	2023-10-20	4475.0	C	5	1	105.79	...	0.1421	0.5098	4437.2651	4437.2651	0	NaN	
530209	^SPX	2023-08-15 16:59:48.382	2981763879	SPXW	2023-08-18	4465.0	C	5	1	13.60	...	0.1526	0.3397	4437.2651	4437.2651	0	NaN	
448858	^SPX	2023-08-15 16:59:57.740	2981784125	SPXW	2023-08-16	4375.0	P	5	1	1.00	...	0.1765	-0.0593	4437.2651	4437.2651	0	NaN	

571195 rows × 24 columns

In [18]:
```
nDTEvolume = pd.DataFrame(columns=['quote_minute', 'ndte', 'option_type', 'volume'])
i = 0

for index, row in data.iterrows():

    quote_minute = datetime(
        row.quote_datetime.year,
        row.quote_datetime.month,
        row.quote_datetime.day,
        row.quote_datetime.hour,
        row.quote_datetime.minute)

    option_type = row.option_type

    quote_date = datetime(2023, 8, 15)
    expiration = row.expiration
    ndte = countTradingDays(quote_date, expiration)

    volume = row.trade_size

    # add data to df

    mask = (
        (nDTEvolume['quote_minute'] == quote_minute) &
        (nDTEvolume['ndte']         == ndte        ) &
        (nDTEvolume['option_type']  == option_type )
    )

    # If the combination exists, update the 'volume'
    if nDTEvolume[mask].shape[0] > 0:
        nDTEvolume.loc[mask, 'volume'] += volume
    else:
        # If the combination doesn't exist, add a new row
        nDTEvolume.loc[i] = [quote_minute, ndte, option_type, volume]
        i += 1
```

Write to CSV

In [19]:
```
# Save the DataFrame to a CSV file
nDTEvolume = nDTEvolume.rename_axis("index")
nDTEvolume.to_csv(f"nDTEvolume.csv")
```

In [ ]:
```
```

Calculate Option Delta

delta option price / delta index price

In [48]:
```
path = os.path.join(datasetPath, "spx.xlsx")
spx30minPrice = pd.read_excel(path, sheet_name="spx30min", parse_dates=['date'], index_col='date')

def getEndOfDayPrice(date):

    return spx30minPrice[spx30minPrice.index.date == date.date()].iloc[0]['last_price']
    #timestamp = date+timedelta(hours=22) #return spx30minPrice.loc[timestamp, 'last_price']
```

In [49]:
```
ndteLst = [0,1,2,3,4]
# I only want options that are between start and end % in the money(strike_index_ratio_x)
start_strike_index_ratio_x_lst = [0, 0.01, 0.05, 0.1, 0.2]


# Create an empty DataFrame with columns
results = pd.DataFrame(columns=['date', 'ndte', 'strike_index_ratio', 'mean_delta'])
index = 0

for n in range(len(csvFilePaths) - 1):
    path1 = csvFilePaths[n]
    path2 = csvFilePaths[n+1]
    df1 = pd.read_csv(path1, parse_dates=['quote_date', 'expiration'])
    df2 = pd.read_csv(path2, parse_dates=['quote_date', 'expiration'])

    # get index price change
    date1 = df1['quote_date'].iloc[0]
```

```
    date2 = df2['quote_date'].iloc[0]

    index_price1 = getEndOfDayPrice(date1)
    index_price2 = getEndOfDayPrice(date2)

    # calculate in the money %
    df1['strike_index_ratio'] = df1['strike'] / index_price1
    df2['strike_index_ratio'] = df2['strike'] / index_price2

    # calculate ndte
    df1['ndte'] = df1.apply(lambda row: countTradingDays(row['quote_date'], row['expiration']), axis=1)
    df2['ndte'] = df2.apply(lambda row: countTradingDays(row['quote_date'], row['expiration']), axis=1)

    # Filter out rows where "bid_eod" or "ask_eod" is equal to 0
    df1 = df1[(df1['bid_eod'] != 0) & (df1['ask_eod'] != 0)]
    df2 = df2[(df2['bid_eod'] != 0) & (df2['ask_eod'] != 0)]

    # Filter out out of the money options. does not make sense to take averge of deltas of both in and out of the money options
    def is_out_of_money(row):
        if row['option_type'] == 'C':
            return row['strike'] > index_price1
        elif row['option_type'] == 'P':
            return row['strike'] < index_price1
        else:
            return False  # Handle other cases if needed

    # filter out out of the money
    mask1 = df1.apply(is_out_of_money, axis=1)
    mask2 = df2.apply(is_out_of_money, axis=1)
    df1 = df1[~mask1]
    df2 = df2[~mask2]

    # calculate mid price
    df1['mid_price_eod'] = df1[['bid_eod', 'ask_eod']].mean(axis=1)
    df2['mid_price_eod'] = df2[['bid_eod', 'ask_eod']].mean(axis=1)

    # group similar options with different "root" values. i.e. SPX and SPXW
    df1 = df1.groupby(['strike', 'expiration', 'option_type', 'ndte']).agg({'mid_price_eod': 'mean', 'quote_date': 'first', 'strike_index_ratio': 'first'}).reset_index()
    df2 = df2.groupby(['strike', 'expiration', 'option_type', 'ndte']).agg({'mid_price_eod': 'mean', 'quote_date': 'first', 'strike_index_ratio': 'first'}).reset_index()

    # inner join
    merged = pd.merge(df1, df2, on=['strike', 'expiration', 'option_type'], how='inner')
    merged["option_price_change"] = merged["mid_price_eod_x"] - merged["mid_price_eod_y"]

    index_price_change = index_price1 - index_price2

    # Filter out rows where index or option price change is equal to 0
    merged["index_price_change"] = index_price_change
    merged = merged[(merged['option_price_change'] != 0) & (merged['index_price_change'] != 0)]

    merged["option_delta"] = merged["option_price_change"] / index_price_change


    for i, ndte in enumerate(ndteLst):
        for j, start in enumerate(start_strike_index_ratio_x_lst):

            end = start + 0.005

            interval1_start = 1 - end
            interval1_end   = 1 - start
            interval2_start = 1 + start
            interval2_end   = 1 + end

            # Filter the DataFrame on similar strike_divided_by_index_price_x
            filtered = merged[((merged['strike_index_ratio_x'] >= interval1_start) & (merged['strike_index_ratio_x'] <= interval1_end)) | ((merged['strike_index_ratio_x'] >= interval2_start) & (mer

            # Make the 'Values' column positive
            filtered = filtered.copy()
            filtered['option_delta'] = filtered['option_delta'].abs()

            # # Define a threshold based on percentiles (e.g., removing top and bottom 5%)
            # lower_threshold = a['option_delta'].quantile(0.05)
            # upper_threshold = a['option_delta'].quantile(0.95)
            #
            # # Filter out values outside the threshold
            # a = a[(a['option_delta'] >= lower_threshold) & (a['option_delta'] <= upper_threshold)]

            filtered = filtered[filtered['ndte_x']==2]
            mean = filtered['option_delta'].mean()

            results.loc[index] = [date1, ndte, start, mean]

            index += 1

    if n%100 == 0:
        print(n)
        results.to_csv("option_delta_backup.csv")
```

```
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
1300
1400
1500
1600
1700
1800
1900
2000
2100
2200
2300
2400
2500
2600
```

Write to CSV

In [53]:

```
# Giving a name to the index
results = results.rename_axis("index")
# Save the DataFrame to a CSV file
results.to_csv(f"option_delta.csv")
```