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1 Gamma Scalping Trading Strategy

1.1 FINM 33150 - Quant Trading Strategies (Winter 2024)

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1.2 1. Introduction

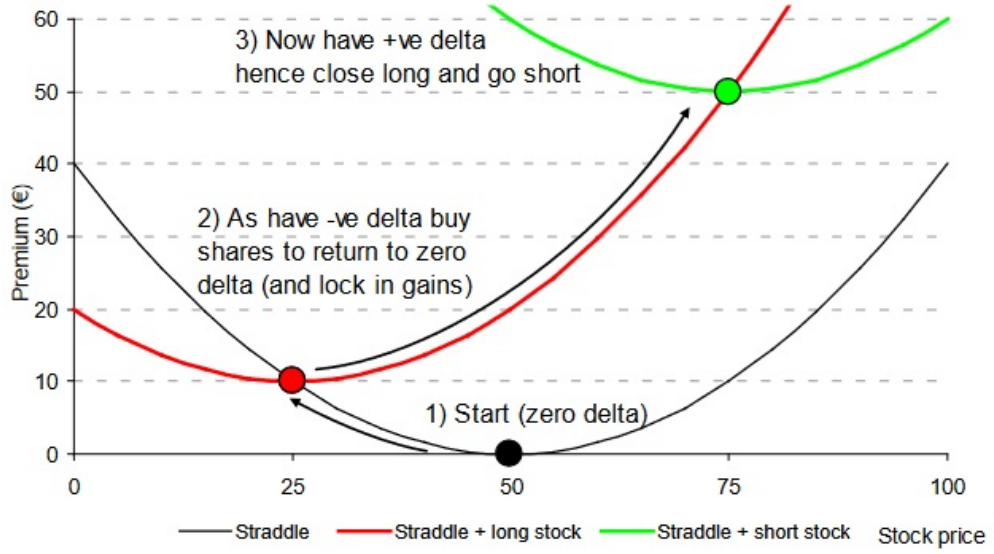
The Black-Scholes (B-S) implied volatility is a forecast of a likely movement in a security's price which indicates expected volatility in the future. The model-free implied volatility from [Jiang et al.] computes the implied volatility directly from the prices of options across different strikes and maturities, without depending on assumptions of any specific options pricing model. The model-free implied volatility subsumes all information contained in the B-S implied volatility and the past realized volatility, and is a more efficient forecast of future realized volatility. We aim to develop a gamma scalping strategy based on model-free implied volatility versus B-S implied volatility.

A straddle combines a call and a put of the same strike and expiration. A long position would mean buying both, and a short position would mean shorting both. Delta measures the rate of change in an option's price relative to changes in the price of the underlying asset. The delta of an at-the-money straddle would come out to near zero, since the negative delta of the put would cancel out the positive delta of the call, as they have the similar magnitude from being at-the-money. Gamma measures the rate of change in an option's delta for a one-point change in the price of the underlying asset. Gamma is highest at-the-money and close to expiry. Gamma scalping involves profiting from short-term price movements in an underlying asset by adjusting positions based on changes in delta and gamma, mainly through delta-hedging. Advantages include: flexibility, limited risk exposure, and high potential for returns. See the below excerpt from *Trading Volatility* by Colin Bennet:

Gamma scalping (delta re-hedging) locks in profit as underlying moves

We shall assume an investor has purchased a zero delta straddle (or strangle), but the argument will hold for long call or put positions as well. If equity markets fall (from position 1 to position 2 in the chart) the position will become profitable and the delta will decrease from zero to a negative value. In order to lock in the profit, the investor must buy stock (or futures) for the portfolio to return to zero delta. Now that the portfolio is equity market neutral, it will profit from a movement up or down in the equity market. If equity markets then rise, the initial profit will be kept and a further profit earned (movement from position 2 to position 3). At position 3 the stock (or futures) position is sold and a short position initiated to return the position to zero delta.

Figure 27. Locking in Gains through Delta Hedging



The SPDR S&P 500 ETF Trust (NYSEARCA: SPY) was selected due to high liquidity in both the underlying and options markets. Options data was extracted from Jan 2018 to Feb 2024 (five-year period) to balance effectively capturing the most recent trading environment and using sufficient data. **Jiang, George J., and Yisong S. Tian. "The model-free implied volatility and its information content." Review of Financial Studies, vol. 18, no. 4, 2005, pp. 1305–1342, https://doi.org/10.1093/rfs/hhi027.** The paper by Jiang and Tian discusses the concept of a model-free implied volatility (MFIV), a measure of the market's expectation of future volatility that does not depend on any specific option pricing model, such as the Black-Scholes model. This approach to calculating implied volatility is significant because it potentially offers a more accurate and robust indicator of future market volatility, free from the biases and limitations inherent in model-based approaches. The equation from the paper can be seen below:

$$\sum_{i=1}^{m} \left[g(T, K_i) + g(T, K_{i-1}) \right] \Delta K$$

Where m is the number of tradable strike prices, $\Delta K = \frac{K_{\max} - K_{\min}}{m}$, $K_i = K_{\min} + i\Delta K$, and $g(T, K_i) = \frac{C^F(T,K_i) - \max(0, F_0 - K_i)}{K_i^2}$.

The research paper delves into the methodology for calculating MFIV, which involves aggregating the implied volatilities derived from a wide range of options across different strike prices and maturities. By doing so, the MFIV captures a more comprehensive picture of the market's expectations for volatility, encompassing information from both deep out-of-the-money and in-the-money options. The paper also explores the informational content of MFIV, examining how it reflects market participants' collective views and expectations about future volatility. This includes an analysis of how MFIV predicts future market movements, its response to macroeconomic announcements or significant market events, and its relationship with historical volatility and other financial indicators. The paper also uses market data to compare the predictive power and informational efficiency of MFIV against other volatility measures. Finally, Jiang and Tian discuss the implications of their findings for both practitioners and theorists. For practitioners, the use of MFIV could lead to better hedging strategies, more accurate pricing of derivatives, and improved portfolio management. For theorists, the findings could challenge existing models of market behavior and contribute to the development of new theories that more accurately reflect the complexities of financial markets.

Oliveira, Rogerio, and Gustavo Wasserstein. "The Quest for Alpha in Equity Gamma." https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4474815.

Hirsa, Ali, and Dilip B. Madan. "Pricing American Options Under Variance Gamma." https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=16061c8cc6ee13947162a35ceb

Bennett, C. (2014). Trading Volatility: Trading Volatility, Correlation, Term Structure and Skew. CreateSpace Independent Publishing Platform. ISBN: 978-146110875. https://www.trading-volatility.com/Trading-Volatility.pdf.

Konikov, Mikhail, and Dilip B. Madan. "Option Pricing Using Variance Gamma Markov Chains." https://link.springer.com/article/10.1023/A:1013816400834.

Sepp, Artur. "When You Hedge Discretely: Optimization of Sharpe Ratio for Delta-Hedging Strategy under Discrete Hedging and Transaction Costs.https://papers.ssrn.com/sol3/papers.cfm?abstract_id=186599815.

1.3 2. Methodology Overview

We enter a long or short gamma position based on implied volatility [Oliveira et al]. The B-S implied volatility is compared with the model-free implied volatility from [Jiang et al] to provide a decision boundary on which to enter the position. If the model-free implied volatility value is higher than the Black-Scholes implied volatility by a certain threshold, we we go long gamma, and if the model-free implied volatility value is lower than the Black-Scholes implied volatility value by the same threshold, we will go short gamma. We analyze daily whether to enter a long or short position on a delta-hedged straddle based on this decision boundary. A straddle reduces the number of shares necessary to initially delta hedge, as the delta of the put and the delta of the call will cancel each other out. By entering daily, it is possible to net the number of shares required for rebalancing to a near zero-delta state, thus saving on transaction costs. Each straddle position that we hold is evaluated independent of other positons for rebalancing each day. If its delta value is above a certain threshold, we rebalance by buying or selling delta shares of the underlying with the aim of getting to net zero delta. We enter each straddle with an expiry of approximately 1 month and exit each straddle after an approximately 3-week holding period (1 week before expiration), as most gamma should have been realized by this point. This minimizes the blow-up risk associated with being short gamma, since we no longer need to delta-hedge potentially volatile moves in

the week leading up to expiration (gamma is highest close to expiration). Also, by exiting our options positions with 1 week until expiration, we reduce our exposure to market microstructure idiosyncrasies. We will simulate our strategy using a number of different thresholds for when to enter positions and when to rebalance positions. We we also experiment with the effects of assuming zero trading costs versus fixed trading costs at 0.01% of the notional value traded on each trade we make. Additionally, we plan on examining the impact of assuming fractional positions can be traded versus if they cannot be traded. We assume the midpoint between best offer and best ask as the price we will get in our simulation. To evaluate the performance of our strategy, we will look at metrics such as sharpe ratio, market beta, and downside beta. The only equity that this strategy's PnL is dependent on is the SPY ETF so we anticipate the strategy may have somewhat strong correlations with the market.

Oliveira, Rogerio, and Gustavo Wasserstein. "The Quest for Alpha in Equity Gamma." https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4474815.

1.4 Code init

Imports Import all dependencies and functions via source file.

[1]:
```
from source import *
```

Quandl/WRDS Credentials Importing quandl API key. Individual keys are protected in a `.json` file.

[2]:
```
with open('quandl_config.json', 'r') as f:
    config = json.load(f)
    quandl_api_key = config['api_key']

#quandl.ApiConfig.api_key = quandl_api_key
```

[3]:
```
with open('wrds_config.json', 'r') as config_file:
    wrds_credentials = json.load(config_file)
```

Local use

The API keys and WRDS login are loaded from *quandl_config.json* in the same directory as this notebook locally, which has the following content,

```
{
    "api_key": ""
}
```

and *wrds_config.json*,

```
{
    "wrds": {
        "username": "",
        "password": ""
    }
}
```

To skip WRDS input on pulls, we have `.pgpass` with,

```
hostname:port:database:username:password
wrds-pgdata.wharton.upenn.edu:9737:wrds:(user):(pass)
```

1.5 3. Data Retrieval

For our data load process, we worked through github to upload functions and called them locally to each grab data, so we have several checkpoints where we save data to .csv format in the local directory so they can be reloaded directly when continuing work.

1.5.1 SPY price data via Quandl

[4]:
```
datapull = fetch_quandl_table('QUOTEMEDIA/PRICES', quandl_api_key,␣
↪ticker='SPY', avoid_download=True)
```

```
Skipping any possible download of QUOTEMEDIA/PRICES
```

Optional saving checkpoint:

[5]:
```
datapull.to_csv('spy_tickerdata.csv', index=False)
```

[6]:
```
display(datapull)
```

```
     ticker        date        open        high         low       close  \
0       SPY  1993-08-13   45.093700   45.156200   45.093700   45.125000
1       SPY  1993-08-16   45.156200   45.500000   45.156200   45.375000
2       SPY  1993-08-17   45.343700   45.531200   45.343700   45.531200
3       SPY  1993-08-18   45.687500   45.875000   45.656200   45.781200
4       SPY  1993-08-19   45.812500   45.812500   45.718700   45.781200
…     …          …           …           …           …           …
7827    SPY  1993-06-22   44.656200   44.656200   44.562500   44.625000
7828    SPY  1994-11-16   46.765598   46.843700   46.609299   46.843700
7829    SPY  2010-03-10  114.510002  115.279999  114.410004  114.970001
7830    SPY  2022-02-15  443.730000  446.280000  443.180000  446.100000
7831    SPY  1993-02-09   44.812500   44.812500   44.562500   44.656200

           volume  dividend  split    adj_open    adj_high     adj_low  \
0        103500.0       0.0    1.0   25.778428   25.814157   25.778428
1        241800.0       0.0    1.0   25.814157   26.010695   25.814157
2        369300.0       0.0    1.0   25.921344   26.028531   25.921344
3        414300.0       0.0    1.0   26.117882   26.225069   26.099989
4         28500.0       0.0    1.0   26.189340   26.189340   26.135718
…           …       …    …          …           …           …
7827     137500.0       0.0    1.0   25.528325   25.528325   25.474761
7828     106900.0       0.0    1.0   27.589587   27.635663   27.497377
7829  186088800.0       0.0    1.0   87.964535   88.556033   87.887719
7830   88435136.0       0.0    1.0  430.043935  432.515285  429.510899
7831     122100.0       0.0    1.0   25.316163   25.316163   25.174929
```

```
       adj_close   adj_volume
0      25.796321     103500.0
1      25.939237     241800.0
2      26.028531     369300.0
3      26.171447     414300.0
4      26.171447      28500.0
…            …           …
7827   25.510490     137500.0
7828   27.635663     106900.0
7829   88.317898  186088800.0
7830  432.340837   88435136.0
7831   25.227864     122100.0

[7832 rows x 14 columns]
```

1.5.2 WRDS Options Data for SPY

Connection Toggle Not meant to run in sequence; rather, toggles an open connection to WRDS to pull data.

[7]:
```
db = wrds.Connection(
    wrds_username=wrds_credentials['wrds']['username'],
)
```

```
Loading library list…
Done
```

[11]:
```
db.close()
```

Data Pull Pulls the data and stores in .csv file in the same directory, to allow reloading from local. This could be done more elegantly like the provided Quandl function, but since the data doesn't change day-by-day, it only needs to be pulled once.

[8]:
```
start_year = 2018
end_year = 2023
```

[9]:
```
optiondata = pd.DataFrame()

for year in range(start_year, end_year + 1):
    sql_query = f"""
    SELECT date, exdate, last_date, cp_flag, strike_price, best_bid, best_offer,
           volume, open_interest, impl_volatility, delta, gamma, vega, theta,
           expiry_indicator
    FROM optionm_all.opprcd{year}
    WHERE secid = '109820'
    AND date BETWEEN '{year}-01-01' AND '2023-02-28'
    AND exdate - date < 800
    """
```

```
    year_data = db.raw_sql(sql_query)
    optiondata = pd.concat([optiondata, year_data], ignore_index=True)
```

We could add "AND volume >= 100" to filter volume, if we choose. We ended up keeping all volumes, otherwise there were not enough strikes with proper bid/ask and Greeks data.

[10]:
```
csv_file_path = 'option_data.csv'
optiondata.to_csv(csv_file_path, index=False)
print(f"All data saved to {csv_file_path}")
```

```
All data saved to option_data.csv
```

1.6 4. Initial Data Restructuring

1.6.1 Checkpoint 1: Retrieve as Variable (csv save 1)

Retrieving the first checkpoint:

[2]:
```
csv_file_path = 'option_data.csv'
spydata = pd.read_csv(csv_file_path)
```

[3]:
```
display(spydata)
```

```
                date      exdate   last_date cp_flag  strike_price  best_bid  \
0         2018-01-02  2018-01-03  2017-12-28       C      235000.0     33.59
1         2018-01-02  2018-01-03  2018-01-02       C      240000.0     28.59
2         2018-01-02  2018-01-03  2017-12-27       C      242500.0     26.09
3         2018-01-02  2018-01-03  2018-01-02       C      245000.0     23.59
4         2018-01-02  2018-01-03         NaN       C      247500.0     21.08
…                …           …           …     …             …          …
10448189  2023-02-28  2025-03-21  2022-12-28       P      600000.0    200.50
10448190  2023-02-28  2025-03-21         NaN       P      605000.0    205.50
10448191  2023-02-28  2025-03-21         NaN       P      610000.0    210.00
10448192  2023-02-28  2025-03-21         NaN       P      615000.0    215.00
10448193  2023-02-28  2025-03-21         NaN       P      620000.0    220.00

          best_offer  volume  open_interest  impl_volatility  delta  gamma  \
0              33.81     0.0          187.0              NaN    NaN    NaN
1              28.76     1.0           88.0              NaN    NaN    NaN
2              26.32     0.0            2.0              NaN    NaN    NaN
3              23.81    12.0           58.0              NaN    NaN    NaN
4              21.32     0.0            0.0              NaN    NaN    NaN
…                  …       …              …                …      …      …
10448189      205.50     0.0            0.0              NaN    NaN    NaN
10448190      210.50     0.0            0.0              NaN    NaN    NaN
10448191      215.00     0.0            0.0              NaN    NaN    NaN
10448192      220.00     0.0            0.0              NaN    NaN    NaN
10448193      225.00     0.0            0.0              NaN    NaN    NaN

          vega  theta expiry_indicator
```

```
0           NaN    NaN                w
1           NaN    NaN                w
2           NaN    NaN                w
3           NaN    NaN                w
4           NaN    NaN                w
…         …    …              …
10448189    NaN    NaN              NaN
10448190    NaN    NaN              NaN
10448191    NaN    NaN              NaN
10448192    NaN    NaN              NaN
10448193    NaN    NaN              NaN

[10448194 rows x 15 columns]
```

Order by the appropriate date, then expiry date, then strike price within the date spread.

[4]:
```
spydata_sorted = spydata.sort_values(by=['date', 'exdate', 'cp_flag',␣
 ↪'strike_price'])
spydata_final = spydata_sorted.reset_index(drop=True)
```

[5]:
```
display(spydata_final)
```

```
                date      exdate   last_date cp_flag  strike_price  best_bid  \
0         2018-01-02  2018-01-03  2017-12-28       C      235000.0     33.59
1         2018-01-02  2018-01-03  2018-01-02       C      240000.0     28.59
2         2018-01-02  2018-01-03  2017-12-27       C      242500.0     26.09
3         2018-01-02  2018-01-03  2018-01-02       C      245000.0     23.59
4         2018-01-02  2018-01-03         NaN       C      247500.0     21.08
…                …           …           …     …            …        …
10448189  2023-02-28  2025-03-21  2022-12-28       P      600000.0    200.50
10448190  2023-02-28  2025-03-21         NaN       P      605000.0    205.50
10448191  2023-02-28  2025-03-21         NaN       P      610000.0    210.00
10448192  2023-02-28  2025-03-21         NaN       P      615000.0    215.00
10448193  2023-02-28  2025-03-21         NaN       P      620000.0    220.00

          best_offer  volume  open_interest  impl_volatility  delta  gamma  \
0              33.81     0.0          187.0              NaN    NaN    NaN
1              28.76     1.0           88.0              NaN    NaN    NaN
2              26.32     0.0            2.0              NaN    NaN    NaN
3              23.81    12.0           58.0              NaN    NaN    NaN
4              21.32     0.0            0.0              NaN    NaN    NaN
…                …     …            …              …    …    …
10448189      205.50     0.0            0.0              NaN    NaN    NaN
10448190      210.50     0.0            0.0              NaN    NaN    NaN
10448191      215.00     0.0            0.0              NaN    NaN    NaN
10448192      220.00     0.0            0.0              NaN    NaN    NaN
10448193      225.00     0.0            0.0              NaN    NaN    NaN

          vega  theta expiry_indicator
```

```
0           NaN    NaN                 w
1           NaN    NaN                 w
2           NaN    NaN                 w
3           NaN    NaN                 w
4           NaN    NaN                 w
…           …      …                   …
10448189    NaN    NaN               NaN
10448190    NaN    NaN               NaN
10448191    NaN    NaN               NaN
10448192    NaN    NaN               NaN
10448193    NaN    NaN               NaN

[10448194 rows x 15 columns]
```

[6]:
```
spydata_final.to_csv('sorteddata.csv', index=False)
```

1.6.2 Checkpoint 2: Retrieve sorted data; make adjustments (csv save 2)

[2]:
```
spy_optiondata = pd.read_csv('sorteddata.csv')
```

Load the ticker price data, directly from local.

[4]:
```
spy_tickerdata = pd.read_csv('spy_tickerdata.csv')
```

Make some adjustments and attach to our data table for options. * Set a start and end date. We chose this initially to be 2018 to the end of the data; in particular, this is what is considered to be the modern trading regime for SPY and its options. * Regularize the price

[6]:
```
start_date = '2018-01-01'
end_date = '2023-02-28'
```

[7]:
```
spy_tickerdata_reduced = prepare_ticker_data(spy_tickerdata, '2018-01-01',␣
 ↪'2023-02-28')
spy_optiondata_prepared = prepare_option_data(spy_optiondata)
spy_optiondata_enriched = enrich_option_data(spy_optiondata_prepared,␣
 ↪spy_tickerdata_reduced)
display(spy_optiondata_enriched)
```

```
                date      exdate   last_date cp_flag  strike_price  best_bid  \
0         2018-01-02  2018-01-03  2017-12-28       C         235.0     33.59
1         2018-01-02  2018-01-03  2018-01-02       C         240.0     28.59
2         2018-01-02  2018-01-03  2017-12-27       C         242.5     26.09
3         2018-01-02  2018-01-03  2018-01-02       C         245.0     23.59
4         2018-01-02  2018-01-03         NaN       C         247.5     21.08
…                …           …           …     …             …        …
10448189  2023-02-28  2025-03-21  2022-12-28       P         600.0    200.50
10448190  2023-02-28  2025-03-21         NaN       P         605.0    205.50
10448191  2023-02-28  2025-03-21         NaN       P         610.0    210.00
10448192  2023-02-28  2025-03-21         NaN       P         615.0    215.00
```

```
10448193 2023-02-28  2025-03-21         NaN       P         620.0    220.00

          best_offer  volume  open_interest  impl_volatility  delta  gamma  \
0              33.81     0.0          187.0              NaN    NaN    NaN
1              28.76     1.0           88.0              NaN    NaN    NaN
2              26.32     0.0            2.0              NaN    NaN    NaN
3              23.81    12.0           58.0              NaN    NaN    NaN
4              21.32     0.0            0.0              NaN    NaN    NaN
…                …     …              …                …    …    …
10448189      205.50     0.0            0.0              NaN    NaN    NaN
10448190      210.50     0.0            0.0              NaN    NaN    NaN
10448191      215.00     0.0            0.0              NaN    NaN    NaN
10448192      220.00     0.0            0.0              NaN    NaN    NaN
10448193      225.00     0.0            0.0              NaN    NaN    NaN

          vega  theta expiry_indicator   close    adj_open   adj_close  \
0          NaN    NaN                w  268.77  242.053393  242.893856
1          NaN    NaN                w  268.77  242.053393  242.893856
2          NaN    NaN                w  268.77  242.053393  242.893856
3          NaN    NaN                w  268.77  242.053393  242.893856
4          NaN    NaN                w  268.77  242.053393  242.893856
…        …    …               …      …         …          …
10448189   NaN    NaN              NaN  396.26  391.240559  390.285185
10448190   NaN    NaN              NaN  396.26  391.240559  390.285185
10448191   NaN    NaN              NaN  396.26  391.240559  390.285185
10448192   NaN    NaN              NaN  396.26  391.240559  390.285185
10448193   NaN    NaN              NaN  396.26  391.240559  390.285185

          adj_volume
0         86655749.0
1         86655749.0
2         86655749.0
3         86655749.0
4         86655749.0
…              …
10448189  96141367.0
10448190  96141367.0
10448191  96141367.0
10448192  96141367.0
10448193  96141367.0

[10448194 rows x 19 columns]
```

Two more saving checkpoints - this saves the data, one with all datapoints, and the other removing those where Greeks and IV are missing from the data. For this, we will use the further cleaned file to see where exactly the missing data is.

[8]:
```
spy_optiondata_enriched.to_csv('combinedata.csv', index=False)
```

[9]:
```
spydata_cleaned = spy_optiondata_enriched.dropna(subset=['impl_volatility',␣
↪'delta', 'gamma', 'vega', 'theta'])
spydata_dropna = spydata_cleaned.reset_index(drop=True)
spydata_dropna.to_csv('combinedata_dropna.csv', index=False)
```

1.6.3 Checkpoint 3: Retrieve combined data; determining missing data, combined strikes

This is another load checkpoint.

[2]:
```
filepath = 'combinedata.csv'
filepath1 = 'combinedata_dropna.csv'
options_df = pd.read_csv(filepath)
options_df1 = pd.read_csv(filepath1)
```

Now we'll take a look to see if for our strategy, which we will initially set as approximately month-long options to be closed 1 week to expiry, have data in the dataset for the entire time that we hold them.

Looking at the combined dataset, at a glance:

[3]:
```
exdates = set(options_df['exdate'])
quotedates = set(options_df['date'])
```

[4]:
```
exdates - quotedates
```

[4]:
```
{'2018-12-05',
 '2023-03-01',
 '2023-03-02',
 '2023-03-03',
 '2023-03-06',
 '2023-03-07',
 '2023-03-08',
 '2023-03-09',
 '2023-03-10',
 '2023-03-13',
 '2023-03-14',
 '2023-03-17',
 '2023-03-24',
 '2023-03-31',
 '2023-04-06',
 '2023-04-21',
 '2023-05-19',
 '2023-06-16',
 '2023-06-30',
 '2023-07-21',
 '2023-08-18',
 '2023-09-15',
 '2023-09-29',
```

```
 '2023-12-15',
 '2023-12-29',
 '2024-01-19',
 '2024-03-15',
 '2024-06-21',
 '2024-12-20',
 '2025-01-17',
 '2025-03-21'}
```

[5]:
```
quotedates - exdates
```

[5]:
```
{'2018-01-02',
 '2018-01-04',
 '2018-01-08',
 '2018-01-09',
 '2018-01-11',
 '2018-01-16',
 '2018-01-18',
 '2018-01-22',
 '2018-01-23',
 '2018-01-25',
 '2018-01-29',
 '2018-01-30',
 '2018-02-01',
 '2018-02-05',
 '2018-02-06',
 '2018-02-08',
 '2018-02-12',
 '2018-02-13',
 '2018-02-15',
 '2018-02-20',
 '2018-02-22',
 '2018-02-27',
 '2018-03-01',
 '2018-03-06',
 '2018-03-08',
 '2018-03-13',
 '2018-03-15',
 '2018-03-20',
 '2018-03-22',
 '2018-03-27',
 '2018-04-03',
 '2018-04-05',
 '2018-04-10',
 '2018-04-12',
 '2018-04-17',
 '2018-04-19',
```

```
 '2022-10-13',
 '2022-10-18',
 '2022-10-20',
 '2022-10-25',
 '2022-10-27',
 '2022-11-01',
 '2022-11-03',
 '2022-11-08',
 '2022-11-10'}
```

[6]:
```
exdates & quotedates
```

[6]:
```
{'2018-01-03',
 '2018-01-05',
 '2018-01-10',
 '2018-01-12',
 '2018-01-17',
 '2018-01-19',
 '2018-01-24',
 '2018-01-26',
 '2018-01-31',
 '2018-02-02',
 '2018-02-07',
 '2018-02-09',
 '2018-02-14',
 '2018-02-16',
 '2018-02-21',
 '2018-02-23',
 '2018-02-26',
 '2018-02-28',
 '2018-03-02',
 '2018-03-05',
 '2018-03-07',
 '2018-03-09',
 '2018-03-12',
 '2018-03-14',
 '2018-03-16',
 '2018-03-19',
 '2018-03-21',
 '2018-03-23',
 '2018-03-26',
 '2018-03-28',
 '2018-03-29',
 '2018-04-02',
 '2018-04-04',
 '2018-04-06',
 '2018-04-09',
```

```
 '2022-12-27',
 '2022-12-28',
 '2022-12-29',
 '2022-12-30',
 '2023-01-03',
 '2023-01-04',
 '2023-01-05',
 '2023-01-06',
 '2023-01-09',
 '2023-01-10',
 '2023-01-11',
 '2023-01-12',
 '2023-01-13',
 '2023-01-17',
 '2023-01-18',
 '2023-01-19',
 '2023-01-20',
 '2023-01-23',
 '2023-01-24',
 '2023-01-25',
 '2023-01-26',
 '2023-01-27',
 '2023-01-30',
 '2023-01-31',
 '2023-02-01',
 '2023-02-02',
 '2023-02-03',
 '2023-02-06',
 '2023-02-07',
 '2023-02-08',
 '2023-02-09',
 '2023-02-10',
 '2023-02-13',
 '2023-02-14',
 '2023-02-15',
 '2023-02-16',
 '2023-02-17',
 '2023-02-21',
 '2023-02-22',
 '2023-02-23',
 '2023-02-24',
 '2023-02-27',
 '2023-02-28'}
```

Here, we calculate the time to expiry for each contract, in days.

[7]:
```
options_df['TTE'] = (pd.to_datetime(options_df['exdate']) - pd.
↪to_datetime(options_df['date'])).dt.days
options_df
```

[7]:

	date	exdate	last_date	cp_flag	strike_price	best_bid	best_offer	volume	open_interest	impl_volatility	delta	gamma	vega	theta	expiry_indicator	close	adj_open	adj_close	adj_volume	TTE
0	2018-01-02	2018-01-03	2017-12-28	C	235.0	33.59	33.81	0.0	187.0	NaN	NaN	NaN	NaN	NaN	w	268.77	242.053393	242.893856	86655749.0	1
1	2018-01-02	2018-01-03	2018-01-02	C	240.0	28.59	28.76	1.0	88.0	NaN	NaN	NaN	NaN	NaN	w	268.77	242.053393	242.893856	86655749.0	1
2	2018-01-02	2018-01-03	2017-12-27	C	242.5	26.09	26.32	0.0	2.0	NaN	NaN	NaN	NaN	NaN	w	268.77	242.053393	242.893856	86655749.0	1
3	2018-01-02	2018-01-03	2018-01-02	C	245.0	23.59	23.81	12.0	58.0	NaN	NaN	NaN	NaN	NaN	w	268.77	242.053393	242.893856	86655749.0	1
4	2018-01-02	2018-01-03	NaN	C	247.5	21.08	21.32	0.0	0.0	NaN	NaN	NaN	NaN	NaN	w	268.77	242.053393	242.893856	86655749.0	1
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
10448189	2023-02-28	2025-03-21	2022-12-28	P	600.0	200.50	205.50	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	396.26	391.240559	390.285185	86655749.0	1
10448190	2023-02-28	2025-03-21	NaN	P	605.0	205.50	210.50	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	396.26	391.240559	390.285185	86655749.0	1
10448191	2023-02-28	2025-03-21	NaN	P	610.0	210.00	215.00	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	396.26	391.240559	390.285185	86655749.0	1
10448192	2023-02-28	2025-03-21	NaN	P	615.0	215.00	220.00	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	396.26	391.240559	390.285185	86655749.0	1
10448193	2023-02-28	2025-03-21	NaN	P	620.0	220.00	225.00	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	396.26	391.240559	390.285185	86655749.0	1

```
3          86655749.0    1
4          86655749.0    1
…                …   …
10448189   96141367.0  752
10448190   96141367.0  752
10448191   96141367.0  752
10448192   96141367.0  752
10448193   96141367.0  752

[10448194 rows x 20 columns]
```

Then, we filter for the closest few days to 30 DtE. We will later modify this to be the absolute closest to 30.

[8]:
```
filtered_df = options_df[(options_df['TTE'] >= 27) & (options_df['TTE'] <= 33)]
filtered_df
```

[8]:
```
                date      exdate   last_date cp_flag  strike_price  best_bid  \
972       2018-01-02  2018-01-31         NaN       C         165.0    103.82
973       2018-01-02  2018-01-31  2017-12-28       C         240.0     29.06
974       2018-01-02  2018-01-31  2017-12-28       C         245.0     24.12
975       2018-01-02  2018-01-31  2017-12-28       C         250.0     19.20
976       2018-01-02  2018-01-31  2017-12-28       C         255.0     14.33
…                …           …           …     …             …        …
10444209  2023-02-28  2023-03-31  2022-06-23       P         570.0    172.26
10444210  2023-02-28  2023-03-31  2022-11-18       P         575.0    177.25
10444211  2023-02-28  2023-03-31  2022-06-23       P         580.0    182.23
10444212  2023-02-28  2023-03-31  2022-11-15       P         585.0    187.22
10444213  2023-02-28  2023-03-31  2023-01-04       P         590.0    192.20

          best_offer  volume  open_interest  impl_volatility     delta  \
972           104.01     0.0            0.0              NaN       NaN
973            29.26     0.0           12.0         0.193414  0.983311
974            24.32     0.0            2.0         0.175939  0.972425
975            19.38     0.0          152.0         0.153960  0.957185
976            14.52     0.0           52.0         0.133378  0.926605
…                …     …             …               …       …
10444209      173.45     0.0            0.0              NaN       NaN
10444210      178.44     0.0            0.0              NaN       NaN
10444211      183.43     0.0            0.0              NaN       NaN
10444212      188.42     0.0            0.0              NaN       NaN
10444213      193.41     0.0            0.0              NaN       NaN

             gamma       vega      theta expiry_indicator   close    adj_open  \
972            NaN        NaN        NaN                w  268.77  242.053393
973       0.002835   3.151210  -7.538074                w  268.77  242.053393
974       0.004764   4.816286  -9.064763                w  268.77  242.053393
975       0.007811   6.907079 -10.439730                w  268.77  242.053393
```

```
976        0.013784  10.547560 -12.556030                 w  268.77  242.053393
…             …         …         …                  …     …      …
10444209      NaN       NaN       NaN                  m  396.26  391.240559
10444210      NaN       NaN       NaN                  m  396.26  391.240559
10444211      NaN       NaN       NaN                  m  396.26  391.240559
10444212      NaN       NaN       NaN                  m  396.26  391.240559
10444213      NaN       NaN       NaN                  m  396.26  391.240559

           adj_close  adj_volume  TTE
972       242.893856  86655749.0   29
973       242.893856  86655749.0   29
974       242.893856  86655749.0   29
975       242.893856  86655749.0   29
976       242.893856  86655749.0   29
…              …          …   …
10444209  390.285185  96141367.0   31
10444210  390.285185  96141367.0   31
10444211  390.285185  96141367.0   31
10444212  390.285185  96141367.0   31
10444213  390.285185  96141367.0   31

[686810 rows x 20 columns]
```

We can do the same with the dataset where contracts with nonexistent Greek calculations are dropped (we won't end up using this data set, but it will help us consider which values to initially drop for our calculations before we try to see if mock Black-Scholes values or similar can be used to fill missing Greeks/IV)

[9]:
```
exdates1 = set(options_df1['exdate'])
quotedates1 = set(options_df1['date'])
```

[10]:
```
len(exdates1 - quotedates1)
```

[10]: 31

[11]:
```
len(quotedates1 - exdates1)
```

[11]: 468

[12]:
```
len(exdates1 & quotedates1)
```

[12]: 830

Again calculating time to expiry:

[13]:
```
options_df1['TTE'] = (pd.to_datetime(options_df1['exdate']) - pd.
 ↪to_datetime(options_df1['date'])).dt.days
options_df1
```

[13]:

	date	exdate	last_date	cp_flag	strike_price	best_bid	best_offer	volume	open_interest	impl_volatility	delta	gamma	vega	theta	expiry_indicator	close	adj_open	adj_close	adj_volume	TTE
0	2018-01-02	2018-01-03	2018-01-02	C	267.5	1.28	1.34	5514.0	7184.0	0.062960	0.926657	0.157172	1.959172	-26.221690	w	268.77	242.053393	242.893856	86655749.0	1
1	2018-01-02	2018-01-03	2018-01-02	C	268.0	0.85	0.88	14476.0	5520.0	0.060924	0.819616	0.306547	3.697382	-44.389840	w	268.77	242.053393	242.893856	86655749.0	1
2	2018-01-02	2018-01-03	2018-01-02	C	268.5	0.48	0.50	12516.0	5895.0	0.058946	0.633232	0.453884	5.294787	-59.509580	w	268.77	242.053393	242.893856	86655749.0	1
3	2018-01-02	2018-01-03	2018-01-02	C	269.0	0.21	0.22	14745.0	5761.0	0.055630	0.390490	0.490317	5.399054	-56.377560	w	268.77	242.053393	242.893856	86655749.0	1
4	2018-01-02	2018-01-03	2018-01-02	C	269.5	0.07	0.08	1742.0	7512.0	0.055298	0.178472	0.335492	3.670619	-37.772850	w	268.77	242.053393	242.893856	86655749.0	1
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
9261854	2023-02-28	2025-03-21	2023-02-08	P	450.0	57.50	62.50	0.0	75.0	0.161451	-0.714413	0.007297	154.462000	1.957872	NaN	396.26	391.240559	390.285185	96141367.0	752
9261855	2023-02-28	2025-03-21	2023-01-09	P	455.0	61.00	66.00	0.0	0.0	0.158546	-0.758524	0.007626	151.188600	2.874898	NaN	396.26	391.240559			
9261856	2023-02-28	2025-03-21	2023-01-09	P	460.0	64.50	69.50	0.0	14.0	0.154637	-0.805469	0.007817	123.774400	4.337152	NaN	396.26	391.240559			
9261857	2023-02-28	2025-03-21	2023-01-09	P	465.0	68.50	73.50	0.0	21.0	0.152118	-0.846083	0.007509	79.376680	6.359011	NaN	396.26	391.240559			
9261858	2023-02-28	2025-03-21	2023-02-16	P	470.0	72.50	77.50	0.0	62.0	0.144876	-0.906887	0.006313	54.487690	10.982410	NaN	396.26	391.240559			

```
9261855  390.285185  96141367.0  752
9261856  390.285185  96141367.0  752
9261857  390.285185  96141367.0  752
9261858  390.285185  96141367.0  752

[9261859 rows x 20 columns]
```

[14]:
```
filtered_df1 = options_df1[(options_df1['TTE'] >= 27) & (options_df1['TTE'] <=
↪33)]
filtered_df1
```

[14]:
```
              date      exdate   last_date cp_flag  strike_price  best_bid  \
828     2018-01-02  2018-01-31  2017-12-28       C         240.0     29.06
829     2018-01-02  2018-01-31  2017-12-28       C         245.0     24.12
830     2018-01-02  2018-01-31  2017-12-28       C         250.0     19.20
831     2018-01-02  2018-01-31  2017-12-28       C         255.0     14.33
832     2018-01-02  2018-01-31  2017-12-28       C         260.0      9.58
…              …           …           …     …             …         …
9258523 2023-02-28  2023-03-31  2023-02-28       P         411.0     16.09
9258524 2023-02-28  2023-03-31  2023-02-28       P         412.0     16.82
9258525 2023-02-28  2023-03-31  2023-02-28       P         413.0     17.57
9258526 2023-02-28  2023-03-31  2023-02-28       P         414.0     18.34
9258527 2023-02-28  2023-03-31  2023-02-28       P         415.0     19.17

         best_offer  volume  open_interest  impl_volatility     delta  \
828           29.26     0.0           12.0         0.193414  0.983311
829           24.32     0.0            2.0         0.175939  0.972425
830           19.38     0.0          152.0         0.153960  0.957185
831           14.52     0.0           52.0         0.133378  0.926605
832            9.74     0.0           31.0         0.110864  0.868021
…              …     …             …               …       …
9258523       17.26   102.0          906.0         0.127514 -0.854706
9258524       18.00     5.0         2911.0         0.121468 -0.882473
9258525       18.77     7.0         2126.0         0.114016 -0.911503
9258526       19.56     1.0         1120.0         0.103528 -0.943419
9258527       20.31    25.0         3530.0         0.076447 -0.987661

            gamma       vega      theta expiry_indicator   close    adj_open  \
828      0.002835   3.151210  -7.538074                w  268.77  242.053393
829      0.004764   4.816286  -9.064763                w  268.77  242.053393
830      0.007811   6.907079 -10.439730                w  268.77  242.053393
831      0.013784  10.547560 -12.556030                w  268.77  242.053393
832      0.025454  16.200190 -14.825650                w  268.77  242.053393
…           …         …         …                …     …         …
9258523  0.016339  25.346960  -6.080472                m  396.26  391.240559
9258524  0.014863  21.527260  -1.950742                m  396.26  391.240559
9258525  0.012890  17.372680   2.619810                m  396.26  391.240559
```

```
9258526  0.009995  11.793440   7.923930                m  396.26  391.240559
9258527  0.002897   2.215591  15.766890                m  396.26  391.240559

          adj_close  adj_volume  TTE
828      242.893856  86655749.0   29
829      242.893856  86655749.0   29
830      242.893856  86655749.0   29
831      242.893856  86655749.0   29
832      242.893856  86655749.0   29
…              …          …  …
9258523  390.285185  96141367.0   31
9258524  390.285185  96141367.0   31
9258525  390.285185  96141367.0   31
9258526  390.285185  96141367.0   31
9258527  390.285185  96141367.0   31

[627236 rows x 20 columns]
```

We need strikes for each day where we evaluate positions to cover the range of 30 days of stock movements. We'll look at calls and puts separately. We need the ATM option to have data for the next 21-30 days.

First, calculate the closest possible date to 30.

[15]:
```
puts_df = filtered_df[filtered_df['cp_flag'] == 'P']
calls_df = filtered_df[filtered_df['cp_flag'] == 'C']

puts_df1 = filtered_df1[filtered_df1['cp_flag'] == 'P']
calls_df1 = filtered_df1[filtered_df1['cp_flag'] == 'C']
```

Note: Resolve DeprecationWarning by adding ', include_groups=False' to apply function.

[16]:
```
puts_result_df = puts_df.groupby('date', as_index=False).
 ↪apply(find_closest_tte).reset_index(drop=True)[['date', 'TTE']].
 ↪drop_duplicates()
calls_result_df = calls_df.groupby('date', as_index=False).
 ↪apply(find_closest_tte).reset_index(drop=True)[['date', 'TTE']].
 ↪drop_duplicates()

puts_result_df1 = puts_df1.groupby('date', as_index=False).
 ↪apply(find_closest_tte).reset_index(drop=True)[['date', 'TTE']].
 ↪drop_duplicates()
calls_result_df1 = calls_df1.groupby('date', as_index=False).
 ↪apply(find_closest_tte).reset_index(drop=True)[['date', 'TTE']].
 ↪drop_duplicates()
```

[17]:
```
calls_result_df
```

[17]:
```
            date  TTE
0     2018-01-02   29
1     2018-01-03   30
2     2018-01-04   29
3     2018-01-05   28
4     2018-01-08   30
…            …   …
1293  2023-02-22   30
1294  2023-02-23   29
1295  2023-02-24   28
1296  2023-02-27   32
1297  2023-02-28   31

[1298 rows x 2 columns]
```

Check if there are any days where the TtE is less than 28, then check that the data matches.

[18]:
```
calls_result_df1.loc[calls_result_df1['TTE'] < 28]
```

[18]:
```
Empty DataFrame
Columns: [date, TTE]
Index: []
```

[19]:
```
set(options_df['date']) - set(calls_result_df['date'])
```

[19]:
```
set()
```

Now, we'll iterate and filter based on date and time to expiry.

[20]:
```
original_dfs = {'puts': puts_df, 'calls': calls_df, 'puts1': puts_df1, 'calls1':
 ↪ calls_df1}
result_dfs = {'puts': puts_result_df, 'calls': calls_result_df, 'puts1':␣
 ↪puts_result_df1, 'calls1': calls_result_df1}
filtered_dfs = merge_dataframes(original_dfs, result_dfs)
```

[21]:
```
filtered_dfs['puts']
```

[21]:
```
              date      exdate   last_date cp_flag  strike_price  best_bid  \
0       2018-01-02  2018-01-31         NaN       P         165.0      0.00
1       2018-01-02  2018-01-31  2018-01-02       P         240.0      0.13
2       2018-01-02  2018-01-31  2018-01-02       P         245.0      0.17
3       2018-01-02  2018-01-31  2018-01-02       P         250.0      0.24
4       2018-01-02  2018-01-31  2018-01-02       P         255.0      0.36
…              …           …           …      …             …         …
128920  2023-02-28  2023-03-31  2022-06-23       P         570.0    172.26
128921  2023-02-28  2023-03-31  2022-11-18       P         575.0    177.25
128922  2023-02-28  2023-03-31  2022-06-23       P         580.0    182.23
128923  2023-02-28  2023-03-31  2022-11-15       P         585.0    187.22
```

```
128924  2023-02-28  2023-03-31  2023-01-04       P         590.0    192.20

        best_offer  volume  open_interest  impl_volatility     delta  \
0             0.01     0.0            0.0         0.535503 -0.000456
1             0.14   147.0         1282.0         0.205954 -0.022718
2             0.18    66.0          182.0         0.182066 -0.031889
3             0.25   269.0          166.0         0.159122 -0.048143
4             0.37    59.0          749.0         0.135986 -0.077530
…              …     …              …               …        …
128920      173.45     0.0            0.0               NaN       NaN
128921      178.44     0.0            0.0               NaN       NaN
128922      183.43     0.0            0.0               NaN       NaN
128923      188.42     0.0            0.0               NaN       NaN
128924      193.41     0.0            0.0               NaN       NaN

           gamma       vega     theta expiry_indicator   close    adj_open  \
0       0.000040   0.123239 -0.414822                w  268.77  242.053393
1       0.003462   4.080427 -5.205224                w  268.77  242.053393
2       0.005197   5.423385 -6.083812                w  268.77  242.053393
3       0.008314   7.569383 -7.395249                w  268.77  242.053393
4       0.014119  10.996340 -9.096192                w  268.77  242.053393
…          …         …       …                 …     …         …
128920       NaN        NaN       NaN                m  396.26  391.240559
128921       NaN        NaN       NaN                m  396.26  391.240559
128922       NaN        NaN       NaN                m  396.26  391.240559
128923       NaN        NaN       NaN                m  396.26  391.240559
128924       NaN        NaN       NaN                m  396.26  391.240559

         adj_close  adj_volume  TTE
0       242.893856  86655749.0   29
1       242.893856  86655749.0   29
2       242.893856  86655749.0   29
3       242.893856  86655749.0   29
4       242.893856  86655749.0   29
…            …         …  …
128920  390.285185  96141367.0   31
128921  390.285185  96141367.0   31
128922  390.285185  96141367.0   31
128923  390.285185  96141367.0   31
128924  390.285185  96141367.0   31

[128925 rows x 20 columns]
```

We'll choose the one closest to the money:

[22]:
```
final_dfs = filter_dfs_on_criteria(filtered_dfs, select_row_with_smallest_diff)
final_dfs['calls1']
```

[22]:

	date	exdate	last_date	cp_flag	strike_price	best_bid	best_offer	volume	open_interest	impl_volatility	delta	gamma	vega	theta	expiry_indicator	close	adj_open	adj_close	adj_volume	TTE
0	2018-01-02	2018-01-31	2018-01-02	C	269.0	2.11	2.16	477.0	37.0	0.068871	0.512031	0.076400	30.21236	-15.22501	w	268.77	242.053393	242.893856	86655749.0	29
1	2018-01-03	2018-02-02	2018-01-03	C	270.0	2.65	2.69	289.0	719.0	0.072398	0.562218	0.070177	30.55966	-15.81073	w	270.47	243.065564	244.430187	90070416.0	30
2	2018-01-04	2018-02-02	2018-01-04	C	272.0	2.13	2.17	769.0	6178.0	0.071179	0.500445	0.073186	30.54542	-15.79170	w	271.61	245.089905	245.460432	80595402.0	29
3	2018-01-05	2018-02-02	2018-01-05	C	273.0	2.60	2.66	1387.0	1307.0	0.074068	0.557338	0.070366	29.90136	-16.79527	w	273.42	246.273783	247.096172	83468662.0	28
4	2018-01-08	2018-02-07	2018-01-08	C	275.0	1.93	1.94	924.0	3846.0	0.072545	0.454108	0.069544	31.12119	-15.69601	w	273.92	246.996762	247.548034	57288979.0	30
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
1293	2023-02-22	2023-03-24	2023-02-22	C	399.0	9.08	9.12	1875.0	344.0	0.202075	0.517410	0.018019	45.10776	-66.59158	w	398.54	393.496030	392.530807	83574386.0	30
1294	2023-02-23	2023-03-24	2023-02-23	C	401.0	8.79	8.82	936.0	923.0	0.196720	0.518997	0.018739	44.17986	-66.44084	w	400.66	395.505271	394.618841		
1295	2023-02-24	2023-03-24	2023-02-24	C	396.0	9.05	9.08	1151.0	225.0	0.201088	0.531177	0.018872	43.16854	-68.26598	w	396.38	389.457850	390.403375		
1296	2023-02-27	2023-03-31	2023-02-27	C	398.0	8.92	8.96	976.0	5244.0	0.194675	0.511410	0.018207	46.44293	-62.65579	m	397.73	393.840753	391.733020		
1297	2023-02-28	2023-03-31	2023-02-28	C	396.0	9.55	9.58	611.0	3758.0	0.207305	0.519384	0.017402	45.37965	-66.87704	m	396.26	391.240559	390.285185		

```
1294   95842681.0   29
1295  108144866.0   28
1296   80318244.0   32
1297   96141367.0   31

[1298 rows x 20 columns]
```

Then, we'll find the close date of each of the contracts that we simulate (ie. approximately one week prior to expiry. We choose this because close to expiry, delta and gamma are far more difficult to hedge on a day-to-day basis and we do not have minute bars).

[23]:
```
final_dfs = calculate_closest_dates(final_dfs)
final_dfs['calls1']
```

[23]:

	date	exdate	last_date	cp_flag	strike_price	best_bid	\
0	2018-01-02	2018-01-31	2018-01-02	C	269.0	2.11	
1	2018-01-03	2018-02-02	2018-01-03	C	270.0	2.65	
2	2018-01-04	2018-02-02	2018-01-04	C	272.0	2.13	
3	2018-01-05	2018-02-02	2018-01-05	C	273.0	2.60	
4	2018-01-08	2018-02-07	2018-01-08	C	275.0	1.93	
…	…	…	…	…	…	…	
1293	2023-02-22	2023-03-24	2023-02-22	C	399.0	9.08	
1294	2023-02-23	2023-03-24	2023-02-23	C	401.0	8.79	
1295	2023-02-24	2023-03-24	2023-02-24	C	396.0	9.05	
1296	2023-02-27	2023-03-31	2023-02-27	C	398.0	8.92	
1297	2023-02-28	2023-03-31	2023-02-28	C	396.0	9.55	

	best_offer	volume	open_interest	impl_volatility	…	gamma	\
0	2.16	477.0	37.0	0.068871	…	0.076400	
1	2.69	289.0	719.0	0.072398	…	0.070177	
2	2.17	769.0	6178.0	0.071179	…	0.073186	
3	2.66	1387.0	1307.0	0.074068	…	0.070366	
4	1.94	924.0	3846.0	0.072545	…	0.069544	
…	…	…	…	…	…	…	
1293	9.12	1875.0	344.0	0.202075	…	0.018019	
1294	8.82	936.0	923.0	0.196720	…	0.018739	
1295	9.08	1151.0	225.0	0.201088	…	0.018872	
1296	8.96	976.0	5244.0	0.194675	…	0.018207	
1297	9.58	611.0	3758.0	0.207305	…	0.017402	

	vega	theta	expiry_indicator	close	adj_open	adj_close	\
0	30.21236	-15.22501	w	268.77	242.053393	242.893856	
1	30.55966	-15.81073	w	270.47	243.065564	244.430187	
2	30.54542	-15.79170	w	271.61	245.089905	245.460432	
3	29.90136	-16.79527	w	273.42	246.273783	247.096172	
4	31.12119	-15.69601	w	273.92	246.996762	247.548034	
…	…	…	…	…	…	…	
1293	45.10776	-66.59158	w	398.54	393.496030	392.530807	

```
1294  44.17986 -66.44084                w  400.66  395.505271  394.618841
1295  43.16854 -68.26598                w  396.38  389.457850  390.403375
1296  46.44293 -62.65579                m  397.73  393.840753  391.733020
1297  45.37965 -66.87704                m  396.26  391.240559  390.285185

       adj_volume  TTE  close_date
0       86655749.0   29  2018-01-23
1       90070416.0   30  2018-01-24
2       80595402.0   29  2018-01-25
3       83468662.0   28  2018-01-26
4       57288979.0   30  2018-01-29
…              …  …           …
1293    83574386.0   30  2023-02-28
1294    95842681.0   29  2023-02-28
1295   108144866.0   28  2023-02-28
1296    80318244.0   32  2023-02-28
1297    96141367.0   31  2023-02-28

[1298 rows x 21 columns]
```

Check for dates where values are not all present for either calls or puts for the entirety of the 20-30 days or so that we hold the contracts (straddle)

[24]:
```
options_df1['date'] = pd.to_datetime(options_df1['date'])
options_df1['exdate'] = pd.to_datetime(options_df1['exdate'])

final_dfs = merge_with_options(final_dfs, options_df1)
```

[25]:
```
len(final_dfs['calls1'].loc[final_dfs['calls1']['is_present'] == False])
```

[25]: 48

[26]:
```
len(final_dfs['calls'].loc[final_dfs['calls']['is_present'] == False])
```

[26]: 48

[27]:
```
len(final_dfs['puts'].loc[final_dfs['puts']['is_present'] == False])
```

[27]: 110

[28]:
```
len(final_dfs['puts1'].loc[final_dfs['puts1']['is_present'] == False])
```

[28]: 110

So we see that missing values for puts and calls is slightly different.

[29]:
```
final_dfs['puts1']
```

[29]:

	date_x	exdate	last_date_x	cp_flag	strike_price	best_bid_x	\
0	2018-01-02	2018-01-31	2018-01-02	P	269.0	2.05	
1	2018-01-03	2018-02-02	2018-01-03	P	270.0	1.77	
2	2018-01-04	2018-02-02	2018-01-04	P	272.0	2.12	
3	2018-01-05	2018-02-02	2018-01-05	P	273.0	1.81	
4	2018-01-08	2018-02-07	2018-01-08	P	275.0	2.53	
…	…	…	…	…	…	…	
1293	2023-02-22	2023-03-24	2023-02-22	P	399.0	9.67	
1294	2023-02-23	2023-03-24	2023-02-23	P	401.0	8.83	
1295	2023-02-24	2023-03-24	2023-02-24	P	396.0	8.81	
1296	2023-02-27	2023-03-31	2023-02-27	P	398.0	9.23	
1297	2023-02-28	2023-03-31	2023-02-28	P	396.0	8.15	

	best_offer_x	volume_x	open_interest_x	impl_volatility_x	…	\
0	2.10	198.0	33.0	0.069577	…	
1	1.80	1060.0	330.0	0.069568	…	
2	2.15	416.0	304.0	0.068201	…	
3	1.85	509.0	149.0	0.071740	…	
4	2.56	82.0	269.0	0.067924	…	
…	…	…	…	…	…	
1293	9.71	2678.0	1317.0	0.201626	…	
1294	8.86	1233.0	1566.0	0.186139	…	
1295	8.84	3156.0	1086.0	0.198990	…	
1296	9.26	1568.0	4088.0	0.188579	…	
1297	8.17	1375.0	6481.0	0.174174	…	

	vega_x	theta_x	expiry_indicator_x	close_x	adj_open_x	\
0	30.11151	-11.46749	w	268.77	242.053393	
1	30.52431	-11.33461	w	270.47	243.065564	
2	30.40449	-11.28616	w	271.61	245.089905	
3	29.86764	-12.34094	w	273.42	246.273783	
4	30.79770	-10.80407	w	273.92	246.996762	
…	…	…	…	…	…	
1293	45.30915	-47.38424	w	398.54	393.496030	
1294	44.77837	-44.24160	w	400.66	395.505271	
1295	43.53449	-48.60954	w	396.38	389.457850	
1296	46.60089	-42.60824	m	397.73	393.840753	
1297	45.68817	-39.53407	m	396.26	391.240559	

	adj_close_x	adj_volume_x	TTE_x	close_date	is_present
0	242.893856	86655749.0	29	2018-01-23	True
1	244.430187	90070416.0	30	2018-01-24	True
2	245.460432	80595402.0	29	2018-01-25	True
3	247.096172	83468662.0	28	2018-01-26	True
4	247.548034	57288979.0	30	2018-01-29	True
…	…	…	…	…	…
1293	392.530807	83574386.0	30	2023-02-28	True

```
1294   394.618841    95842681.0     29  2023-02-28        True
1295   390.403375   108144866.0     28  2023-02-28        True
1296   391.733020    80318244.0     32  2023-02-28        True
1297   390.285185    96141367.0     31  2023-02-28        True

[1298 rows x 22 columns]
```

Checkpoint to save the potential call/put options (which we will open in tandem as long or short positions on straddles).

[30]:
```
for key, df in final_dfs.items():
    csv_filename = f"{key}.csv"
    df.to_csv(csv_filename, index=False)
    print(f"DataFrame '{key}' has been saved to '{csv_filename}'")
```

```
DataFrame 'puts' has been saved to 'puts.csv'
DataFrame 'calls' has been saved to 'calls.csv'
DataFrame 'puts1' has been saved to 'puts1.csv'
DataFrame 'calls1' has been saved to 'calls1.csv'
```

1.6.4 3.1: Checking which dates are missing intermediate data - continued data from C3

[31]:
```
calls_in_puts = check_dates_in_calls_and_puts('calls', 'puts', final_dfs)
calls1_in_puts1 = check_dates_in_calls_and_puts('calls1', 'puts1', final_dfs)

print(f"All dates in 'calls' with is_present=False are in 'puts' with␣
 ↪is_present=False: {calls_in_puts}")
print(f"All dates in 'calls1' with is_present=False are in 'puts1' with␣
 ↪is_present=False: {calls1_in_puts1}")
```

```
All dates in 'calls' with is_present=False are in 'puts' with is_present=False:
False
All dates in 'calls1' with is_present=False are in 'puts1' with
is_present=False: False
```

[32]:
```
count_unique_in_calls, count_unique_in_puts, count_overlapping =␣
 ↪count_dates_comparison('calls', 'puts', final_dfs)
count_unique_in_calls1, count_unique_in_puts1, count_overlapping1 =␣
 ↪count_dates_comparison('calls1', 'puts1', final_dfs)

print(f"Unique dates in 'calls' not in 'puts' where is_present=False:␣
 ↪{count_unique_in_calls}")
print(f"Unique dates in 'puts' not in 'calls' where is_present=False:␣
 ↪{count_unique_in_puts}")
print(f"Overlapping dates in 'calls' and 'puts' where is_present=False:␣
 ↪{count_overlapping}")
```

```
print(f"Unique dates in 'calls1' not in 'puts1' where is_present=False:␣
  ↪{count_unique_in_calls1}")
print(f"Unique dates in 'puts1' not in 'calls1' where is_present=False:␣
  ↪{count_unique_in_puts1}")
print(f"Overlapping dates in 'calls1' and 'puts1' where is_present=False:␣
  ↪{count_overlapping1}")
```

```
Unique dates in 'calls' not in 'puts' where is_present=False: 48
Unique dates in 'puts' not in 'calls' where is_present=False: 110
Overlapping dates in 'calls' and 'puts' where is_present=False: 0
Unique dates in 'calls1' not in 'puts1' where is_present=False: 48
Unique dates in 'puts1' not in 'calls1' where is_present=False: 110
Overlapping dates in 'calls1' and 'puts1' where is_present=False: 0
```

With this, unfortunately we do see that these sets are actually exclusive, so we will ignore them for now and for the final version, we'll try to fill them in with Black-Scholes calculations if they are close enough to the other provided data values and ignore these dates as starting points otherwise.

This concludes the initial data structuring. Further data structuring will be done in the simulation section. We now have the following important files to be retrieved when necessary: * `combinedata.csv` * `puts.csv` * `calls.csv`

1.7 5. Initial Graphs and Basic Data Exploration

We graph several different aspects of the data to take an initial look at the structures within our data.

Note that each individual graphing was done by a different group member working asynchronously, so each subsection has data imports such that it should work as a standalone if the correct data processing functions had been run to obtain the .csv files. Do note that because of this, if running the notebook directly you may end up importing multiple copies of the same data under different variable names.

1.7.1 At-The-Money, over time

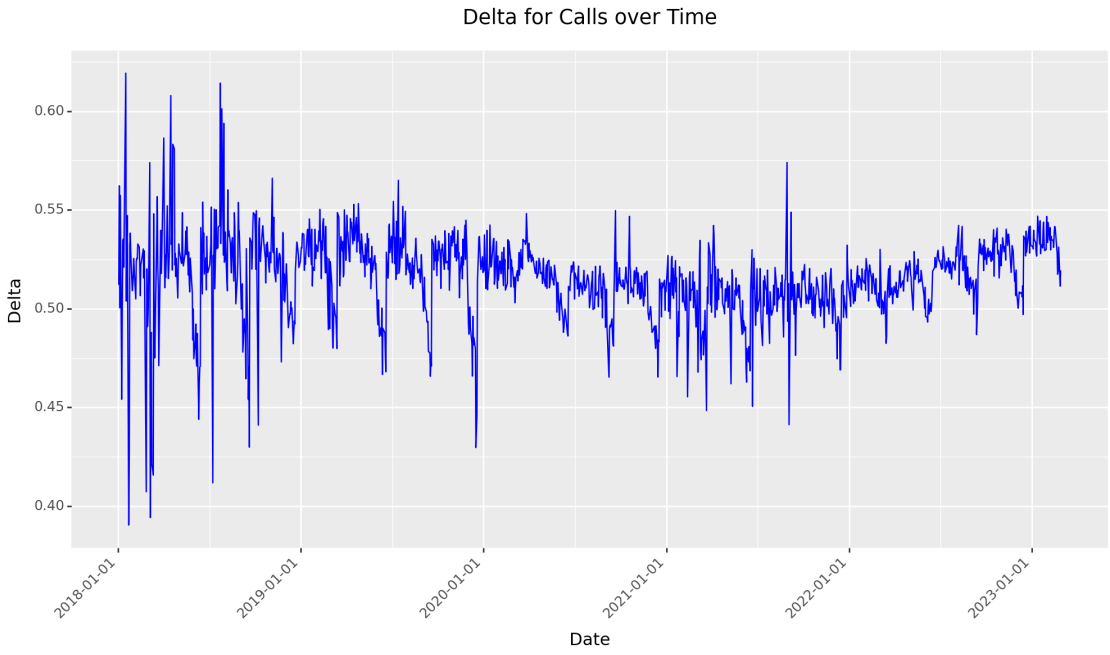
We graph various greeks and metrics for ATM options over time.

[2]:
```
calls_filepath = 'calls.csv'
puts_filepath = 'puts.csv'
calls_df = pd.read_csv(calls_filepath)
puts_df = pd.read_csv(puts_filepath)
```

[3]:
```
# Add a 'type' column to distinguish between calls and puts
calls_df['Type'] = 'Calls'
puts_df['Type'] = 'Puts'

# Combine into a single DataFrame
combined_df = pd.concat([calls_df, puts_df], ignore_index=True)

combined_df['date_x'] = pd.to_datetime(combined_df['date_x'])
```

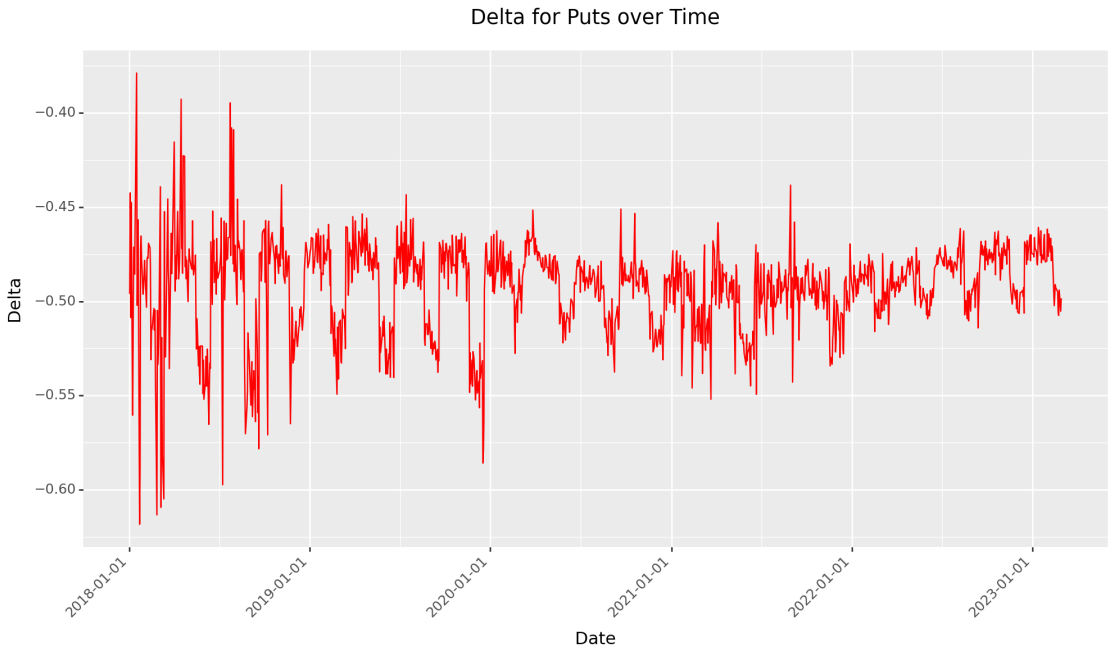
```
calls_df['date_x'] = pd.to_datetime(calls_df['date_x'])
puts_df['date_x'] = pd.to_datetime(puts_df['date_x'])
```

[4]:
```
p_delta_calls = (ggplot(calls_df, aes(x='date_x', y='delta_x')) +
                 geom_line(color='blue') +
                 labs(title='Delta for Calls over Time', x='Date', y='Delta',␣
 ↪color='Type') +
                 theme(axis_text_x=element_text(rotation=45, hjust=1),
                       figure_size=(10, 6),
                       plot_title=element_text(ha='center')))
p_delta_calls
```



[4]:
```
<Figure Size: (1000 x 600)>
```

[5]:
```
p_delta_puts = (ggplot(puts_df, aes(x='date_x', y='delta_x')) +
                geom_line(color='red') +
                labs(title='Delta for Puts over Time', x='Date', y='Delta',␣
 ↪color='Type') +
                theme(axis_text_x=element_text(rotation=45, hjust=1),
                      figure_size=(10, 6),
                      plot_title=element_text(ha='center')))
p_delta_puts
```

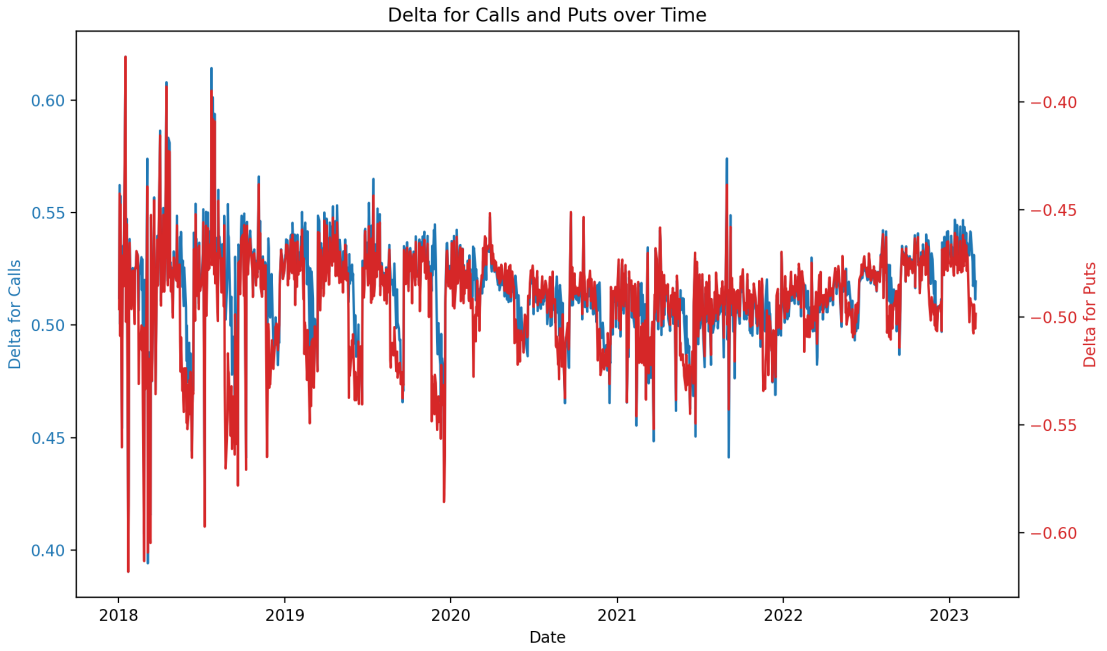


[5]: <Figure Size: (1000 x 600)>

We can see that at-the-money calls and puts center around a magnitude of 0.5 delta. There also appears seasonality.

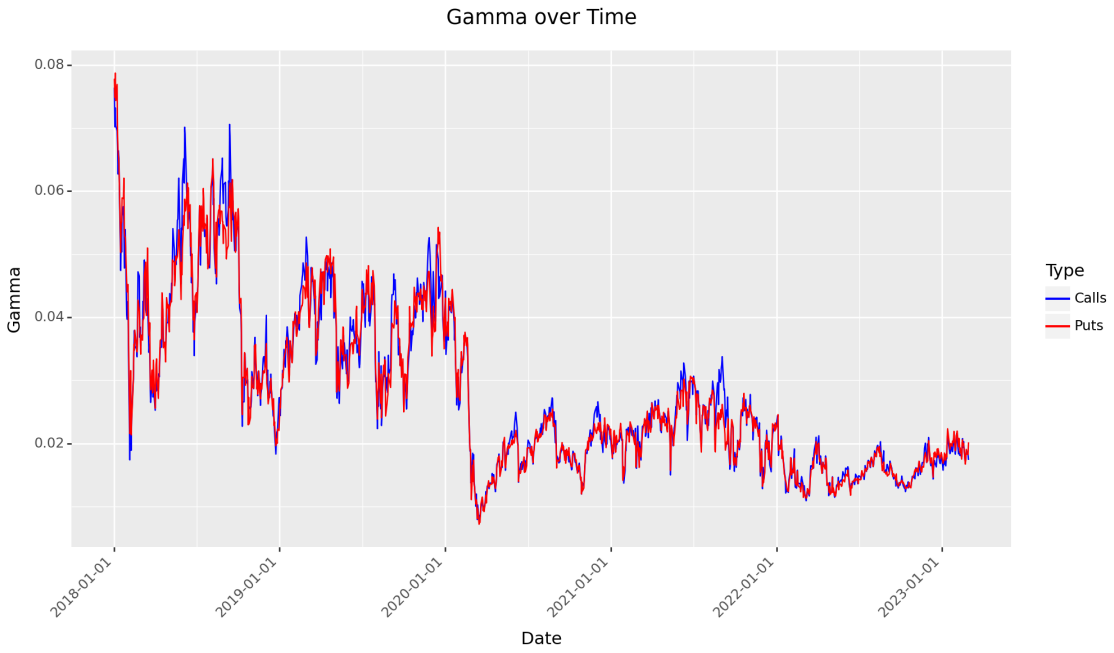
[6]:
```
# Create the plot
fig, ax1 = plt.subplots(figsize=(10, 6))

# Plot Delta for Calls on the left y-axis
color = 'tab:blue'
ax1.set_xlabel('Date')
ax1.set_ylabel('Delta for Calls', color=color)
ax1.plot(calls_df['date_x'], calls_df['delta_x'], color=color)
ax1.tick_params(axis='y', labelcolor=color)

# Create a second y-axis for Delta for Puts
ax2 = ax1.twinx()
color = 'tab:red'
ax2.set_ylabel('Delta for Puts', color=color)
ax2.plot(puts_df['date_x'], puts_df['delta_x'], color=color)
ax2.tick_params(axis='y', labelcolor=color)

# Title and layout adjustments
plt.title('Delta for Calls and Puts over Time')
fig.tight_layout()
```

```
plt.show()
```



We can see that at-the-money calls and puts have similar gamma across multiple times. There also appears to be a regime shift, where gamma is noticably lower post-COVID.

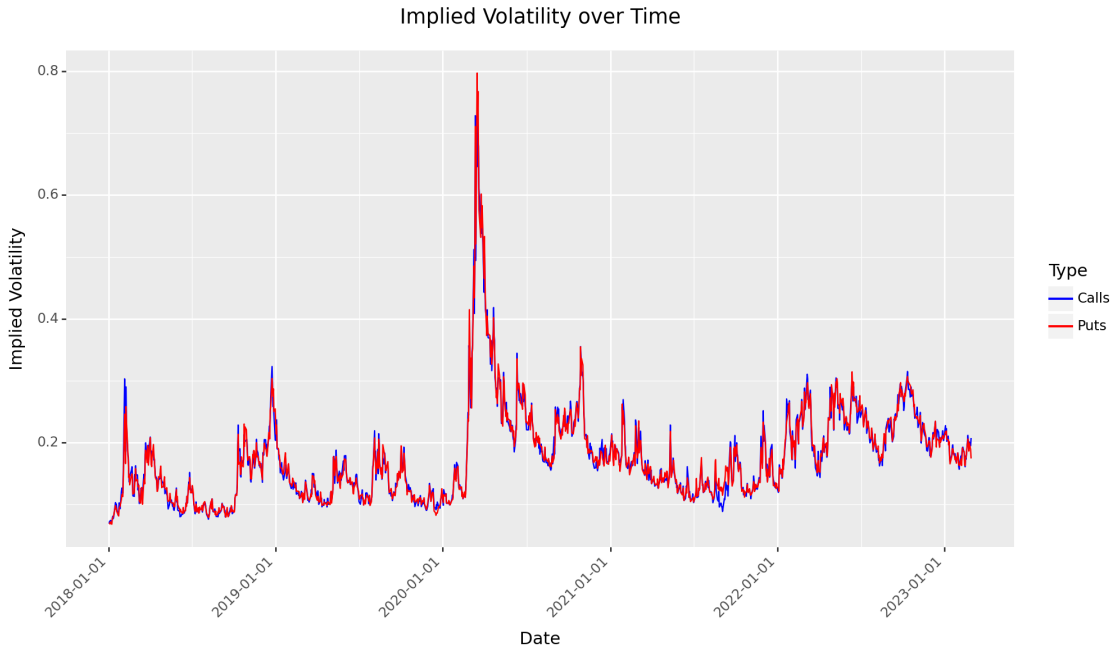
[7]:
```
p_gamma = (ggplot(combined_df, aes(x='date_x', y='gamma_x', color='Type')) +
           geom_line() +
           labs(title='Gamma over Time', x='Date', y='Gamma', color='Type') +
           theme(axis_text_x=element_text(rotation=45, hjust=1),
                 figure_size=(10, 6),
                 plot_title=element_text(ha='center')) +
           scale_color_manual(values={"Calls": "blue", "Puts": "red"}))
p_gamma
```



[7]: <Figure Size: (1000 x 600)>

We can see that implied volatility has remained largely flat until the spike during COVID, and it has largely regressed back to pre-pandemic levels albeit perhaps slightly elevated.

[8]:
```
p_impl_volatility = (ggplot(combined_df, aes(x='date_x', y='impl_volatility_x',␣
↪color='Type')) +
                     geom_line() +
                     labs(title='Implied Volatility over Time', x='Date',␣
↪y='Implied Volatility', color='Type') +
                     theme(axis_text_x=element_text(rotation=45, hjust=1),
                           figure_size=(10, 6),
                           plot_title=element_text(ha='center')) +
                     scale_color_manual(values={"Calls": "blue", "Puts":␣
↪"red"}))
p_impl_volatility
```



[8]: <Figure Size: (1000 x 600)>

1.7.2 Delta, Gamma, and IV for Individual Pairs opened ATM

We'll select a few examples of individual option pairs that we may use for straddles from the beginning, middle, and end sections of the data, and take a look at their progression over time (of the same contracts for our holding period).

[2]:
```
calls = pd.read_csv('calls.csv')
puts = pd.read_csv('puts.csv')
datapull = pd.read_csv('spy_tickerdata.csv')
csv_file_path = 'option_data.csv'
spydata = pd.read_csv(csv_file_path)
```

[3]:
```
spydata['date']=pd.to_datetime(spydata['date'], format = '%Y-%m-%d')
spydata['exdate']=pd.to_datetime(spydata['exdate'], format = '%Y-%m-%d')
spydata['dte'] = (spydata['exdate'] - spydata['date']).dt.days
mapping = {'C': 'Call', 'P': 'Put'}
spydata['Type'] = spydata['cp_flag'].map(mapping)
```

[4]:
```
datapull[datapull['date'] == '2018-03-06']
```

[4]:

	ticker	date	open	high	low	close	volume	dividend	\
6104	SPY	2018-03-06	273.3	273.39	271.18	272.88	78407902.0	0.0	

split	adj_open	adj_high	adj_low	adj_close	adj_volume

```
6104    1.0  246.987725  247.06906  245.071831  246.608161  78407902.0
```

[5]:
```
calls[calls['date_x'] == '2021-02-08']
```

[5]:
```
         date_x      exdate last_date_x cp_flag  strike_price  best_bid_x  \
780  2021-02-08  2021-03-10  2021-02-08       C         391.0         6.8

     best_offer_x  volume_x  open_interest_x  impl_volatility_x  …  \
780          6.88      19.0              3.0           0.157962  …

       vega_x   theta_x  expiry_indicator_x  close_x  adj_open_x  adj_close_x  \
780  44.66742 -43.18171                   w   390.51  372.256242   373.442045

     adj_volume_x  TTE_x  close_date  is_present
780    37887680.0     30  2021-03-01        True

[1 rows x 22 columns]
```

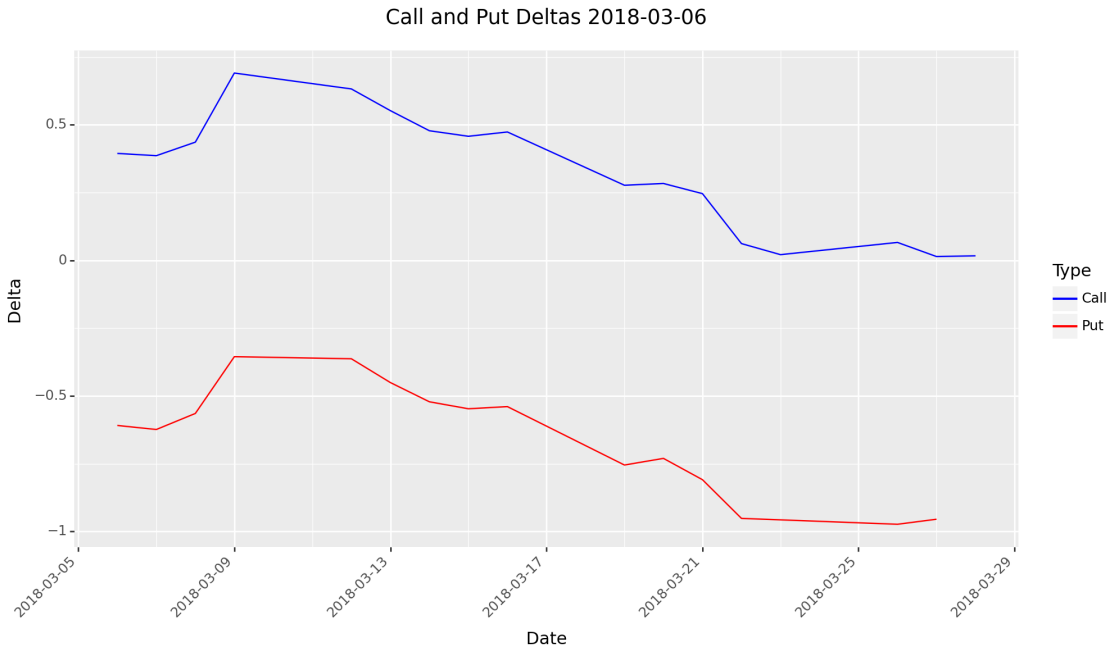
[6]:
```
first_options = spydata[(spydata['exdate'] == '2018-04-04') & (spydata['dte'] <
 ↪30) & (spydata['dte'] >=7) & (spydata['strike_price'] == 275000)]
middle_options = spydata[(spydata['exdate'] == '2021-03-10') & (spydata['dte']
 ↪< 30) & (spydata['dte'] >=7) & (spydata['strike_price'] == 391000)]
last_options = spydata[(spydata['exdate'] == '2022-07-06') & (spydata['dte'] <
 ↪30) & (spydata['dte'] >=7) & (spydata['strike_price'] == 412000)]
```

[7]:
```
first_options = first_options.dropna()
middle_options = middle_options.dropna()
last_options = last_options.dropna()
```

From the Delta Graphs below we can see that our positions open with call and put deltas each close to one half. As we hold the positions, the underlying moves up or down, and we can see the delta values diverge from one half and go either up or down. Our trading strategy will rebalance by buying and selling the underlying as the delta values change to keep a consistent portfolio Gamma.

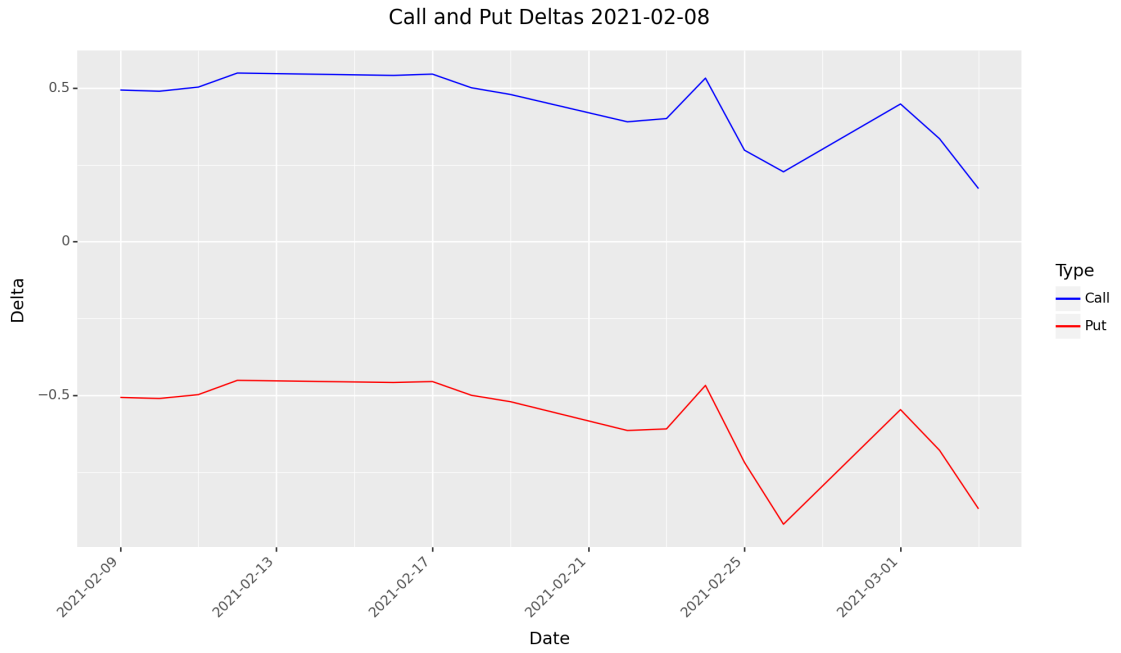
Note that under put-call parity, the Delta of a call option is always exactly 1 greater than the delta of a put option. In practice, this is almost always true, but with slight delays or lags/exceptions between time points.

[8]:
```
p_d_1 = (ggplot(first_options, aes(x='date', y='delta', color='Type')) +
           geom_line() +
           labs(title='Call and Put Deltas 2018-03-06', x='Date', y='Delta',
 ↪color='Type') +
           theme(axis_text_x=element_text(rotation=45, hjust=1),
                 figure_size=(10, 6),
                 plot_title=element_text(ha='center')) +
           scale_color_manual(values={"Call": "blue", "Put": "red"}))
p_d_1
```



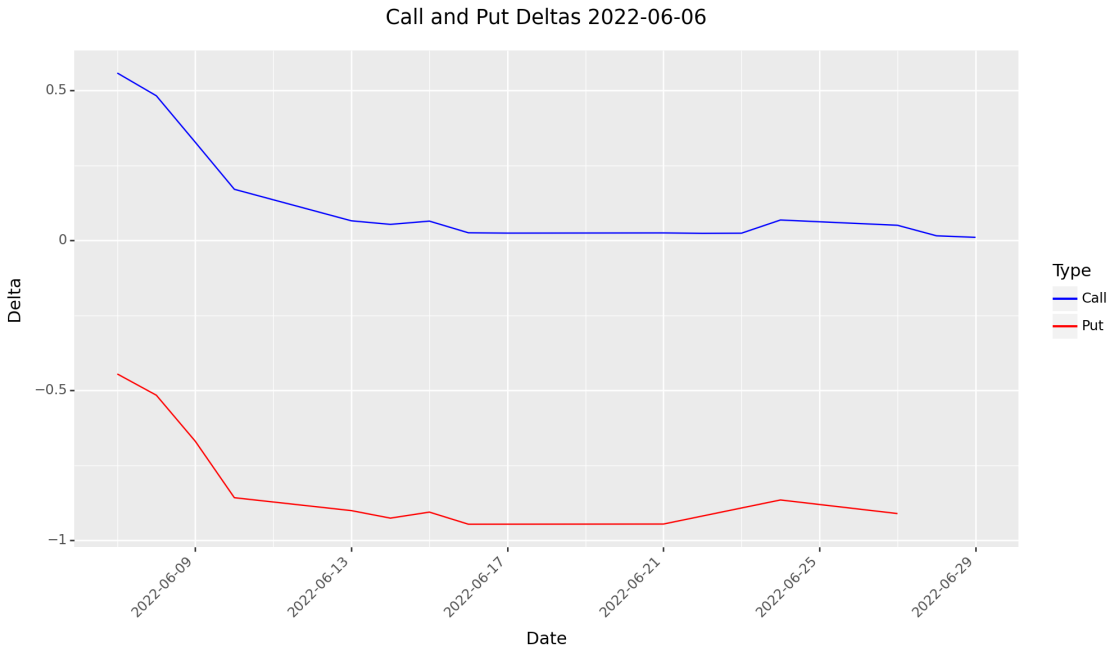
[8]: <Figure Size: (1000 x 600)>

[9]:
```
p_d_2 = (ggplot(middle_options, aes(x='date', y='delta', color='Type')) +
           geom_line() +
           labs(title='Call and Put Deltas 2021-02-08', x='Date', y='Delta',␣
 ↪color='Type') +
           theme(axis_text_x=element_text(rotation=45, hjust=1),
                 figure_size=(10, 6),
                 plot_title=element_text(ha='center')) +
           scale_color_manual(values={"Call": "blue", "Put": "red"}))
p_d_2
```



[9]: <Figure Size: (1000 x 600)>

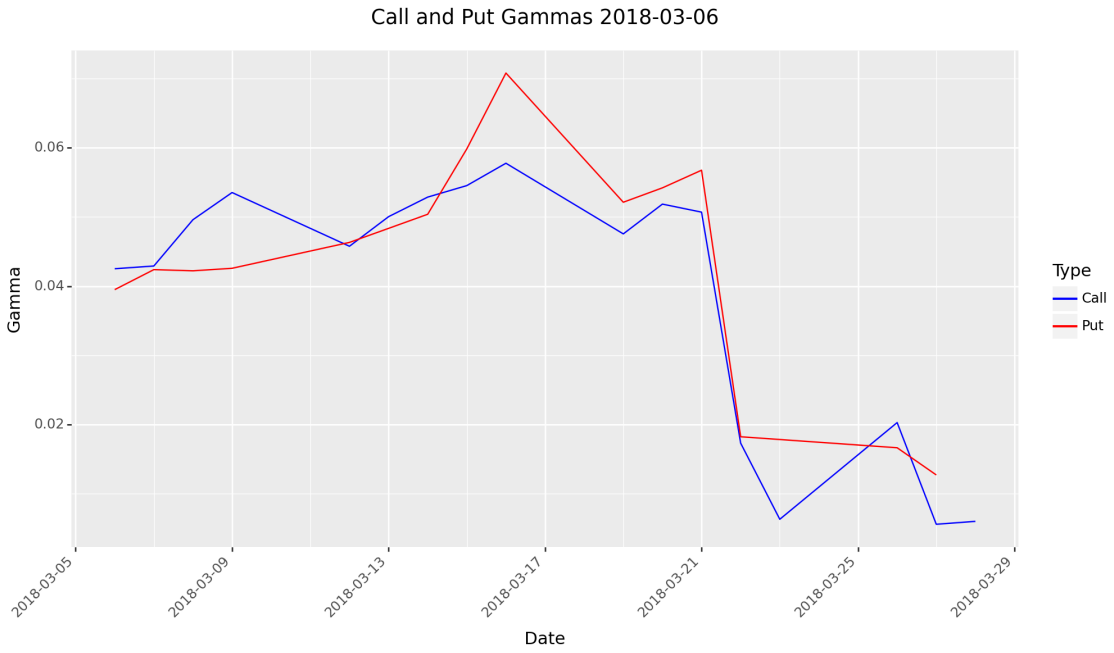
[10]:
```
p_d_3 = (ggplot(last_options, aes(x='date', y='delta', color='Type')) +
           geom_line() +
           labs(title='Call and Put Deltas 2022-06-06', x='Date', y='Delta',␣
 ↪color='Type') +
           theme(axis_text_x=element_text(rotation=45, hjust=1),
                 figure_size=(10, 6),
                 plot_title=element_text(ha='center')) +
           scale_color_manual(values={"Call": "blue", "Put": "red"}))
p_d_3
```



[10]: <Figure Size: (1000 x 600)>

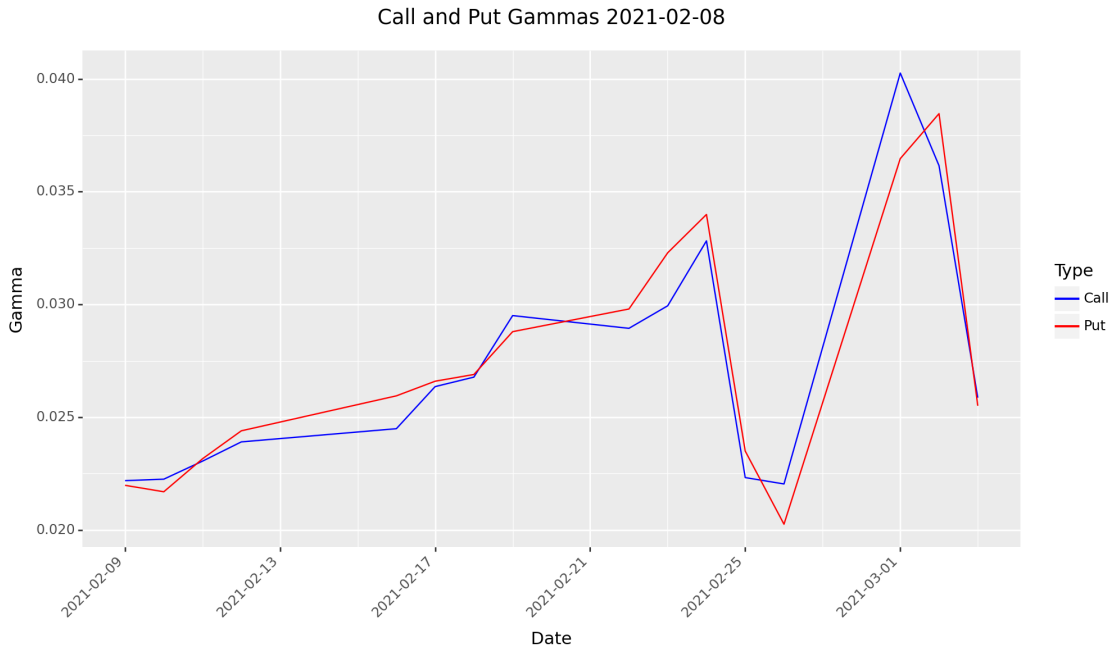
The graphs below show how Call and Put Gammas may change while we hold them. If the price of the underlying remains constant, the Gamma value will increase; if the price of the underlying decreases, the Gamma value will decrease. Our strategy hopes to identify times when Gamma will increase or decrease with a greater magnitude than the rest of the market assumes. If we anticipate more volatility in the underlying than the market does, we will go long Gamma. Conversely, if we anticipate less volatility than the market does, we will go short Gamma.

[11]:
```
p_g_1 = (ggplot(first_options, aes(x='date', y='gamma', color='Type')) +
           geom_line() +
           labs(title='Call and Put Gammas 2018-03-06', x='Date', y='Gamma',␣
 ↪color='Type') +
           theme(axis_text_x=element_text(rotation=45, hjust=1),
                 figure_size=(10, 6),
                 plot_title=element_text(ha='center')) +
           scale_color_manual(values={"Call": "blue", "Put": "red"}))
p_g_1
```



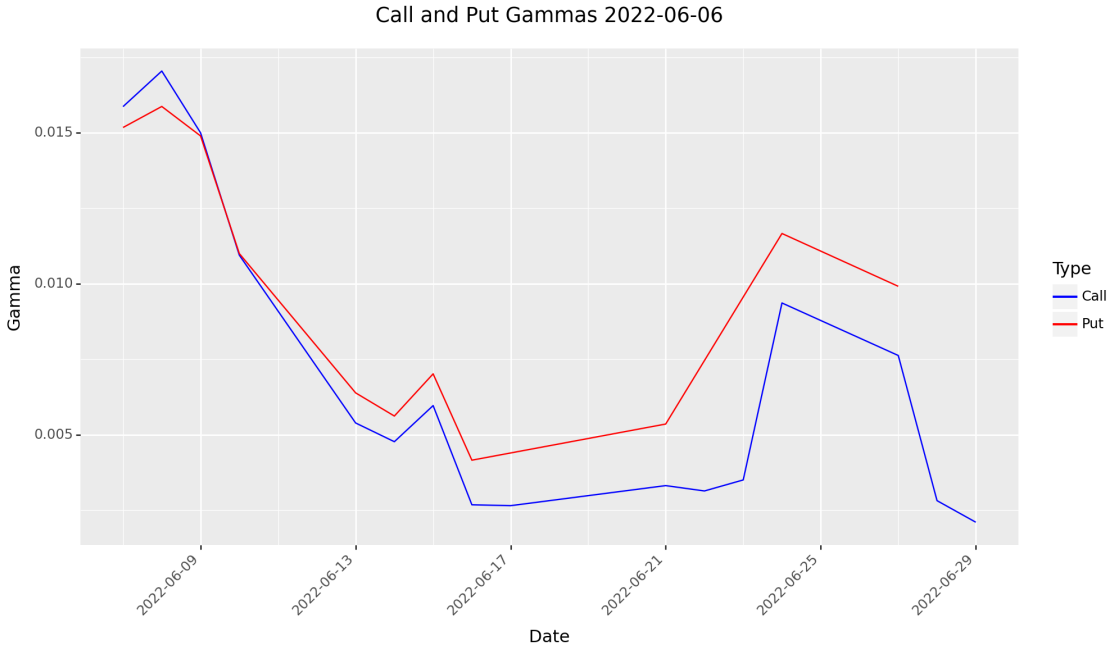
[11]: <Figure Size: (1000 x 600)>

[12]:
```
p_g_2 = (ggplot(middle_options, aes(x='date', y='gamma', color='Type')) +
           geom_line() +
           labs(title='Call and Put Gammas 2021-02-08', x='Date', y='Gamma',␣
 ↪color='Type') +
           theme(axis_text_x=element_text(rotation=45, hjust=1),
                 figure_size=(10, 6),
                 plot_title=element_text(ha='center')) +
           scale_color_manual(values={"Call": "blue", "Put": "red"}))
p_g_2
```



[12]: <Figure Size: (1000 x 600)>

[13]:
```
p_g_3 = (ggplot(last_options, aes(x='date', y='gamma', color='Type')) +
           geom_line() +
           labs(title='Call and Put Gammas 2022-06-06', x='Date', y='Gamma',␣
 ↪color='Type') +
           theme(axis_text_x=element_text(rotation=45, hjust=1),
                 figure_size=(10, 6),
                 plot_title=element_text(ha='center')) +
           scale_color_manual(values={"Call": "blue", "Put": "red"}))
p_g_3
```



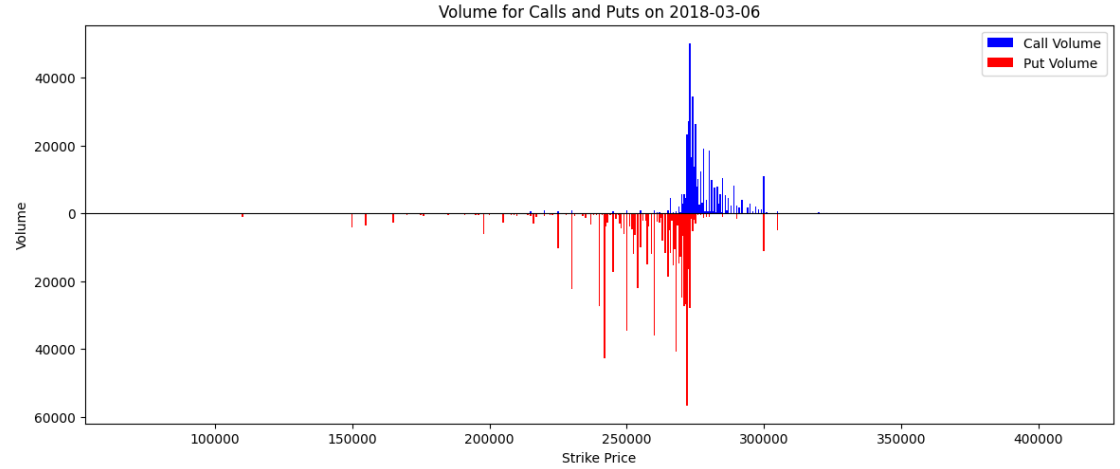
[13]: <Figure Size: (1000 x 600)>

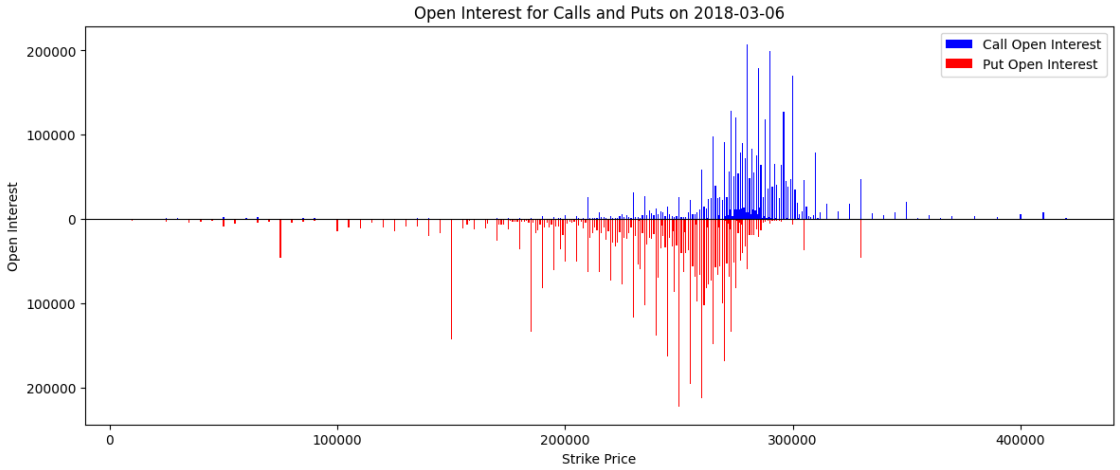
1.7.3 Volume and Open Interest for Individual Days

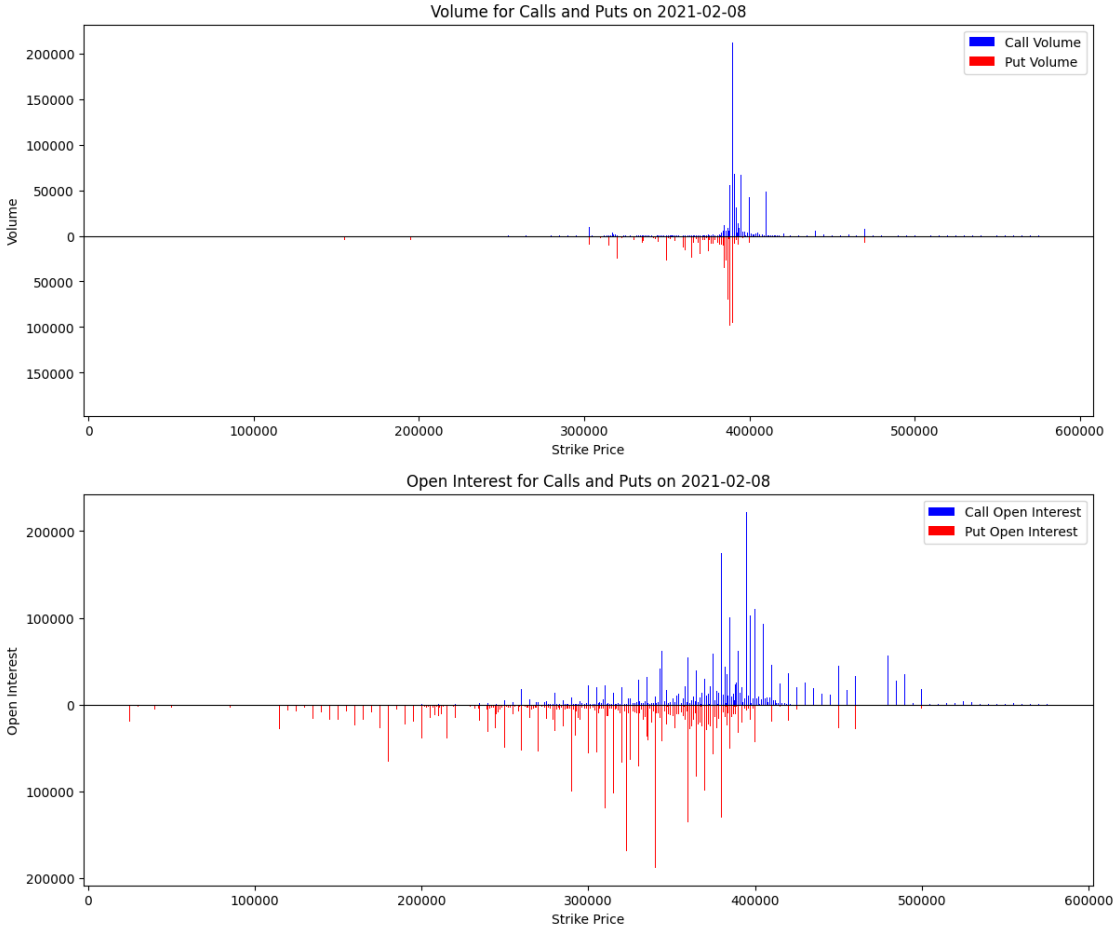
We can also visualize the volume and open interest for various strikes on single days - for consistency, we can take a look at the same few days we visualized above.

[2]:
```
data = pd.read_csv("option_data.csv")

data['date'] = pd.to_datetime(data['date'])

specific_dates = ['2018-03-06', '2021-02-08', '2022-06-06']

for specific_date in specific_dates:
    data_on_specific_date = data[data['date'] == specific_date]

    calls = data_on_specific_date[data_on_specific_date['cp_flag'] == 'C']
    puts = data_on_specific_date[data_on_specific_date['cp_flag'] == 'P']

    puts_volume = puts.copy()
    puts_oi = puts.copy()
    puts_volume['volume'] = -puts_volume['volume']
    puts_oi['open_interest'] = -puts_oi['open_interest']

    combined_volume = pd.concat([calls, puts_volume]).
↪sort_values(by='strike_price')
```

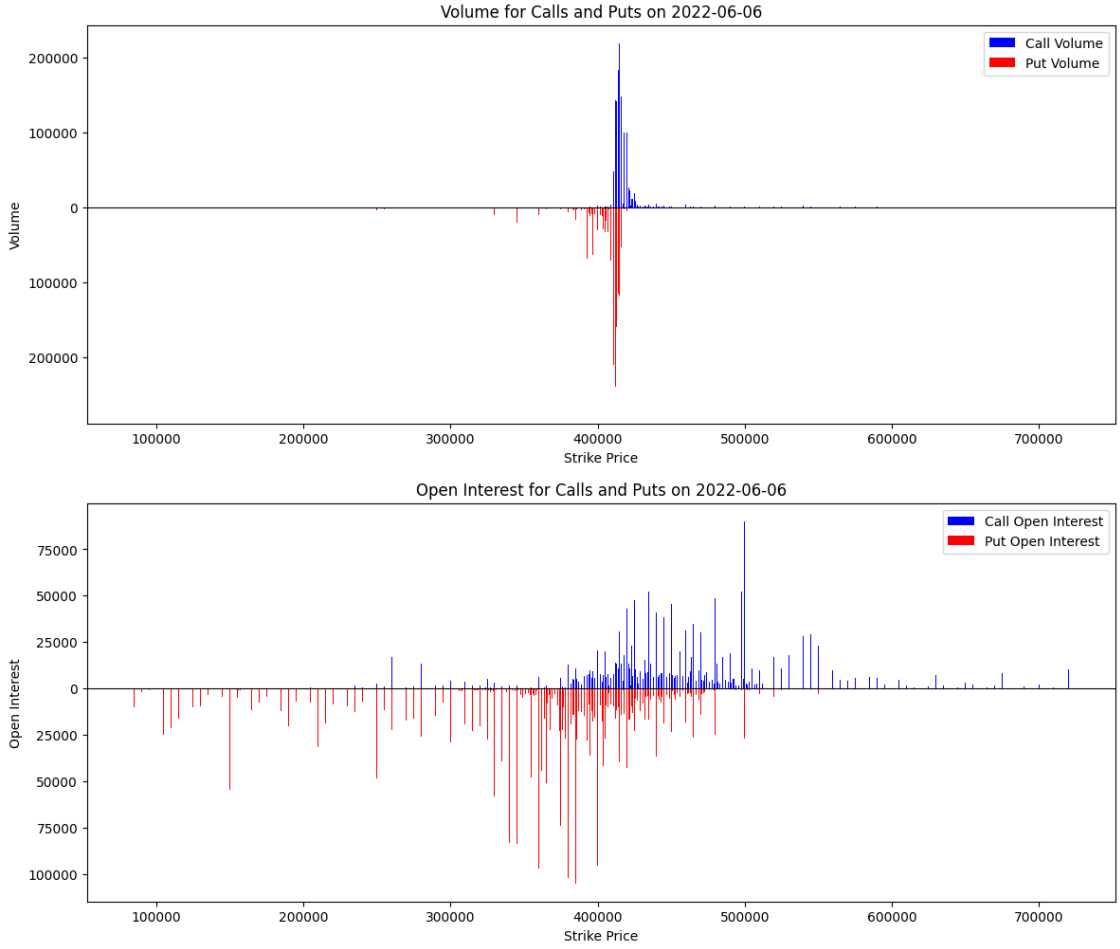
```
    combined_oi = pd.concat([calls, puts_oi]).sort_values(by='strike_price')

    fig, axs = plt.subplots(2, 1, figsize=(14, 12))

    axs[0].bar(combined_volume['strike_price'][combined_volume['volume'] > 0],␣
↪combined_volume['volume'][combined_volume['volume'] > 0], color='blue',␣
↪width=500, label='Call Volume')
    axs[0].bar(combined_volume['strike_price'][combined_volume['volume'] < 0],␣
↪combined_volume['volume'][combined_volume['volume'] < 0], color='red',␣
↪width=500, label='Put Volume')
    axs[0].set_title(f'Volume for Calls and Puts on {specific_date}')
    axs[0].set_xlabel('Strike Price')
    axs[0].set_ylabel('Volume')
    axs[0].axhline(0, color='black', linewidth=0.8)
    axs[0].get_yaxis().set_major_formatter(plt.FuncFormatter(lambda x, _:␣
↪int(abs(x))))
    axs[0].legend()

    axs[1].bar(combined_oi['strike_price'][combined_oi['open_interest'] > 0],␣
↪combined_oi['open_interest'][combined_oi['open_interest'] > 0],␣
↪color='blue', width=500, label='Call Open Interest')
    axs[1].bar(combined_oi['strike_price'][combined_oi['open_interest'] < 0],␣
↪combined_oi['open_interest'][combined_oi['open_interest'] < 0], color='red',␣
↪width=500, label='Put Open Interest')
    axs[1].set_title(f'Open Interest for Calls and Puts on {specific_date}')
    axs[1].set_xlabel('Strike Price')
    axs[1].set_ylabel('Open Interest')
    axs[1].axhline(0, color='black', linewidth=0.8)
    axs[1].get_yaxis().set_major_formatter(plt.FuncFormatter(lambda x, _:␣
↪int(abs(x))))
    axs[1].legend()
```


Volume for Calls and Puts on 2018-03-06
Call Volume
Put Volume
Volume
40000
20000
0
20000
40000
60000
100000
150000
200000
250000
300000
350000
400000
Strike Price


Open Interest for Calls and Puts on 2018-03-06
Call Open Interest
Put Open Interest
Open Interest
200000
100000
0
100000
200000
0
100000
200000
300000
400000
Strike Price


Volume for Calls and Puts on 2021-02-08
Call Volume
Put Volume
Volume
200000
150000
100000
50000
0
50000
100000
150000
0
100000
200000
300000
400000
500000
600000
Strike Price

Open Interest for Calls and Puts on 2021-02-08
Call Open Interest
Put Open Interest
Open Interest
200000
100000
0
100000
200000
0
100000
200000
300000
400000
500000
600000
Strike Price



The plots above show the volume and open interest quantities for both calls and puts for three different dates throughout the five-year time period. We first observed that the volume quantity for our chosen date in 2018 was nearly 1/5th the quantities observed in the chosen 2021 and 2022 dates near the middle and end of the time span. Individually this does not say too much other than noting that different days will have different distributions, but can provide, considering the other graphs, some additional context for different time perioids. Additionally, as consistently observed for all 3 dates, quantites for volume and open interest for calls are right-skewed while quantities for volume and open interest for puts are left-skewed, ie. there are certain moves far out of the money. Additionally, the open interest values were more spread out than those for volume. Moreover, volume and open interest quantities are heavily concentrated at-the-money while the tails are heavily spread out towards out-of-the-money.

1.8 6. Further Data Manipulations and Logic for Simulating All Individual Contracts

As part of the outlined strategy, we'll be simulating the strategy and also considering using a calculation of IV found in a paper to open trades relative to the gamma.

1.8.1 Further data restructuring

This uses the previous checkpoint to load the data. For the final version, we will clean up the variables to consistently use a single variable. For now, we'll allow different variables.

[2]:
```
csv_file_path = 'combinedata.csv'
data = pd.read_csv(csv_file_path)
calls_df = pd.read_csv('calls.csv')
puts_df = pd.read_csv('puts.csv')
```

[3]:
```
calls_df, puts_df = preprocess_options_data(calls_df, puts_df)
```

To make our analysis easier, we'll merge the dataframes from puts and calls on the same strike for the days that we may potentially open positions at (ie. every day with data filled for the next holding period for that contract).

We'll check that they match, of course.

[4]:
```
dates_strike_prices_dont_match = compare_strike_prices(calls_df, puts_df)
print(dates_strike_prices_dont_match)
```

```
Series([], Name: date, dtype: datetime64[ns])
```

[5]:
```
dates_data_dont_match = compare_strike_prices_and_exdates(calls_df, puts_df)
print(dates_data_dont_match)
```

```
Series([], Name: date, dtype: datetime64[ns])
```

Now merge,

[6]:
```
calls_df.rename(columns={
    'close_x': 'close',
    'adj_open_x': 'adj_open',
    'adj_close_x': 'adj_close',
    'adj_volume_x': 'adj_volume',
    'TTE_x': 'TTE',
    'last_date_x': 'last_date_c',
    'best_bid_x': 'best_bid_c',
    'best_offer_x': 'best_offer_c',
    'volume_x': 'volume_c',
    'open_interest_x': 'open_interest_c',
    'impl_volatility_x': 'impl_volatility_c',
    'delta_x': 'delta_c',
    'gamma_x': 'gamma_c',
    'vega_x': 'vega_c',
    'theta_x': 'theta_c',
    'expiry_indicator_x': 'expiry_indicator_c',
    'is_present': 'is_present_c'
}, inplace=True)
```

```
calls_df = calls_df[['date', 'exdate', 'strike_price', 'close_date', 'close',␣
 ↪'adj_open', 'adj_close', 'adj_volume', 'TTE', 'last_date_c', 'best_bid_c',␣
 ↪'best_offer_c', 'volume_c', 'open_interest_c', 'impl_volatility_c',␣
 ↪'delta_c', 'gamma_c', 'vega_c', 'theta_c', 'expiry_indicator_c',␣
 ↪'is_present_c']]
```

[7]:
```
puts_df.rename(columns={
    'last_date_x': 'last_date_p',
    'best_bid_x': 'best_bid_p',
    'best_offer_x': 'best_offer_p',
    'volume_x': 'volume_p',
    'open_interest_x': 'open_interest_p',
    'impl_volatility_x': 'impl_volatility_p',
    'delta_x': 'delta_p',
    'gamma_x': 'gamma_p',
    'vega_x': 'vega_p',
    'theta_x': 'theta_p',
    'expiry_indicator_x': 'expiry_indicator_p',
    'is_present': 'is_present_p'
}, inplace=True)

puts_df_selected = puts_df[['date', 'last_date_p', 'best_bid_p',␣
 ↪'best_offer_p', 'volume_p', 'open_interest_p', 'impl_volatility_p',␣
 ↪'delta_p', 'gamma_p', 'vega_p', 'theta_p', 'expiry_indicator_p',␣
 ↪'is_present_p']]
```

[8]:
```
option_df = pd.merge(calls_df, puts_df_selected, on='date', how='left')
display(option_df)
```

```
           date     exdate  strike_price  close_date   close    adj_open  \
0    2018-01-02 2018-01-31         269.0  2018-01-23  268.77  242.053393
1    2018-01-03 2018-02-02         270.0  2018-01-24  270.47  243.065564
2    2018-01-04 2018-02-02         272.0  2018-01-25  271.61  245.089905
3    2018-01-05 2018-02-02         273.0  2018-01-26  273.42  246.273783
4    2018-01-08 2018-02-07         275.0  2018-01-29  273.92  246.996762
…           …          …             …           …       …         …
1293 2023-02-22 2023-03-24         399.0  2023-02-28  398.54  393.496030
1294 2023-02-23 2023-03-24         401.0  2023-02-28  400.66  395.505271
1295 2023-02-24 2023-03-24         396.0  2023-02-28  396.38  389.457850
1296 2023-02-27 2023-03-31         398.0  2023-02-28  397.73  393.840753
1297 2023-02-28 2023-03-31         396.0  2023-02-28  396.26  391.240559

       adj_close   adj_volume  TTE last_date_c  …  best_offer_p  volume_p  \
0     242.893856   86655749.0   29  2018-01-02  …          2.10     198.0
1     244.430187   90070416.0   30  2018-01-03  …          1.80    1060.0
2     245.460432   80595402.0   29  2018-01-04  …          2.15     416.0
3     247.096172   83468662.0   28  2018-01-05  …          1.85     509.0
4     247.548034   57288979.0   30  2018-01-08  …          2.56      82.0
```

```
…          …          …  …          …  …            …        …
1293  392.530807   83574386.0   30  2023-02-22  …          9.71    2678.0
1294  394.618841   95842681.0   29  2023-02-23  …          8.86    1233.0
1295  390.403375  108144866.0   28  2023-02-24  …          8.84    3156.0
1296  391.733020   80318244.0   32  2023-02-27  …          9.26    1568.0
1297  390.285185   96141367.0   31  2023-02-28  …          8.17    1375.0

      open_interest_p  impl_volatility_p   delta_p   gamma_p    vega_p  \
0                33.0           0.069577 -0.496183  0.077797  30.11151
1               330.0           0.069568 -0.442522  0.074853  30.52431
2               304.0           0.068201 -0.508652  0.078707  30.40449
3               149.0           0.071740 -0.447556  0.074347  29.86764
4               269.0           0.067924 -0.560465  0.076891  30.79770
…                 …                  …       …       …       …
1293           1317.0           0.201626 -0.506205  0.017387  45.30915
1294           1566.0           0.186139 -0.507514  0.019064  44.77837
1295           1086.0           0.198990 -0.494048  0.018342  43.53449
1296           4088.0           0.188579 -0.505251  0.018253  46.60089
1297           6481.0           0.174174 -0.498412  0.020189  45.68817

       theta_p  expiry_indicator_p is_present_p
0    -11.46749                   w         True
1    -11.33461                   w         True
2    -11.28616                   w         True
3    -12.34094                   w         True
4    -10.80407                   w         True
…        …                   …           …
1293 -47.38424                   w         True
1294 -44.24160                   w         True
1295 -48.60954                   w         True
1296 -42.60824                   m         True
1297 -39.53407                   m         True

[1298 rows x 33 columns]
```

Creating a new dataframe where start dates with missing values are removed, according to our initial analysis.

[9]:
```
option_df1 = option_df[(option_df['is_present_c'] == True) &␣
 ↪(option_df['is_present_p'] == True)]
display(option_df1)
```

```
          date     exdate  strike_price  close_date   close    adj_open  \
0   2018-01-02 2018-01-31         269.0  2018-01-23  268.77  242.053393
1   2018-01-03 2018-02-02         270.0  2018-01-24  270.47  243.065564
2   2018-01-04 2018-02-02         272.0  2018-01-25  271.61  245.089905
4   2018-01-08 2018-02-07         275.0  2018-01-29  273.92  246.996762
5   2018-01-09 2018-02-07         275.0  2018-01-30  274.54  247.981821
```

```
…          …          …              …           …      …          …
1293 2023-02-22 2023-03-24         399.0  2023-02-28  398.54  393.496030
1294 2023-02-23 2023-03-24         401.0  2023-02-28  400.66  395.505271
1295 2023-02-24 2023-03-24         396.0  2023-02-28  396.38  389.457850
1296 2023-02-27 2023-03-31         398.0  2023-02-28  397.73  393.840753
1297 2023-02-28 2023-03-31         396.0  2023-02-28  396.26  391.240559

       adj_close   adj_volume  TTE last_date_c  …  best_offer_p  volume_p  \
0     242.893856   86655749.0   29  2018-01-02  …          2.10     198.0
1     244.430187   90070416.0   30  2018-01-03  …          1.80    1060.0
2     245.460432   80595402.0   29  2018-01-04  …          2.15     416.0
4     247.548034   57288979.0   30  2018-01-08  …          2.56      82.0
5     248.108343   57253957.0   29  2018-01-09  …          2.47     453.0
…           …          …  …          …  …             …        …
1293  392.530807   83574386.0   30  2023-02-22  …          9.71    2678.0
1294  394.618841   95842681.0   29  2023-02-23  …          8.86    1233.0
1295  390.403375  108144866.0   28  2023-02-24  …          8.84    3156.0
1296  391.733020   80318244.0   32  2023-02-27  …          9.26    1568.0
1297  390.285185   96141367.0   31  2023-02-28  …          8.17    1375.0

      open_interest_p  impl_volatility_p   delta_p   gamma_p    vega_p  \
0                33.0           0.069577 -0.496183  0.077797  30.11151
1               330.0           0.069568 -0.442522  0.074853  30.52431
2               304.0           0.068201 -0.508652  0.078707  30.40449
4               269.0           0.067924 -0.560465  0.076891  30.79770
5               229.0           0.076654 -0.510832  0.069026  30.74049
…                 …                …         …         …       …
1293           1317.0           0.201626 -0.506205  0.017387  45.30915
1294           1566.0           0.186139 -0.507514  0.019064  44.77837
1295           1086.0           0.198990 -0.494048  0.018342  43.53449
1296           4088.0           0.188579 -0.505251  0.018253  46.60089
1297           6481.0           0.174174 -0.498412  0.020189  45.68817

       theta_p  expiry_indicator_p is_present_p
0    -11.46749                   w         True
1    -11.33461                   w         True
2    -11.28616                   w         True
4    -10.80407                   w         True
5    -12.99855                   w         True
…          …                   …           …
1293 -47.38424                   w         True
1294 -44.24160                   w         True
1295 -48.60954                   w         True
1296 -42.60824                   m         True
1297 -39.53407                   m         True

[1140 rows x 33 columns]
```

Creating a checkpoint,

[10]:
```
option_df1.to_csv('option_df.csv', index=False)
```

1.8.2 Simulating Individual Contracts and Hedging

In the final version, we will simulate this later on - however, this section explains the simulation process for each individual possible contract position.

`source.py` contains the original code to implement this, as `create_simulations_original` and calculates metrics as `calculate_realized_PL`. We have updated these metrics in the full strategy section; however, these simulations can still be run and saved (and returned to) via the appendix.

This is another checkpoint. If the data has been run until this point, we can directly run from this point. This section simulates ALL possible contracts that we may open and trade/balance, individually. This way we can save them as an intermediate or retrieve them, mapping them onto a single timeline when we evaluate which positions will be opened at which time using various strategies later on. Because each individual simulation will NOT change depending on which we open, we can simulate each individual contract's progress ahead of time. Then, when we map depending on where we decide to open positions, we get the sum progression of our strategy.

[115]:
```
data = pd.read_csv('combinedata.csv')
options = pd.read_csv('option_df.csv')
```

Pseudocode format for mass simulation of individual date-strike rebalance. Essentially, we will: 1. Pull in `calls_df` and `puts_df` 2. For dates in both dataframes where is_present is true for both, perform additional analysis 3. Align calls/puts on that day, specify the contract 4. For the contract in the main dataframe, find the period of info until the end date, inclusive, for that strike, contract, and expiry 5. For each day, calculate the delta sum as the sum of the call delta and put delta 6. Based on this, calculate how many shares we must hold on that day (+ or -) and use this to calculate our share movement daily 7. Calculate the share price times shares as stock position value 8. Calculate PL of day-to-day as change in shares times diff in share price 9. Calculate current available closing price of the option straddle, which will also be used to add to the total PL with open positions (ie. price based on the closest book level, should we choose to close the position) 10. On the end date, close ALL positions

We will save each dataframe as an item in a variable () then store it under a same-directory data folder, naming each simulation after the date it was opened and whether we were long or short gamma. The function call to do this is in the appendix.

[ ]:
```
data['exdate'] = pd.to_datetime(data['exdate'])
options['exdate'] = pd.to_datetime(options['exdate'])

data['exdate_str'] = data['exdate'].dt.strftime('%Y%m%d')
data['strikeID'] = data['exdate_str'] + '_' + data['strike_price'].astype(str)
data.drop(columns=['exdate_str'], inplace=True)

options['exdate_str'] = options['exdate'].dt.strftime('%Y%m%d')
options['strikeID'] = options['exdate_str'] + '_' + options['strike_price'].
 ↪astype(str)
```

```
options.drop(columns=['exdate_str'], inplace=True)
```

[119]:
```
options['date'] = pd.to_datetime(options['date'])
data['date'] = pd.to_datetime(data['date'])
```

Simulate a small subset, just to show what we expect; note that this simulates with a single option contract (for one share, 1:1). We go into much more detail later with our modified simulation, but this outlines the method used to get our results.

[120]:
```
options_subset = options.head(2)
simulations1 = create_simulations_original(options_subset, data,␣
 ↪dropna_greeks=True)
```

[ ]:
```
for date, df in simulations1.items():
    simulations1[date] = calculate_realized_PL(df, long_op=True)
```

[ ]:
```
for key, df in list(simulations1.items())[:2]:
    print(f"DataFrame for {key}:")
    print(df.columns)
    display(df)
    print("\n")
```

```
DataFrame for 2018-01-02:
Index(['date', 'exdate', 'strike_price', 'expiry_indicator', 'close',
       'adj_open', 'adj_close', 'adj_volume', 'strikeID', 'cp_flag_c',
       'best_bid_c', 'best_offer_c', 'volume_c', 'open_interest_c',
       'impl_volatility_c', 'delta_c', 'gamma_c', 'vega_c', 'theta_c',
       'cp_flag_p', 'best_bid_p', 'best_offer_p', 'volume_p',
       'open_interest_p', 'impl_volatility_p', 'delta_p', 'gamma_p', 'vega_p',
       'theta_p', 'delta_sum', 'shares_held', 'sharechange', 'stock_pos',
       'avg_cost', 'realized_PL', 'option_PL', 'stock_PL'],
      dtype='object')
```

	date	exdate	strike_price	expiry_indicator	close	adj_open	\
0	2018-01-02	2018-01-31	269.0	w	268.77	242.053393	
1	2018-01-03	2018-01-31	269.0	w	270.47	243.065564	
2	2018-01-04	2018-01-31	269.0	w	271.61	245.089905	
3	2018-01-05	2018-01-31	269.0	w	273.42	246.273783	
4	2018-01-08	2018-01-31	269.0	w	273.92	246.996762	
5	2018-01-09	2018-01-31	269.0	w	274.54	247.981821	
6	2018-01-10	2018-01-31	269.0	w	274.12	247.331140	
7	2018-01-11	2018-01-31	269.0	w	276.12	248.298125	
8	2018-01-12	2018-01-31	269.0	w	277.92	249.807344	
9	2018-01-16	2018-01-31	269.0	w	276.97	252.455254	
10	2018-01-17	2018-01-31	269.0	w	279.61	251.262339	
11	2018-01-18	2018-01-31	269.0	w	279.14	252.572738	
12	2018-01-19	2018-01-31	269.0	w	280.41	252.861930	
13	2018-01-23	2018-01-31	269.0	w	283.29	255.518878	

	adj_close	adj_volume	strikeID	cp_flag_c	…	vega_p	\
0	242.893856	86655749.0	20180131_269.0	C	…	30.111510	
1	244.430187	90070416.0	20180131_269.0	C	…	28.250190	
2	245.460432	80595402.0	20180131_269.0	C	…	25.781000	
3	247.096172	83468662.0	20180131_269.0	C	…	21.481350	
4	247.548034	57288979.0	20180131_269.0	C	…	18.362690	
5	248.108343	57253957.0	20180131_269.0	C	…	17.498160	
6	247.728779	69499524.0	20180131_269.0	C	…	17.468620	
7	249.536226	62306557.0	20180131_269.0	C	…	13.118760	
8	251.162929	90789911.0	20180131_269.0	C	…	10.328780	
9	250.304392	106555142.0	20180131_269.0	C	…	11.123210	
10	252.690223	113201396.0	20180131_269.0	C	…	7.665309	
11	252.265472	100682250.0	20180131_269.0	C	…	8.089207	
12	253.413202	140895374.0	20180131_269.0	C	…	5.106381	
13	256.015926	97084700.0	20180131_269.0	C	…	2.290031	

	theta_p	delta_sum	shares_held	sharechange	stock_pos	avg_cost	\
0	-11.467490	0.015848	-0.015848	NaN	-0.015848	268.770000	
1	-11.921280	0.259359	-0.259359	-0.243511	-0.259359	270.366122	
2	-12.327160	0.391860	-0.391860	-0.132501	-0.391860	270.786719	
3	-11.877760	0.560376	-0.560376	-0.168516	-0.560376	271.578598	
4	-11.728420	0.613018	-0.613018	-0.052642	-0.613018	271.779662	
5	-13.020330	0.646666	-0.646666	-0.033648	-0.646666	271.923291	
6	-13.232750	0.626662	-0.626662	0.020004	-0.626662	271.923291	
7	-11.482330	0.780802	-0.780802	-0.154140	-0.780802	272.751774	
8	-10.552090	0.840416	-0.840416	-0.059614	-0.840416	273.118376	
9	-16.564950	0.747087	-0.747087	0.093329	-0.747087	273.118376	
10	-13.657280	0.866499	-0.866499	-0.119412	-0.866499	274.012985	
11	-16.159490	0.815875	-0.815875	0.050624	-0.815875	274.012985	
12	-10.722630	0.916563	-0.916563	-0.100688	-0.916563	274.715722	
13	-9.210225	0.921621	-0.921621	-0.005058	0.000000	274.762779	

	realized_PL	option_PL	stock_PL
0	0.000000	-0.10	0.000000
1	0.000000	0.32	-0.026942
2	0.000000	0.90	-0.322611
3	0.000000	2.00	-1.031877
4	0.000000	2.19	-1.312065
5	0.000000	2.67	-1.692137
6	-0.043943	2.29	-1.420537
7	0.000000	3.68	-2.673861
8	0.000000	5.29	-4.035362
9	-0.359468	4.73	-3.236966
10	0.000000	6.84	-5.209276
11	-0.259550	6.63	-4.442553
12	0.000000	7.41	-5.478715
13	-7.858866	10.33	-7.858866

```
[14 rows x 37 columns]


DataFrame for 2018-01-03:
Index(['date', 'exdate', 'strike_price', 'expiry_indicator', 'close',
       'adj_open', 'adj_close', 'adj_volume', 'strikeID', 'cp_flag_c',
       'best_bid_c', 'best_offer_c', 'volume_c', 'open_interest_c',
       'impl_volatility_c', 'delta_c', 'gamma_c', 'vega_c', 'theta_c',
       'cp_flag_p', 'best_bid_p', 'best_offer_p', 'volume_p',
       'open_interest_p', 'impl_volatility_p', 'delta_p', 'gamma_p', 'vega_p',
       'theta_p', 'delta_sum', 'shares_held', 'sharechange', 'stock_pos',
       'avg_cost', 'realized_PL', 'option_PL', 'stock_PL'],
      dtype='object')
```

	date	exdate	strike_price	expiry_indicator	close	adj_open	\
0	2018-01-03	2018-02-02	270.0	w	270.47	243.065564	
1	2018-01-04	2018-02-02	270.0	w	271.61	245.089905	
2	2018-01-05	2018-02-02	270.0	w	273.42	246.273783	
3	2018-01-08	2018-02-02	270.0	w	273.92	246.996762	
4	2018-01-09	2018-02-02	270.0	w	274.54	247.981821	
5	2018-01-10	2018-02-02	270.0	w	274.12	247.331140	
6	2018-01-11	2018-02-02	270.0	w	276.12	248.298125	
7	2018-01-12	2018-02-02	270.0	w	277.92	249.807344	
8	2018-01-16	2018-02-02	270.0	w	276.97	252.455254	
9	2018-01-17	2018-02-02	270.0	w	279.61	251.262339	
10	2018-01-18	2018-02-02	270.0	w	279.14	252.572738	
11	2018-01-19	2018-02-02	270.0	w	280.41	252.861930	
12	2018-01-22	2018-02-02	270.0	w	282.69	253.196308	
13	2018-01-23	2018-02-02	270.0	w	283.29	255.518878	
14	2018-01-24	2018-02-02	270.0	w	283.18	256.675645	

	adj_close	adj_volume	strikeID	cp_flag_c	…	vega_p	\
0	244.430187	90070416.0	20180202_270.0	C	…	30.524310	
1	245.460432	80595402.0	20180202_270.0	C	…	28.778260	
2	247.096172	83468662.0	20180202_270.0	C	…	25.017800	
3	247.548034	57288979.0	20180202_270.0	C	…	22.018190	
4	248.108343	57253957.0	20180202_270.0	C	…	21.022120	
5	247.728779	69499524.0	20180202_270.0	C	…	21.179100	
6	249.536226	62306557.0	20180202_270.0	C	…	16.636580	
7	251.162929	90789911.0	20180202_270.0	C	…	13.466870	
8	250.304392	106555142.0	20180202_270.0	C	…	14.348100	
9	252.690223	113201396.0	20180202_270.0	C	…	10.380940	
10	252.265472	100682250.0	20180202_270.0	C	…	10.897700	
11	253.413202	140895374.0	20180202_270.0	C	…	7.613017	
12	255.473692	91322408.0	20180202_270.0	C	…	4.818615	
13	256.015926	97084700.0	20180202_270.0	C	…	3.783040	
14	255.916517	134816117.0	20180202_270.0	C	…	3.228602	

```
     theta_p  delta_sum  shares_held  sharechange  stock_pos    avg_cost  \
0  -11.33461   0.119696    -0.119696          NaN  -0.119696  270.470000
1  -12.15496   0.265768    -0.265768    -0.146072  -0.265768  271.096569
2  -12.28042   0.457539    -0.457539    -0.191771  -0.457539  272.070402
3  -12.28724   0.514544    -0.514544    -0.057005  -0.514544  272.275315
4  -13.72542   0.549888    -0.549888    -0.035344  -0.549888  272.420877
5  -14.17493   0.523363    -0.523363     0.026525  -0.523363  272.420877
6  -12.78389   0.692574    -0.692574    -0.169211  -0.692574  273.324654
7  -12.09646   0.768158    -0.768158    -0.075584  -0.768158  273.776819
8  -18.15760   0.670163    -0.670163     0.097995  -0.670163  273.776819
9  -15.57961   0.802791    -0.802791    -0.132628  -0.802791  274.740511
10 -18.16232   0.753469    -0.753469     0.049322  -0.753469  274.740511
11 -13.19071   0.854576    -0.854576    -0.101107  -0.854576  275.411282
12 -12.65994   0.921580    -0.921580    -0.067004  -0.921580  275.940486
13 -11.24559   0.891718    -0.891718     0.029862  -0.891718  275.940486
14 -10.78056   0.898643    -0.898643    -0.006925   0.000000  275.996274

    realized_PL  option_PL  stock_PL
0      0.000000      -0.07  0.000000
1      0.000000       0.39 -0.136453
2      0.000000       1.33 -0.617494
3      0.000000       1.49 -0.846263
4      0.000000       2.01 -1.165280
5     -0.045069       1.63 -0.934327
6      0.000000       2.83 -1.981053
7      0.000000       4.39 -3.182617
8     -0.312916       3.93 -2.452867
9      0.000000       5.92 -4.222098
10    -0.216992       5.76 -3.531870
11     0.000000       6.47 -4.488776
12     0.000000       8.47 -6.220217
13    -0.219471       9.25 -6.773165
14    -6.455605       9.08 -6.455605

[15 rows x 37 columns]
```

1.9 7. Calculate model-free IV to compare with IV given in data

As per [Jiang et al.] we calculate IV in a model-free way, to experiment with how using the model-free IV to open positions compares against taking a long or short gamma position through this period.

We've downloaded some additional data, with which to calculate an output `iv_calculations.csv`, and for this we require t-bill data.

[2]:
```
tbills = load_and_transform_tbills('tbill_data.csv')
```

Finding the calls and puts we calculated earlier, to implement the model-free IV.

[3]:
```
calls = load_and_transform_calls('calls.csv')
puts = load_and_transform_puts('puts.csv')
option_data = load_and_transform_option_data('option_data.csv')
```

We also perform some small manipulations - we will use the option midprices, and find days to expiry based on the expiry date.

[4]:
```
option_data
```

[4]:

	date	exdate	last_date	cp_flag	strike_price	best_bid	best_offer	volume	open_interest	impl_volatility	delta	gamma	vega	theta	expiry_indicator	midpt	dte
0	2018-01-02	2018-01-03	2017-12-28	C	235000.0	33.59	33.81	0.0	187.0	NaN	NaN	NaN	NaN	NaN	w	33.700	1
1	2018-01-02	2018-01-03	2018-01-02	C	240000.0	28.59	28.76	1.0	88.0	NaN	NaN	NaN	NaN	NaN	w	28.675	1
2	2018-01-02	2018-01-03	2017-12-27	C	242500.0	26.09	26.32	0.0	2.0	NaN	NaN	NaN	NaN	NaN	w	26.205	1
3	2018-01-02	2018-01-03	2018-01-02	C	245000.0	23.59	23.81	12.0	58.0	NaN	NaN	NaN	NaN	NaN	w	23.700	1
4	2018-01-02	2018-01-03	NaN	C	247500.0	21.08	21.32	0.0	0.0	NaN	NaN	NaN	NaN	NaN	w	21.200	1
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
10448189	2023-02-28	2025-03-21	2022-12-28	P	600000.0	200.50	205.50	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	203.000	752
10448190	2023-02-28	2025-03-21	NaN	P	605000.0	205.50	210.50	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	208.000	752
10448191	2023-02-28	2025-03-21	NaN	P	610000.0	210.00	215.00	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	212.500	752
10448192	2023-02-28	2025-03-21	NaN	P	615000.0	215.00	220.00	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN	217.500	752
10448193	2023-02-28	2025-03-21	NaN	P	620000.0	220.00	225.00	0.0	0.0	NaN	NaN	NaN	NaN	NaN	NaN		

```
10448193   NaN    NaN              NaN  222.500  752

[10448194 rows x 17 columns]
```

Reading in SPY daily data.

[5]:
```
spydata = pd.read_csv('spy_tickerdata.csv')
spydata['date'] = pd.to_datetime(spydata['date'])
```

And now, we calculate the model-free IV, according to the formula first presented in the introduction:

$$\sum_{i=1}^{m} \left[g(T, K_i) + g(T, K_{i-1}) \right] \Delta K$$

Where m is the number of tradable strike prices, $\Delta K = \frac{K_{\max} - K_{\min}}{m}$, $K_i = K_{\min} + i\Delta K$, and $g(T, K_i) = \frac{C^F(T, K_i) - \max(0, F_0 - K_i)}{K_i^2}$.

We also wrote a function `calc_s0`, which calculates the discounted price of the underlying SPY by subtracting the present value of any dividends that will be disbursed before the option expires.

Below we calculate model-free implied volatility for each day in our analysis period. We filter our options that are trading at less than \$0.375, and options that are in the money. We define 'in-the-money' as call options with a strike price less than 97% of the spot price of the underlying. We filter out these options because the paper suggested to do this, as their volatilites behave differently than normal for various reasons.

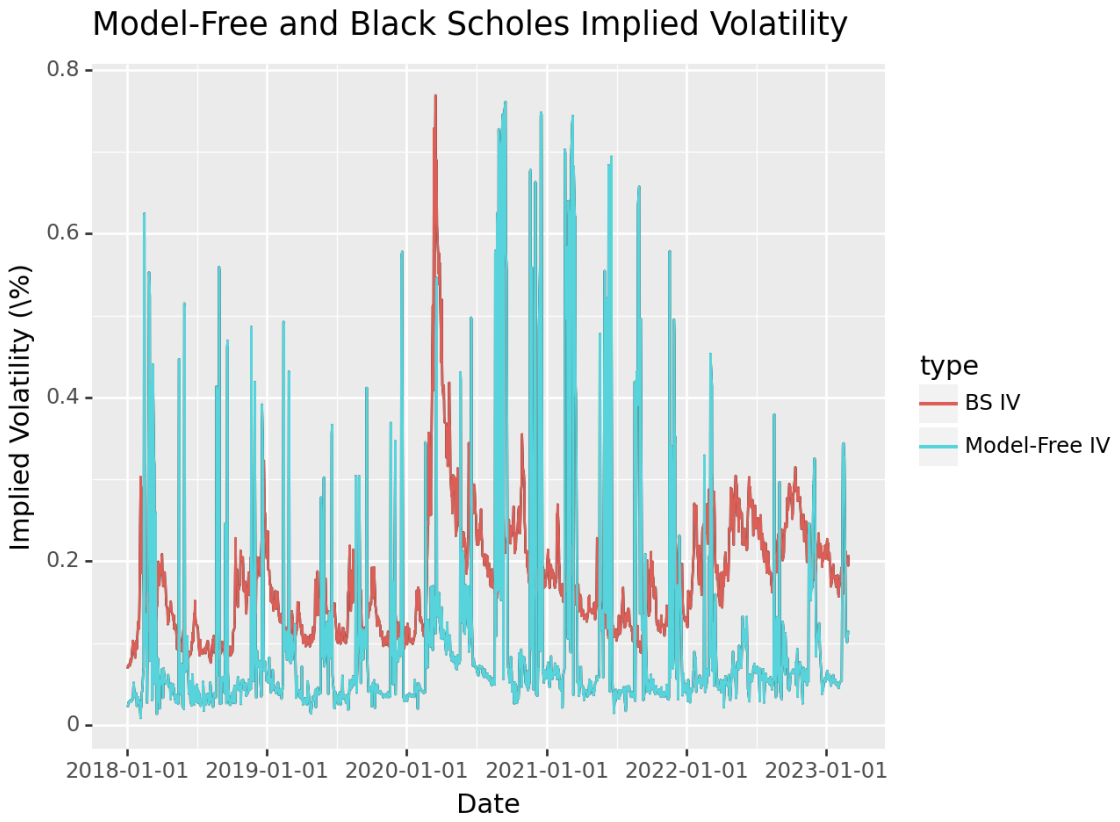
[6]:
```
our_ivs, sizes = calculate_iv_for_calls(calls, option_data, tbills, spydata)
```

Next, we cleaned the results and plotted our findings against the Black-Scholes Implied volatility values for the analysis period.

[7]:
```
our_ivs = our_ivs.reset_index().rename(columns = {'index':'date'})
our_ivs['BS'] = calls['impl_volatility_x']
our_ivs['iv'] = our_ivs['iv']**(0.5)
```

[8]:
```
plotting_df = our_ivs.melt('date')

plotting_df = plotting_df.rename(columns = {'variable':'type', 'value':'IV'})

mapper = {'iv':'Model-Free IV', 'BS':'BS IV'}
plotting_df['type'] = plotting_df['type'].map(mapper)
```

[9]:
```
ggplot(plotting_df, aes(x ='date', y = 'IV', group = 'type')) +  \
       geom_line()  +  \
       labs(x = 'Date', y = 'Implied Volatility (\%)')  +  \
       ggtitle('Model-Free and Black Scholes Implied Volatility')  +  \
       geom_line(aes(color = 'type'))
```



[9]: <Figure Size: (640 x 480)>

Our hardware is generally lacking, so we save a checkpoint:

[10]:
```
our_ivs.to_csv('iv_calculations.csv')
```

1.10 8. STRATEGY SIMULATION

Now we have our IV, we can implement our strategy, which assesses whether we open positions depending on the model-free IV, and sizing positions according to market volume. Note we simulate several additional considerations: * SPY dividends * Costs of borrowing, with initial capital set to \$1MM and borrowing limit set to \$9MM * Long-short, long only, and short only positions * Cash available to trade * Costs of shorting * Interest from holding cash * Costs associated with trading/crossing the book * Percentage trading fees

1.10.1 Dividends

We will need dividends for SPY, which will need to be factored into our strategy depending on the amount of SPY we hold at the ex-dividend date. However, as we are keeping track of cash flows, we will not receive the cash until the payment date, which is on the last trading day of the following month for SPY.

[3]:
```
spy_divdata, trading_days = process_spy_dividends('spy_tickerdata.csv',␣
↪'2018-01-01', '2023-02-28')
spy_divdata
```

[3]:

	date	dividend	pay_date
51	2018-03-16	1.096780	2018-04-30
114	2018-06-15	1.246000	2018-07-31
182	2018-09-21	1.323000	2018-10-31
245	2018-12-21	1.435400	2019-01-31
301	2019-03-15	1.233100	2019-04-30
369	2019-06-21	1.431600	2019-07-31
432	2019-09-20	1.383620	2019-10-31
496	2019-12-20	1.570000	2020-01-31
557	2020-03-20	1.405560	2020-04-30
620	2020-06-19	1.366200	2020-07-31
683	2020-09-18	1.339200	2020-10-30
747	2020-12-18	1.580000	2021-01-29
808	2021-03-19	1.277790	2021-04-30
871	2021-06-18	1.375870	2021-07-30
934	2021-09-17	1.428117	2021-10-29
998	2021-12-17	1.633485	2022-01-31
1060	2022-03-18	1.366009	2022-04-29
1123	2022-06-17	1.576871	2022-07-29
1185	2022-09-16	1.596000	2022-10-31
1249	2022-12-16	1.781000	2023-01-31

1.10.2 Simulations

This loads a new checkpoint to simulate the data from earlier checkpoints. We manipulate the data a bit first.

[4]:
```
data_file_path = 'combinedata.csv'
options_file_path = 'option_df.csv'
data, options = prepare_dataframes(data_file_path, options_file_path)
```

Let's simulate the ATM options we are going to be trading now:

[5]:
```
simulations = create_simulations(options, data, dropna_greeks=True)
```

[6]:
```
len(trading_days) - len(simulations) # Adds up to contracts with missing greeks
```

[6]: 158

This gets rid of simulations missing trading days (could occur due to various issues, mainly due to bad data):

[7]:
```
filtered_simulations = filter_simulations(simulations, trading_days)
```

[8]:
```
len(trading_days) - len(filtered_simulations)
```

[8]: 325

Now, again showing an example of the simulations.

[9]:
```
for key, df in list(filtered_simulations.items())[0:1]:
    print(f"DataFrame for {key}:")
    print(df.columns)
    display(df)
    print("\n")
```

```
DataFrame for 2018-01-03:
Index(['date', 'exdate', 'strike_price', 'close', 'strikeID', 'cp_flag_c',
       'best_bid_c', 'best_offer_c', 'impl_volatility_c', 'delta_c',
       'cp_flag_p', 'best_bid_p', 'best_offer_p', 'impl_volatility_p',
       'delta_p', 'delta_sum', 'shares_held', 'sharechange'],
      dtype='object')
```

	date	exdate	strike_price	close	strikeID	cp_flag_c	\
0	2018-01-03	2018-02-02	270.0	270.47	20180202_270.0	C	
1	2018-01-04	2018-02-02	270.0	271.61	20180202_270.0	C	
2	2018-01-05	2018-02-02	270.0	273.42	20180202_270.0	C	
3	2018-01-08	2018-02-02	270.0	273.92	20180202_270.0	C	
4	2018-01-09	2018-02-02	270.0	274.54	20180202_270.0	C	
5	2018-01-10	2018-02-02	270.0	274.12	20180202_270.0	C	
6	2018-01-11	2018-02-02	270.0	276.12	20180202_270.0	C	
7	2018-01-12	2018-02-02	270.0	277.92	20180202_270.0	C	
8	2018-01-16	2018-02-02	270.0	276.97	20180202_270.0	C	
9	2018-01-17	2018-02-02	270.0	279.61	20180202_270.0	C	
10	2018-01-18	2018-02-02	270.0	279.14	20180202_270.0	C	
11	2018-01-19	2018-02-02	270.0	280.41	20180202_270.0	C	
12	2018-01-22	2018-02-02	270.0	282.69	20180202_270.0	C	
13	2018-01-23	2018-02-02	270.0	283.29	20180202_270.0	C	
14	2018-01-24	2018-02-02	270.0	283.18	20180202_270.0	C	

	best_bid_c	best_offer_c	impl_volatility_c	delta_c	cp_flag_p	\
0	2.65	2.69	0.072398	0.562218	P	
1	3.45	3.49	0.077848	0.632690	P	
2	4.80	4.84	0.083820	0.727658	P	
3	5.17	5.20	0.089623	0.749240	P	
4	5.67	5.72	0.093639	0.773171	P	
5	5.27	5.33	0.092791	0.759070	P	
6	6.76	6.91	0.090857	0.854846	P	
7	8.45	8.60	0.102281	0.890014	P	
8	7.82	7.97	0.130638	0.827166	P	
9	10.03	10.25	0.131682	0.904279	P	
10	9.81	9.97	0.152184	0.867476	P	
11	10.72	10.90	0.135815	0.927491	P	
12	12.81	12.99	0.144638	0.968565	P	
13	13.63	13.78	0.202072	0.928614	P	

```
14       13.48         13.65           0.208464  0.931044         P

    best_bid_p  best_offer_p  impl_volatility_p   delta_p  delta_sum  \
0         1.77          1.80           0.069568 -0.442522   0.119696
1         1.43          1.46           0.074706 -0.366922   0.265768
2         1.02          1.04           0.081783 -0.270119   0.457539
3         0.81          0.82           0.082307 -0.234696   0.514544
4         0.83          0.84           0.091492 -0.223283   0.549888
5         0.85          0.87           0.089866 -0.235707   0.523363
6         0.56          0.58           0.097319 -0.162272   0.692574
7         0.43          0.44           0.107499 -0.121856   0.768158
8         0.60          0.61           0.121851 -0.157003   0.670163
9         0.38          0.39           0.135023 -0.101488   0.802791
10        0.44          0.45           0.140239 -0.114007   0.753469
11        0.24          0.25           0.135983 -0.072915   0.854576
12        0.15          0.16           0.160805 -0.046985   0.921580
13        0.11          0.12           0.164982 -0.036896   0.891718
14        0.09          0.10           0.166801 -0.032401   0.898643

    shares_held  sharechange
0     -0.119696          NaN
1     -0.265768    -0.146072
2     -0.457539    -0.191771
3     -0.514544    -0.057005
4     -0.549888    -0.035344
5     -0.523363     0.026525
6     -0.692574    -0.169211
7     -0.768158    -0.075584
8     -0.670163     0.097995
9     -0.802791    -0.132628
10    -0.753469     0.049322
11    -0.854576    -0.101107
12    -0.921580    -0.067004
13    -0.891718     0.029862
14    -0.898643    -0.006925
```

1.10.3 PL and Various Metrics

We calculate simulation metrics, adding more concise metrics and altering some columns between daily and cumulative for better mapping onto the single timelines. Here, *Cash - total cost basis + net realized PL* gives how much cash is available to use, i.e. deployable capital. Here we assume that our leverage is completely dependent on how much money we choose to borrow from the $9MM in our flexible credit facility.

[ ]:
```
simulations_long = {date: calculate_realized_PL(df.copy(), long_op=True) for␣
↪date, df in filtered_simulations.items()}
simulations_short = {date: calculate_realized_PL(df.copy(), long_op=False) for␣
↪date, df in filtered_simulations.items()}
```

Let's take a look:

[35]:
```
for key, df in list(simulations_short.items())[-5:]:
    print(f"DataFrame for {key}:")
    print(df.columns)
    display(df)
    print("\n")
```

```
DataFrame for 2023-02-22:
Index(['date', 'exdate', 'strike_price', 'close', 'strikeID', 'cp_flag_c',
       'best_bid_c', 'best_offer_c', 'impl_volatility_c', 'delta_c',
       'cp_flag_p', 'best_bid_p', 'best_offer_p', 'impl_volatility_p',
       'delta_p', 'delta_sum', 'stock_pos', 'pos_change', 'change_cost_basis',
       'stock_cost_basis', 'daily_stock_value', 'stock_PL',
       'option_cost_basis', 'change_cost_basis_op', 'daily_option_value',
       'option_PL', 'total_cost_basis', 'total_pos_value', 'total_PL',
       'realized_stock_PL', 'realized_option_PL', 'realized_PL', 'UID',
       'to_open'],
      dtype='object')
```

	date	exdate	strike_price	close	strikeID	cp_flag_c	\
0	2023-02-22	2023-03-24	399.0	398.54	20230324_399.0	C	
1	2023-02-23	2023-03-24	399.0	400.66	20230324_399.0	C	
2	2023-02-24	2023-03-24	399.0	396.38	20230324_399.0	C	
3	2023-02-27	2023-03-24	399.0	397.73	20230324_399.0	C	
4	2023-02-28	2023-03-24	399.0	396.26	20230324_399.0	C	

	best_bid_c	best_offer_c	impl_volatility_c	delta_c	…	\
0	9.08	9.12	0.202075	0.517410	…	
1	9.99	10.03	0.200472	0.555948	…	
2	7.37	7.41	0.195788	0.473339	…	
3	7.54	7.58	0.197377	0.495326	…	
4	7.03	7.05	0.207028	0.465189	…	

	daily_option_value	option_PL	total_cost_basis	total_pos_value	total_PL	\
0	-18.83	-0.08	-14.284359	-14.364359	-0.080000	
1	-18.06	0.69	15.854488	16.568242	0.713755	
2	-17.62	1.13	-49.236657	-48.452815	0.783843	
3	-16.65	2.10	-32.535975	-30.887143	1.648832	
4	0.00	0.00	0.000000	0.000000	0.000000	

	realized_stock_PL	realized_option_PL	realized_PL	\
0	0.000000	0.00	0.000000	
1	0.000000	0.00	0.000000	

```
2           0.000000                0.00     0.000000
3           0.000000                0.00     0.000000
4          -0.398548                2.83     2.431452

                         UID  to_open
0  20230324_399.0_2023-02-22        1
1  20230324_399.0_2023-02-22        0
2  20230324_399.0_2023-02-22        0
3  20230324_399.0_2023-02-22        0
4  20230324_399.0_2023-02-22        0

[5 rows x 34 columns]



DataFrame for 2023-02-23:
Index(['date', 'exdate', 'strike_price', 'close', 'strikeID', 'cp_flag_c',
       'best_bid_c', 'best_offer_c', 'impl_volatility_c', 'delta_c',
       'cp_flag_p', 'best_bid_p', 'best_offer_p', 'impl_volatility_p',
       'delta_p', 'delta_sum', 'stock_pos', 'pos_change', 'change_cost_basis',
       'stock_cost_basis', 'daily_stock_value', 'stock_PL',
       'option_cost_basis', 'change_cost_basis_op', 'daily_option_value',
       'option_PL', 'total_cost_basis', 'total_pos_value', 'total_PL',
       'realized_stock_PL', 'realized_option_PL', 'realized_PL', 'UID',
       'to_open'],
      dtype='object')
        date     exdate  strike_price   close        strikeID cp_flag_c  \
0 2023-02-23 2023-03-24         401.0  400.66  20230324_401.0         C
1 2023-02-24 2023-03-24         401.0  396.38  20230324_401.0         C
2 2023-02-27 2023-03-24         401.0  397.73  20230324_401.0         C
3 2023-02-28 2023-03-24         401.0  396.26  20230324_401.0         C

   best_bid_c  best_offer_c  impl_volatility_c   delta_c  …  \
0        8.79          8.82           0.196720  0.518997  …
1        6.35          6.39           0.192120  0.433775  …
2        6.48          6.51           0.193449  0.453692  …
3        5.99          6.01           0.202116  0.424099  …

  daily_option_value  option_PL  total_cost_basis  total_pos_value  total_PL  \
0             -17.68      -0.06        -13.019221       -13.079221 -0.060000
1             -17.61       0.01        -79.673293       -79.712440 -0.039147
2             -16.55       1.07        -64.680463       -63.871120  0.809343
3               0.00       0.00          0.000000         0.000000  0.000000

   realized_stock_PL  realized_option_PL  realized_PL  \
0           0.000000                0.00     0.000000
1           0.000000                0.00     0.000000
2           0.000000                0.00     0.000000
```

```
3          -0.085759                1.74     1.654241

                         UID  to_open
0  20230324_401.0_2023-02-23        1
1  20230324_401.0_2023-02-23        0
2  20230324_401.0_2023-02-23        0
3  20230324_401.0_2023-02-23        0

[4 rows x 34 columns]



DataFrame for 2023-02-24:
Index(['date', 'exdate', 'strike_price', 'close', 'strikeID', 'cp_flag_c',
       'best_bid_c', 'best_offer_c', 'impl_volatility_c', 'delta_c',
       'cp_flag_p', 'best_bid_p', 'best_offer_p', 'impl_volatility_p',
       'delta_p', 'delta_sum', 'stock_pos', 'pos_change', 'change_cost_basis',
       'stock_cost_basis', 'daily_stock_value', 'stock_PL',
       'option_cost_basis', 'change_cost_basis_op', 'daily_option_value',
       'option_PL', 'total_cost_basis', 'total_pos_value', 'total_PL',
       'realized_stock_PL', 'realized_option_PL', 'realized_PL', 'UID',
       'to_open'],
      dtype='object')
        date     exdate  strike_price   close        strikeID cp_flag_c  \
0 2023-02-24 2023-03-24         396.0  396.38  20230324_396.0         C
1 2023-02-27 2023-03-24         396.0  397.73  20230324_396.0         C
2 2023-02-28 2023-03-24         396.0  396.26  20230324_396.0         C

   best_bid_c  best_offer_c  impl_volatility_c   delta_c  …  \
0        9.05          9.08           0.201088  0.531177  …
1        9.27          9.31           0.202705  0.555327  …
2        8.74          8.77           0.214299  0.524633  …

  daily_option_value  option_PL  total_cost_basis  total_pos_value  total_PL  \
0             -17.92      -0.06         -3.142807        -3.202807 -0.060000
1             -17.07       0.79         15.532207        16.372332  0.840124
2               0.00       0.00          0.000000         0.000000  0.000000

   realized_stock_PL  realized_option_PL  realized_PL  \
0           0.000000                0.00     0.000000
1           0.000000                0.00     0.000000
2          -0.073478                1.56     1.486522

                         UID  to_open
0  20230324_396.0_2023-02-24        1
1  20230324_396.0_2023-02-24        0
2  20230324_396.0_2023-02-24        0
```

```
[3 rows x 34 columns]


DataFrame for 2023-02-27:
Index(['date', 'exdate', 'strike_price', 'close', 'strikeID', 'cp_flag_c',
       'best_bid_c', 'best_offer_c', 'impl_volatility_c', 'delta_c',
       'cp_flag_p', 'best_bid_p', 'best_offer_p', 'impl_volatility_p',
       'delta_p', 'delta_sum', 'stock_pos', 'pos_change', 'change_cost_basis',
       'stock_cost_basis', 'daily_stock_value', 'stock_PL',
       'option_cost_basis', 'change_cost_basis_op', 'daily_option_value',
       'option_PL', 'total_cost_basis', 'total_pos_value', 'total_PL',
       'realized_stock_PL', 'realized_option_PL', 'realized_PL', 'UID',
       'to_open'],
      dtype='object')
        date     exdate  strike_price   close        strikeID cp_flag_c  \
0 2023-02-27 2023-03-31         398.0  397.73  20230331_398.0         C
1 2023-02-28 2023-03-31         398.0  396.26  20230331_398.0         C

   best_bid_c  best_offer_c  impl_volatility_c   delta_c  …  \
0        8.92          8.96           0.194675  0.511410  …
1        8.39          8.42           0.202880  0.483923  …

  daily_option_value  option_PL  total_cost_basis  total_pos_value  total_PL  \
0             -18.22      -0.07        -15.700381       -15.770381     -0.07
1               0.00       0.00          0.000000         0.000000      0.00

   realized_stock_PL  realized_option_PL  realized_PL  \
0           0.000000                 0.0     0.000000
1          -0.009054                 0.7     0.690946

                         UID  to_open
0  20230331_398.0_2023-02-27        1
1  20230331_398.0_2023-02-27        0

[2 rows x 34 columns]


DataFrame for 2023-02-28:
Index(['date', 'exdate', 'strike_price', 'close', 'strikeID', 'cp_flag_c',
       'best_bid_c', 'best_offer_c', 'impl_volatility_c', 'delta_c',
       'cp_flag_p', 'best_bid_p', 'best_offer_p', 'impl_volatility_p',
       'delta_p', 'delta_sum', 'stock_pos', 'pos_change', 'change_cost_basis',
       'stock_cost_basis', 'daily_stock_value', 'stock_PL',
       'option_cost_basis', 'change_cost_basis_op', 'daily_option_value',
       'option_PL', 'total_cost_basis', 'total_pos_value', 'total_PL',
       'realized_stock_PL', 'realized_option_PL', 'realized_PL', 'UID',
```

```
       'to_open'],
      dtype='object')
```

```
        date     exdate  strike_price   close        strikeID cp_flag_c  \
0 2023-02-28 2023-03-31         396.0  396.26  20230331_396.0         C

   best_bid_c  best_offer_c  impl_volatility_c   delta_c  …  \
0        9.55          9.58           0.207305  0.519384  …

  daily_option_value  option_PL  total_cost_basis  total_pos_value  total_PL  \
0                0.0        0.0               0.0              0.0       0.0

   realized_stock_PL  realized_option_PL  realized_PL  \
0                0.0                 0.0          0.0

                         UID  to_open
0  20230331_396.0_2023-02-28        1

[1 rows x 34 columns]
```

1.10.4 IV data

Load calculated IV data.

[36]:
```
iv_data = pd.read_csv('iv_calculations.csv')
iv_data['iv'] = iv_data['iv']
iv_data
```

[36]:
```
      Unnamed: 0        date        iv        BS
0              0  2018-01-02  0.021847  0.068871
1              1  2018-01-03  0.023454  0.072398
2              2  2018-01-04  0.027852  0.071179
3              3  2018-01-05  0.027788  0.074068
4              4  2018-01-08  0.029469  0.072545
…            …         …       …         …
1293        1293  2023-02-22  0.107065  0.202075
1294        1294  2023-02-23  0.111236  0.196720
1295        1295  2023-02-24  0.100687  0.201088
1296        1296  2023-02-27  0.114114  0.194675
1297        1297  2023-02-28  0.112473  0.207305

[1298 rows x 4 columns]
```

Create the IV comparisons to trade, depending on whether model-free IV is more or less than the IV we will go long or short gamma. We also simulate going only long or only short gamma.

[37]:
```
IV_compare = compare_iv(filtered_simulations, iv_data)
IV_compare
```

[37]:

	date	BS_Call_IV	MF_Call_IV	IV_diff
0	2018-01-03	0.072398	0.023454	-0.048944
1	2018-01-04	0.071179	0.027852	-0.043327
2	2018-01-10	0.080641	0.030803	-0.049838
3	2018-01-11	0.076890	0.028318	-0.048572
4	2018-01-12	0.079350	0.029221	-0.050129
..	…	…	…	…
968	2023-02-22	0.202075	0.107065	-0.095010
969	2023-02-23	0.196720	0.111236	-0.085484
970	2023-02-24	0.201088	0.100687	-0.100401
971	2023-02-27	0.194675	0.114114	-0.080561
972	2023-02-28	0.207305	0.112473	-0.094832

[973 rows x 4 columns]

Quick Look at IV Taking a look at the differences in IV, based on quantile:

[38]:
```
(IV_compare['IV_diff'] > 0).sum()
```

[38]: 124

[39]:
```
IV_compare[IV_compare['IV_diff'] > 0]['IV_diff'].quantile(0.5)
```

[39]: 0.31982084842669284

[41]:
```
IV_compare[IV_compare['IV_diff'] > 0]['IV_diff'].quantile(0.25)
```

[41]: 0.16191266523189107

[42]:
```
IV_compare[IV_compare['IV_diff'] > 0]['IV_diff'].quantile(0.2)
```

[42]: 0.12497667184676832

[43]:
```
IV_compare[IV_compare['IV_diff'] < 0]['IV_diff'].quantile(0.75)
```

[43]: -0.0785731074996423

[44]:
```
IV_compare[IV_compare['IV_diff'] < 0]['IV_diff'].quantile(0.80)
```

[44]: -0.07246443270542066

[45]:
```
IV_compare[IV_compare['IV_diff'] < 0]['IV_diff'].quantile(0.70)
```

[45]: -0.08366817795015688

[46]:
```
IV_compare[IV_compare['IV_diff'] < 0]['IV_diff'].quantile(0.50)
```

[46]:
```
-0.11270668550109746
```

[47]:
```
IV_compare['IV_diff'].max()
```

[47]:
```
0.5826495838418329
```

[48]:
```
IV_compare['IV_diff'].min()
```

[48]:
```
-0.6570148924085712
```

1.10.5 Strategies

Essentially, we set a threshold for which we will go long and short gamma, which we use to evaluate on each day whether there is a trading opportunity. We set these threholds based on the quantiles we looked at above.

We simulate three strategies: * 1: Long-Short - if the model-free IV is greater than the IV by a set threshold, we will take a long gamma position. If it is less than the IV by another set threshold, we will take a short gamma position. * 2: Long only - we only take long gamma positions, dependent on a threshold. * 3: Short only - we only take short gamma positions, opening positions depending on a threshold.

[ ]:
```
strat_dict = {'trade_1': trade_strategy_1, 'trade_2': trade_strategy_2,␣
 ↪'trade_3': trade_strategy_3}
```

[50]:
```
for key, func in strat_dict.items():
    IV_compare[key] = IV_compare['IV_diff'].apply(func)
IV_compare
```

[50]:

	date	BS_Call_IV	MF_Call_IV	IV_diff	trade_1	trade_2	trade_3
0	2018-01-03	0.072398	0.023454	-0.048944	0	0	0
1	2018-01-04	0.071179	0.027852	-0.043327	0	0	0
2	2018-01-10	0.080641	0.030803	-0.049838	0	0	0
3	2018-01-11	0.076890	0.028318	-0.048572	0	0	0
4	2018-01-12	0.079350	0.029221	-0.050129	0	0	0
..	…	…	…	…	…	…	…
968	2023-02-22	0.202075	0.107065	-0.095010	0	0	-1
969	2023-02-23	0.196720	0.111236	-0.085484	0	0	-1
970	2023-02-24	0.201088	0.100687	-0.100401	-1	0	-1
971	2023-02-27	0.194675	0.114114	-0.080561	0	0	-1
972	2023-02-28	0.207305	0.112473	-0.094832	0	0	-1

[973 rows x 7 columns]

[51]:
```
IV_compare['date'] = IV_compare['date'].dt.strftime('%Y-%m-%d')
```

[52]:
```
abs(IV_compare['trade_2']).sum()
```

[52]: 53

Here, generate the trade dataframes, by mapping each individual position onto the timeline based on whether we opened the position long or short (either 1 or -1, with additional position sizing added later) or did nothing (0).

[54]:
```
trades_dfs = generate_trades_dfs(strat_dict, IV_compare, simulations_long,␣
↪simulations_short)
volumes = preprocess_options(options)
```

Looking at volumes:

[55]:
```
volumes.loc[volumes['volume_med'] > 0, 'volume_med'].quantile(0.10)
```

[55]: 49.0

[56]:
```
(volumes['volume_c'].quantile(.1) + volumes['volume_p'].quantile(.1))/2
```

[56]: 28.5

We assume an initial capital, from which we can get additional leverage, on which we will also pay costs and fees. We also assume that when we borrow, we will get a rate 25 bps above the risk-free rate.

[57]:
```
# 10 million dollars: 1 million initial capital, up to 9 million as a lending␣
↪facility
KAPITAL = 1e7
INITIAL = 1e6
LEVERAGE = KAPITAL - INITIAL
```

Due to low liquidity on some days in the month-out ATM options, we instead assume that the market can handle options volume at around the 10th percentile of typical volume, which determines our position sizing on those low-liquidity days. Otherwise, we determine position sizing based on the attractiveness of the trade (absolute value of IV differential), capped at a maximum 80% differential as a risk control, in addition to not allowing a trade to exceed 10% of our capital as a capital remains bounded.

[59]:
```
trades_dfs = update_trades_with_pos_size(trades_dfs, volumes, KAPITAL)
```

Let's take a look at our trades after sizing them accordingly:

[60]:
```
trades_dfs['trade_1'].tail(6)
```

[60]:

	date	exdate	strike_price	close	strikeID	delta_sum	\
8730	2023-02-24	2023-03-24	399.0	396.38	20230324_399.0	-0.077786	
8731	2023-02-27	2023-03-10	410.0	397.73	20230310_410.0	-0.688320	
8732	2023-02-27	2023-03-24	396.0	397.73	20230324_396.0	0.084083	
8733	2023-02-27	2023-03-24	399.0	397.73	20230324_399.0	-0.035796	
8734	2023-02-28	2023-03-24	396.0	396.26	20230324_396.0	0.020843	
8735	2023-02-28	2023-03-24	399.0	396.26	20230324_399.0	-0.108683	

```
      stock_pos  pos_change  change_cost_basis  stock_cost_basis  …  \
8730  -0.077786   -0.164214         -65.091145        -30.468441  …
8731   0.000000    0.688026         273.648581          0.000000  …
8732   0.084083    0.046954          18.675014         33.392207  …
8733  -0.035796    0.041990          16.700683        -13.767759  …
8734   0.000000   -0.084083         -33.318730          0.000000  …
8735   0.000000    0.035796          14.184523          0.000000  …

      sized_option_cost_basis  sized_change_cost_basis_op  \
8730                 -21681.0                         0.0
8731                      0.0                     21000.0
8732                 -19646.0                         0.0
8733                 -21681.0                         0.0
8734                      0.0                     17930.0
8735                      0.0                     17512.0

      sized_daily_option_value  sized_option_PL  sized_total_cost_basis  \
8730                  -19382.0           2299.0            -55196.285584
8731                       0.0              0.0                 0.000000
8732                  -18777.0            869.0             17085.428184
8733                  -18315.0           3366.0            -36825.534614
8734                       0.0              0.0                 0.000000
8735                       0.0              0.0                 0.000000

      sized_total_pos_value  sized_total_PL  sized_realized_stock_PL  \
8730          -53298.096148     1898.189436                 0.000000
8731               0.000000        0.000000             -2223.604995
8732           18009.564749      924.136565                 0.000000
8733          -33975.857388     2849.677226                 0.000000
8734               0.000000        0.000000               -80.825646
8735               0.000000        0.000000              -458.440642

      sized_realized_option_PL  sized_realized_PL
8730                       0.0           0.000000
8731                    4680.0        2456.395005
8732                       0.0           0.000000
8733                       0.0           0.000000
8734                    1716.0        1635.174354
8735                    4169.0        3710.559358

[6 rows x 43 columns]
```

1.10.6 Dataframe Metrics

We calculate the PL metrics and costs for each dataframe's trades, minimizing trading transactions to get to the same point wherever possible. To do so, we consolidate the underlying stock position while treating the options as separate securities.

[61]:
```
PL_temp_dfs = summarize_pl_by_date(trades_dfs, trading_days)
PL_temp_dfs['trade_1'][50:84]
```

[61]:

	date	sized_stock_pos	sized_change_cost_basis	\
50	2018-03-15	-4905.3341	-1.995678e+05	
51	2018-03-16	-5069.7366	-4.507917e+04	
52	2018-03-19	2211.3897	1.969472e+06	
53	2018-03-20	-984.7594	-8.659966e+05	
54	2018-03-21	-1481.1900	-1.342497e+05	
55	2018-03-22	27.8096	3.978779e+05	
56	2018-03-23	-497.3449	-1.355161e+05	
57	2018-03-26	662.8197	3.075712e+05	
58	2018-03-27	-437.0603	-2.866287e+05	
59	2018-03-28	-684.9435	-6.440749e+04	
60	2018-03-29	1013.4659	4.469364e+05	
61	2018-04-02	-2161.4125	-8.174359e+05	
62	2018-04-03	148.3848	6.023258e+05	
63	2018-04-04	2361.1328	5.831919e+05	
64	2018-04-05	4496.0433	5.671176e+05	
65	2018-04-06	-1933.1882	-1.669800e+06	
66	2018-04-09	-207.4741	4.504114e+05	
67	2018-04-10	5231.9108	1.442253e+06	
68	2018-04-11	3458.1284	-4.678528e+05	
69	2018-04-12	6930.2940	9.233530e+05	
70	2018-04-13	5479.8851	-3.845759e+05	
71	2018-04-16	8871.3407	9.066378e+05	
72	2018-04-17	10728.5716	5.018052e+05	
73	2018-04-18	9717.9262	-2.732684e+05	
74	2018-04-19	7435.5754	-6.137013e+05	
75	2018-04-20	5223.2715	-5.898223e+05	
76	2018-04-23	4220.6426	-2.672708e+05	
77	2018-04-24	-467.6853	-1.232936e+06	
78	2018-04-25	317.1996	2.069192e+05	
79	2018-04-26	2751.5291	6.482863e+05	
80	2018-04-27	2301.8278	-1.198724e+05	
81	2018-04-30	-239.9211	-6.723180e+05	
82	2018-05-01	113.5991	9.367578e+04	
83	2018-05-02	-982.3976	-2.884663e+05	

	sized_stock_cost_basis	sized_daily_stock_value	sized_stock_PL	\
50	-1.378472e+06	-1.348967e+06	29504.771606	
51	-1.423551e+06	-1.390122e+06	33429.038886	
52	5.459210e+05	5.981588e+05	52237.761672	
53	-2.992710e+05	-2.668206e+05	32450.461897	
54	-4.127809e+05	-4.005582e+05	12222.726100	
55	7.332557e+03	7.332557e+03	0.000000	
56	-1.281836e+05	-1.283399e+05	-156.289952	

```
57            1.793877e+05            1.757201e+05    -3667.544946
58           -1.072411e+05           -1.138979e+05    -6656.861793
59           -1.716485e+05           -1.779689e+05    -6320.325362
60            2.752879e+05            2.666936e+05    -8594.337782
61           -5.421481e+05           -5.564989e+05   -14350.824094
62            6.017779e+04            3.869430e+04   -21483.485344
63            6.433697e+05            6.223002e+05   -21069.491752
64            1.210487e+06            1.194329e+06   -16158.335528
65           -4.593127e+05           -5.020876e+05   -42774.911864
66           -8.901347e+03           -5.415074e+04   -45249.392760
67            1.433352e+06            1.387241e+06   -46110.410275
68            9.654987e+05            9.121159e+05   -53382.766287
69            1.878820e+06            1.842973e+06   -35847.403339
70            1.487542e+06            1.452992e+06   -34550.641821
71            2.384537e+06            2.371576e+06   -12961.411492
72            2.886392e+06            2.898753e+06    12360.606702
73            2.613378e+06            2.627630e+06    14252.045613
74            1.995010e+06            1.999352e+06     4341.476402
75            1.405188e+06            1.392576e+06   -12611.635510
76            1.139984e+06            1.125097e+06   -14887.627570
77           -9.833869e+04           -1.229919e+05   -24653.185979
78            1.015270e+05            8.362333e+04   -17903.698298
79            7.425357e+05            7.327597e+05    -9775.994516
80            6.219180e+05            6.135752e+05    -8342.783195
81           -5.313651e+04           -6.346153e+04   -10325.021220
82            3.693444e+04            3.010149e+04    -6832.954647
83           -2.550280e+05           -2.585670e+05    -3539.017475

    sized_option_cost_basis  sized_change_cost_basis_op  \
50                 157363.0                     11052.0
51                 157363.0                         0.0
52                 157363.0                         0.0
53                 102036.0                    -30927.0
54                  48700.0                    -26963.0
55                 -14053.0                    -46353.0
56                 -29120.0                    -15067.0
57                 -48481.0                    -19361.0
58                 -69343.0                    -20862.0
59                 -88638.0                    -19295.0
60                -105995.0                    -17357.0
61                -124490.0                    -18495.0
62                -141035.0                    -16545.0
63                -161023.0                    -19988.0
64                -178699.0                    -17676.0
65                -193735.0                    -15036.0
66                -210820.0                    -17085.0
67                -226330.0                    -15510.0
```

68	-241855.0	-15525.0
69	-241992.0	-6702.0
70	-226925.0	9425.0
71	-207564.0	9975.0
72	-186702.0	21071.0
73	-167407.0	19278.0
74	-150050.0	12512.0
75	-150050.0	0.0
76	-131555.0	18495.0
77	-115010.0	9465.0
78	-108168.0	-1993.0
79	-90492.0	8802.0
80	-88699.0	-2057.0
81	-71614.0	10170.0
82	-56104.0	6420.0
83	-40579.0	7200.0

	sized_daily_option_value	sized_option_PL	sized_total_cost_basis	\
50	104763.0	-52600.0	-1.221109e+06	
51	100406.0	-56957.0	-1.266188e+06	
52	98938.0	-58425.0	7.032840e+05	
53	61341.0	-40695.0	-1.972350e+05	
54	29150.0	-19550.0	-3.640809e+05	
55	-14261.0	-208.0	-6.720443e+03	
56	-30420.0	-1300.0	-1.573036e+05	
57	-48179.0	302.0	1.309067e+05	
58	-69539.0	-196.0	-1.765841e+05	
59	-89346.0	-708.0	-2.602865e+05	
60	-102344.0	3651.0	1.692929e+05	
61	-126734.0	-2244.0	-6.666381e+05	
62	-134427.0	6608.0	-8.085721e+04	
63	-155875.0	5148.0	4.823467e+05	
64	-172010.0	6689.0	1.031788e+06	
65	-176793.0	16942.0	-6.530477e+05	
66	-194893.0	15927.0	-2.197213e+05	
67	-210457.0	15873.0	1.207022e+06	
68	-208101.0	33754.0	7.236437e+05	
69	-213918.0	28074.0	1.636828e+06	
70	-181459.0	45466.0	1.260617e+06	
71	-173373.0	34191.0	2.176973e+06	
72	-183979.0	2723.0	2.699690e+06	
73	-163757.0	3650.0	2.445971e+06	
74	-134698.0	15352.0	1.844960e+06	
75	-119254.0	30796.0	1.255138e+06	
76	-92942.0	38613.0	1.008429e+06	
77	-76894.0	38116.0	-2.133487e+05	
78	-77865.0	30303.0	-6.640971e+03	

79	-66818.0	23674.0	6.520437e+05
80	-64705.0	23994.0	5.332190e+05
81	-47017.0	24597.0	-1.247505e+05
82	-37783.0	18321.0	-1.916956e+04
83	-30180.0	10399.0	-2.956070e+05

	sized_total_pos_value	sized_total_PL	sized_realized_stock_PL	\
50	-1.244204e+06	-23095.228394	-5556.721428	
51	-1.289716e+06	-23527.961114	0.000000	
52	6.970968e+05	-6187.238328	0.000000	
53	-2.054796e+05	-8244.538103	20804.539037	
54	-3.714082e+05	-7327.273900	20739.810685	
55	-6.928443e+03	-208.000000	22235.570500	
56	-1.587599e+05	-1456.289952	0.000000	
57	1.275411e+05	-3365.544946	0.000000	
58	-1.834369e+05	-6852.861793	0.000000	
59	-2.673149e+05	-7028.325362	0.000000	
60	1.643496e+05	-4943.337782	0.000000	
61	-6.832329e+05	-16594.824094	0.000000	
62	-9.573270e+04	-14875.485344	0.000000	
63	4.664252e+05	-15921.491752	0.000000	
64	1.022319e+06	-9469.335528	0.000000	
65	-6.788806e+05	-25832.911864	0.000000	
66	-2.490437e+05	-29322.392760	0.000000	
67	1.176784e+06	-30237.410275	0.000000	
68	7.040149e+05	-19628.766287	0.000000	
69	1.629055e+06	-7773.403339	-10031.224320	
70	1.271533e+06	10915.358179	-6702.390838	
71	2.198203e+06	21229.588508	-9643.080811	
72	2.714774e+06	15083.606702	50.016208	
73	2.463873e+06	17902.045613	254.275409	
74	1.864654e+06	19693.476402	-4666.320089	
75	1.273322e+06	18184.364490	0.000000	
76	1.032155e+06	23725.372430	2067.061200	
77	-1.998859e+05	13462.814021	-5386.548525	
78	5.758331e+03	12399.301702	-7053.483126	
79	6.659417e+05	13898.005484	-7277.608854	
80	5.488702e+05	15651.216805	-745.329046	
81	-1.104785e+05	14271.978780	-2736.508965	
82	-7.681510e+03	11488.045353	-3604.829490	
83	-2.887470e+05	6859.982525	-3496.143570	

	sized_realized_option_PL	sized_realized_PL
50	5130.0	-426.721428
51	0.0	0.000000
52	0.0	0.000000
53	-24400.0	-3595.460963

54	-26373.0	-5633.189315
55	-16400.0	5835.570500
56	0.0	0.000000
57	0.0	0.000000
58	0.0	0.000000
59	0.0	0.000000
60	0.0	0.000000
61	0.0	0.000000
62	0.0	0.000000
63	0.0	0.000000
64	0.0	0.000000
65	0.0	0.000000
66	0.0	0.000000
67	0.0	0.000000
68	0.0	0.000000
69	6565.0	-3466.224320
70	5642.0	-1060.390838
71	9386.0	-257.080811
72	-209.0	-158.983792
73	17.0	271.275409
74	4845.0	178.679911
75	0.0	0.000000
76	0.0	2067.061200
77	7080.0	1693.451475
78	8835.0	1781.516874
79	8874.0	1596.391146
80	3850.0	3104.670954
81	6915.0	4178.491035
82	9090.0	5485.170510
83	8325.0	4828.856430

Apply dividends:

[64]:
```
divvies = calculate_dividends(PL_temp_dfs, spy_divdata)
divvies['trade_1'].head(50)
```

[64]:

	date	dividend	pay_date	sized_stock_pos	div
0	2018-03-16	1.096780	2018-04-30	-5069.7366	-5560.385708
1	2018-06-15	1.246000	2018-07-31	0.0000	0.000000
2	2018-09-21	1.323000	2018-10-31	-1631.3276	-2158.246415
3	2018-12-21	1.435400	2019-01-31	-1342.4627	-1926.970960
4	2019-03-15	1.233100	2019-04-30	-3734.6172	-4605.156469
5	2019-06-21	1.431600	2019-07-31	659.6096	944.297103
6	2019-09-20	1.383620	2019-10-31	0.0000	0.000000
7	2019-12-20	1.570000	2020-01-31	-1650.5574	-2591.375118
8	2020-03-20	1.405560	2020-04-30	-1472.6726	-2069.929700
9	2020-06-19	1.366200	2020-07-31	822.8804	1124.219202
10	2020-09-18	1.339200	2020-10-30	12863.3701	17226.625238

```
11 2020-12-18  1.580000 2021-01-29       -5687.4344  -8986.146352
12 2021-03-19  1.277790 2021-04-30        2314.1840   2957.041173
13 2021-06-18  1.375870 2021-07-30       16110.8271  22166.403682
14 2021-09-17  1.428117 2021-10-29           0.0000      0.000000
15 2021-12-17  1.633485 2022-01-31         494.4044    807.602171
16 2022-03-18  1.366009 2022-04-29        1542.7890   2107.463659
17 2022-06-17  1.576871 2022-07-29       -2586.1145  -4077.968958
18 2022-09-16  1.596000 2022-10-31       -2510.7063  -4007.087255
19 2022-12-16  1.781000 2023-01-31       -2067.5956  -3682.387764
```

[65]:
```
PL_temp_dfs = merge_dividends_with_pl(PL_temp_dfs, divvies)
PL_temp_dfs['trade_1'][-2:]
```

[65]:
```
           date  sized_stock_pos  sized_change_cost_basis  \
1296 2023-02-27          53.1157             449386.138302
1297 2023-02-28           0.0000             -21047.627282

      sized_stock_cost_basis  sized_daily_stock_value  sized_stock_PL  \
1296             21586.89357             21125.707361     -461.186209
1297                 0.00000                 0.000000        0.000000

      sized_option_cost_basis  sized_change_cost_basis_op  \
1296                -41327.0                     21000.0
1297                    0.0                     35442.0

      sized_daily_option_value  sized_option_PL  sized_total_cost_basis  \
1296                  -37092.0           4235.0            -19740.10643
1297                      0.0              0.0                 0.00000

      sized_total_pos_value  sized_total_PL  sized_realized_stock_PL  \
1296          -15966.292639     3773.813791             -2223.604995
1297               0.000000        0.000000              -539.266288

      sized_realized_option_PL  sized_realized_PL  div
1296                    4680.0        2456.395005  0.0
1297                    5885.0        5345.733712  0.0
```

We use smallest DTE to approximate an overnight risk-free rate.

[66]:
```
tbills_data = process_tbills_data('tbill_data.csv', '2018-01-01', '2023-02-28',␣
 ↪trading_days)
tbills_data
```

[66]:
```
           date  dte maturity_date      price      rate  leverage_rate
0    2018-01-02  2.0    2018-01-04  99.994083  0.000030       0.000036
1    2018-01-03  1.0    2018-01-04  99.996944  0.000031       0.000037
2    2018-01-04  7.0    2018-01-11  99.976375  0.000034       0.000041
3    2018-01-05  6.0    2018-01-11  99.979583  0.000034       0.000041
```

```
4     2018-01-08  3.0    2018-01-11  99.989750  0.000034       0.000041
…          …  …           …         …       …            …
1283  2023-02-22  1.0    2023-02-23  99.987410  0.000126       0.000132
1284  2023-02-23  5.0    2023-02-28  99.935972  0.000128       0.000135
1285  2023-02-24  4.0    2023-02-28  99.950389  0.000124       0.000131
1286  2023-02-27  1.0    2023-02-28  99.987639  0.000124       0.000130
1287  2023-02-28  2.0    2023-03-02  99.975833  0.000121       0.000127

[1288 rows x 6 columns]
```

Calculate the rate:

[67]:
```
rfr = calculate_rfr(trading_days, tbills_data)
rfr
```

[67]:
```
            date      rate  leverage_rate
0     2018-01-02  0.000030       0.000036
1     2018-01-03  0.000031       0.000037
2     2018-01-04  0.000034       0.000041
3     2018-01-05  0.000034       0.000041
4     2018-01-08  0.000034       0.000041
…          …       …              …
1293  2023-02-22  0.000126       0.000132
1294  2023-02-23  0.000128       0.000135
1295  2023-02-24  0.000124       0.000131
1296  2023-02-27  0.000124       0.000130
1297  2023-02-28  0.000121       0.000127

[1298 rows x 3 columns]
```

1.10.7 Final Dataframes

In this simulation, when we are short shares, we do not need to borrow money, hence we don't go above initial capital of 1 million, which is why lever cash is 0. To account for the fees associated with opening a short position, we pay to borrow the shares under short fees (hence not double-paying fees).

Here, we take the simulations for each strategy, and calculate all of the associated metrics.

[68]:
```
PL_dfs = process_pl_dfs(PL_temp_dfs, rfr, INITIAL, KAPITAL)
```

[69]:
```
PL_dfs['trade_1']
```

[69]:
```
            date  gross_stock_trades  gross_option_trades  gross_trades_value  \
0     2018-01-02            0.000000                  0.0            0.000000
1     2018-01-03            0.000000                  0.0            0.000000
2     2018-01-04            0.000000                  0.0            0.000000
3     2018-01-05            0.000000                  0.0            0.000000
4     2018-01-08            0.000000                  0.0            0.000000
```

```
…         …                  …                    …                  …
1293 2023-02-22       364328.728590              20355.0       384683.728590
1294 2023-02-23        62357.239958                  0.0        62357.239958
1295 2023-02-24       174798.030680              19646.0       194444.030680
1296 2023-02-27       449386.138302              21000.0       470386.138302
1297 2023-02-28        21047.627282              35442.0        56489.627282

      stock_trading_costs  option_trading_costs  net_trading_costs  \
0                0.000000                0.0000           0.000000
1                0.000000                0.0000           0.000000
2                0.000000                0.0000           0.000000
3                0.000000                0.0000           0.000000
4                0.000000                0.0000           0.000000
…                     …                     …                  …
1293            36.432873                2.0355          38.468373
1294             6.235724                0.0000           6.235724
1295            17.479803                1.9646          19.444403
1296            44.938614                2.1000          47.038614
1297             2.104763                3.5442           5.648963

      stock_pos_value  option_pos_value  gross_pos_value  …  initial_cash  \
0            0.000000               0.0         0.000000  …  1.000000e+06
1            0.000000               0.0         0.000000  …  1.000030e+06
2            0.000000               0.0         0.000000  …  1.000060e+06
3            0.000000               0.0         0.000000  …  1.000094e+06
4            0.000000               0.0         0.000000  …  1.000128e+06
…                 …                 …                …  …           …
1293   -315409.338480          -43198.0   -358607.338480  …  1.468668e+06
1294   -254729.891962          -39426.0   -294155.891962  …  1.406455e+06
1295   -426806.802646          -62314.0   -489120.802646  …  1.601004e+06
1296     21125.707361          -37092.0    -15966.292639  …  1.130770e+06
1297         0.000000               0.0         0.000000  …  1.116510e+06

        interest  lever_cash  leverage_fee   end_kapital  net_short_fees  \
0      29.584646         0.0           0.0  1.000030e+06        0.000000
1      30.557393         0.0           0.0  1.000060e+06        0.000000
2      33.756587         0.0           0.0  1.000094e+06        0.000000
3      34.035027         0.0           0.0  1.000128e+06        0.000000
4      34.173373         0.0           0.0  1.000162e+06        0.000000
…            …          …             …             …               …
1293  184.932685         0.0           0.0  1.108357e+06    13455.044279
1294  180.173640         0.0           0.0  1.108497e+06    13489.339657
1295  198.630604         0.0           0.0  1.108620e+06    13545.082913
1296  139.792991         0.0           0.0  1.111169e+06    13545.082913
1297  134.936030         0.0           0.0  1.116645e+06    13545.082913

      net_interest_paid  net_interest_earned  net_pos_value      tot_cash
```

```
0              29.584646              0.000000   1.000030e+06  9.999970e+06
1              60.142039              0.000000   1.000060e+06  9.999940e+06
2              93.898626              0.000000   1.000094e+06  9.999906e+06
3             127.933653              0.000000   1.000128e+06  9.999872e+06
4             162.107026              0.000000   1.000162e+06  9.999838e+06
…                    …                     …              …             …
1293       38074.710424          12983.858946   1.110246e+06  1.043213e+07
1294       38254.884065          12983.858946   1.112480e+06  1.036958e+07
1295       38453.514668          12983.858946   1.112082e+06  1.056381e+07
1296       38593.307659          12983.858946   1.114943e+06  1.009324e+07
1297       38728.243689          12983.858946   1.116645e+06  1.007870e+07

[1298 rows x 26 columns]
```

[70]:
```
PL_dfs['trade_2'][-2:]
```

[70]:
```
           date  gross_stock_trades  gross_option_trades  gross_trades_value  \
1296 2023-02-27                 0.0                  0.0                 0.0
1297 2023-02-28                 0.0                  0.0                 0.0

      stock_trading_costs  option_trading_costs  net_trading_costs  \
1296                  0.0                   0.0                0.0
1297                  0.0                   0.0                0.0

      stock_pos_value  option_pos_value  gross_pos_value  …   initial_cash  \
1296              0.0               0.0              0.0  …  683225.069753
1297              0.0               0.0              0.0  …  683309.534404

       interest  lever_cash  leverage_fee    end_kapital  net_short_fees  \
1296  84.464651         0.0           0.0  683309.534404     4719.494988
1297  82.581537         0.0           0.0  683392.115941     4719.494988

      net_interest_paid  net_interest_earned  net_pos_value      tot_cash
1296       39039.947929          1262.251172  683309.534404  9.612474e+06
1297       39122.529466          1262.251172  683392.115941  9.612391e+06

[2 rows x 26 columns]
```

Noting some position lows, drawdowns and maximum PL values, on each of the strategies.

[71]:
```
PL_dfs['trade_1']['net_pos_value'][PL_dfs['trade_1']['net_pos_value'].idxmin()]
```

[71]:
```
868579.2717882802
```

[73]:
```
PL_dfs['trade_2']['net_pos_value'][PL_dfs['trade_2']['net_pos_value'].idxmin()]
```

[73]:
```
596810.1024514363
```

[74]:
```
PL_dfs['trade_3']['net_pos_value'][PL_dfs['trade_3']['net_pos_value'].idxmin()]
```

[74]: 981452.1037887249

[75]:
```
PL_dfs['trade_1']['tot_cash'][PL_dfs['trade_1']['tot_cash'].idxmin()]
```

[75]: 2987330.136676361

[76]:
```
PL_dfs['trade_1']['tot_cash'][PL_dfs['trade_1']['tot_cash'].idxmax()]
```

[76]: 15620853.359602839

[77]:
```
PL_dfs['trade_2']['tot_cash'][PL_dfs['trade_2']['tot_cash'].idxmin()]
```

[77]: 2468237.6778471903

[78]:
```
PL_dfs['trade_2']['tot_cash'][PL_dfs['trade_2']['tot_cash'].idxmax()]
```

[78]: 15140576.721228467

[79]:
```
PL_dfs['trade_3']['tot_cash'][PL_dfs['trade_3']['tot_cash'].idxmin()]
```

[79]: 5649798.585902663

[80]:
```
PL_dfs['trade_3']['tot_cash'][PL_dfs['trade_3']['tot_cash'].idxmax()]
```

[80]: 15511034.440640306

Showing some examples of the final positions and closing them:

[81]:
```
for key in strat_dict.keys():
    formatted_df = PL_dfs[key][-2:][['date', 'net_pos_value']].copy()

    formatted_df['net_pos_value'] = formatted_df['net_pos_value'].apply(lambda␣
 ↪x: "${:,.2f}".format(x))

    print(f"Final positions for {key}:")
    display(formatted_df)
```

```
Final positions for trade_1:
```

	date	net_pos_value
1296	2023-02-27	$1,114,943.29
1297	2023-02-28	$1,116,644.50

```
Final positions for trade_2:
```

	date	net_pos_value
1296	2023-02-27	$683,309.53
1297	2023-02-28	$683,392.12

```
Final positions for trade_3:

           date  net_pos_value
1296 2023-02-27  $1,755,802.90
1297 2023-02-28  $1,759,887.75
```

As you can see above, the strategies trade_1 (long-short) and trade_3 (short only) were profitable, while strategy trade_2 (long only) was not. This corresponds with general knowledge that realized volatility is historically lower than implied volatility, which allows short gamma strategies to be profitable.

[82]:
```
os.makedirs('simdata', exist_ok=True)

for strat, df in PL_dfs.items():
    csv_path = f'simdata/PL_{strat}.csv'
    df.to_csv(csv_path, index=False)
```

1.11 9. Analysis

We visualize and analyze trade data for the 3 trading strategies developed. Additionally, we also import Fama-French factors data available from Ken French's website and set the date column as the index to determine correlations / regression analyses using market factors.

1.11.1 Load Data

[ ]:
```
PL_trade_1 = pd.read_csv("./simdata/PL_trade_1.csv")
PL_trade_1['date'] = pd.to_datetime(PL_trade_1['date'])
PL_trade_1.set_index('date', inplace=True)

PL_trade_2 = pd.read_csv("./simdata/PL_trade_2.csv")
PL_trade_2['date'] = pd.to_datetime(PL_trade_2['date'])
PL_trade_2.set_index('date', inplace=True)

PL_trade_3 = pd.read_csv("./simdata/PL_trade_3.csv")
PL_trade_3['date'] = pd.to_datetime(PL_trade_3['date'])
PL_trade_3.set_index('date', inplace=True)

PL_trade_1 = calculate_daily_pl(PL_trade_1)
PL_trade_2 = calculate_daily_pl(PL_trade_2)
PL_trade_3 = calculate_daily_pl(PL_trade_3)
```

Display an example:

[4]:
```
PL_trade_3
```

[4]:
```
            gross_stock_trades  gross_option_trades  gross_trades_value  \
date
2018-01-02            0.000000                  0.0            0.000000
2018-01-03            0.000000                  0.0            0.000000
2018-01-04            0.000000                  0.0            0.000000
```

```
2018-01-05            0.000000                  0.0            0.000000
2018-01-08            0.000000                  0.0            0.000000
…                          …                    …                 …
2023-02-22       368794.369290               1605.0       370399.369290
2023-02-23        97096.865918              17620.0       114716.865918
2023-02-24       306543.247660              19646.0       326189.247660
2023-02-27       483284.308245               4665.0       487949.308245
2023-02-28        38086.609152              82947.0       121033.609152

            stock_trading_costs  option_trading_costs  net_trading_costs  \
date
2018-01-02            0.000000                0.0000           0.000000
2018-01-03            0.000000                0.0000           0.000000
2018-01-04            0.000000                0.0000           0.000000
2018-01-05            0.000000                0.0000           0.000000
2018-01-08            0.000000                0.0000           0.000000
…                          …                    …                 …
2023-02-22           36.879437                0.1605          37.039937
2023-02-23            9.709687                1.7620          11.471687
2023-02-24           30.654325                1.9646          32.618925
2023-02-27           48.328431                0.4665          48.794931
2023-02-28            3.808661                8.2947          12.103361

            stock_pos_value  option_pos_value  gross_pos_value      stock_PL  \
date
2018-01-02         0.000000               0.0         0.000000  0.000000e+00
2018-01-03         0.000000               0.0         0.000000  0.000000e+00
2018-01-04         0.000000               0.0         0.000000  0.000000e+00
2018-01-05         0.000000               0.0         0.000000  0.000000e+00
2018-01-08         0.000000               0.0         0.000000  0.000000e+00
…                       …                 …                …           …
2023-02-22   -310943.697780          -62028.0   -372971.697780 -1.704122e+06
2023-02-23   -215500.870702          -75166.0   -290666.870702 -1.704131e+06
2023-02-24   -519742.057446          -97544.0   -617286.057446 -1.704162e+06
2023-02-27    -38227.898496          -86690.0   -124917.898496 -1.706434e+06
2023-02-28         0.000000               0.0         0.000000 -1.707469e+06

            …  leverage_fee   end_kapital  net_short_fees  \
date        …
2018-01-02  …           0.0  1.000030e+06        0.000000
2018-01-03  …           0.0  1.000060e+06        0.000000
2018-01-04  …           0.0  1.000094e+06        0.000000
2018-01-05  …           0.0  1.000128e+06        0.000000
2018-01-08  …           0.0  1.000162e+06        0.000000
…         …             …             …               …
2023-02-22  …           0.0  1.746584e+06     8707.858452
2023-02-23  …           0.0  1.746805e+06     8736.872258
```

```
2023-02-24  …           0.0  1.746999e+06     8804.753357
2023-02-27  …           0.0  1.749634e+06     8809.729350
2023-02-28  …           0.0  1.759888e+06     8809.729350

            net_interest_paid  net_interest_earned  net_pos_value  \
date
2018-01-02          29.584646             0.000000   1.000030e+06
2018-01-03          60.142039             0.000000   1.000060e+06
2018-01-04          93.898626             0.000000   1.000094e+06
2018-01-05         127.933653             0.000000   1.000128e+06
2018-01-08         162.107026             0.000000   1.000162e+06
…                         …                    …           …
2023-02-22       39678.615408         10919.221232   1.748393e+06
2023-02-23       39940.185789         10919.221232   1.751442e+06
2023-02-24       40233.999182         10919.221232   1.751205e+06
2023-02-27       40466.477170         10919.221232   1.755803e+06
2023-02-28       40679.143123         10919.221232   1.759888e+06

                tot_cash  daily_option_PL  daily_stock_PL  daily_net_PL
date
2018-01-02  9.999970e+06           0.0000        0.000000      0.000000
2018-01-03  9.999940e+06           0.0000        0.000000      0.000000
2018-01-04  9.999906e+06           0.0000        0.000000      0.000000
2018-01-05  9.999872e+06           0.0000        0.000000      0.000000
2018-01-08  9.999838e+06           0.0000        0.000000      0.000000
…                    …                …               …           …
2023-02-22  1.107255e+07        2669.8395    -2990.039297   -320.199797
2023-02-23  1.099280e+07          -1.7620       -9.709687    -11.471687
2023-02-24  1.131867e+07          -1.9646      -30.654325    -32.618925
2023-02-27  1.083044e+07        4679.5335    -2271.933426   2407.600074
2023-02-28  1.070918e+07       11076.7053    -1035.531006  10041.174294

[1298 rows x 28 columns]
```

[5]:
```
fff_data = pd.read_csv('F-F_Research_Data_Factors_daily.CSV')
fff_data['date'] = pd.to_datetime(fff_data['date'])
fff_data.set_index('date', inplace=True)
fff_data
```

[5]:
```
            Mkt-RF   SMB   HML     RF
date
2026-07-01    0.10 -0.25 -0.27  0.009
2026-07-02    0.45 -0.33 -0.06  0.009
2026-07-06    0.17  0.30 -0.39  0.009
2026-07-07    0.09 -0.58  0.02  0.009
2026-07-08    0.21 -0.38  0.19  0.009
…              …    …    …     …
```

```
2024-01-25    0.46  0.04  0.56  0.022
2024-01-26   -0.02  0.40 -0.27  0.022
2024-01-29    0.85  1.07 -0.59  0.022
2024-01-30   -0.13 -1.26  0.84  0.022
2024-01-31   -1.74 -0.92 -0.30  0.022

[25670 rows x 4 columns]
```

[6]:
```
start_date = '2018-01-01'
end_date = '2023-02-28'
spydata = pd.read_csv('spy_tickerdata.csv')[['date','adj_close']].
 ↪sort_values(by='date').reset_index(drop=True)
spydata = spydata.loc[(spydata['date'] >= start_date) & (spydata['date'] <=␣
 ↪end_date)].copy().reset_index(drop=True)
spydata['spy_return1'] = spydata['adj_close'] / spydata.loc[0, 'adj_close']
spydata['spy_return'] = (spydata['spy_return1'] * 1000000 ) - 1000000
spydata['returns'] = spydata['spy_return1'].diff() *1000000
spydata.set_index('date', inplace=True)
```

1.11.2 Data Analysis

To re-iterate, this analysis will focus on the 3 different trading strategies developed in the previous section: 1. Comparing the Model-Free Implied Vol vs BS Implied Vol to Enter Trades 2. Enter Only Long Gamma Trades 3. Enter Only Short Gamma Trades

[7]:
```
performance_summary(PL_trade_1)
```

[7]:

	Mean	Median	Volatility	Sharpe Ratio	\
gross_stock_trades	5.924315e+05	3.432981e+05	7.339366e+05	0.807197	
gross_option_trades	1.750643e+04	9.078500e+03	2.449568e+04	0.714674	
gross_trades_value	6.099379e+05	3.611404e+05	7.407474e+05	0.823409	
stock_trading_costs	5.924315e+01	3.432981e+01	7.339366e+01	0.807197	
option_trading_costs	1.750643e+00	9.078500e-01	2.449568e+00	0.714674	
net_trading_costs	6.099379e+01	3.611404e+01	7.407474e+01	0.823409	
stock_pos_value	3.752555e+05	1.469597e+05	1.604310e+06	0.233905	
option_pos_value	-8.080070e+04	-6.545700e+04	2.097862e+05	-0.385157	
gross_pos_value	2.944548e+05	8.302307e+04	1.556962e+06	0.189121	
stock_PL	-3.469488e+04	-4.172414e+04	2.496436e+05	-0.138978	
option_PL	1.016892e+05	7.503284e+04	2.210585e+05	0.460011	
net_PL	6.699437e+04	3.729012e+04	1.221955e+05	0.548256	
start_cash	1.079254e+06	1.051728e+06	1.240356e+05	8.701157	
initial_kapital	1.079324e+06	1.051700e+06	1.240365e+05	8.701661	
short_fee	1.043535e+01	0.000000e+00	2.737500e+01	0.381200	
initial_cash	1.052367e+06	9.307892e+05	1.142975e+06	0.920726	
interest	2.983686e+01	3.541307e+00	4.619027e+01	0.645956	
lever_cash	2.669067e+05	0.000000e+00	7.212898e+05	0.370041	
leverage_fee	1.000297e+01	0.000000e+00	3.897554e+01	0.256647	

```
end_kapital           1.079343e+06  1.051819e+06  1.240204e+05      8.702949
net_short_fees        6.414806e+03  6.976890e+03  3.387926e+03      1.893431
net_interest_paid     2.134996e+04  2.599523e+04  9.355687e+03      2.282031
net_interest_earned   2.586065e+03  2.055672e+03  2.199032e+03      1.176001
net_pos_value         1.079935e+06  1.054309e+06  1.247928e+05      8.653825
tot_cash              9.754367e+06  9.890187e+06  1.546236e+06      6.308458
daily_option_PL       5.726654e+02  0.000000e+00  8.968539e+03      0.063853
daily_stock_PL       -4.921991e+02 -2.651589e+01  8.369149e+03     -0.058811
daily_net_PL          8.046626e+01 -1.157372e+01  5.188377e+03      0.015509

                      Skewness  Excess Kurtosis           Min           Max  \
gross_stock_trades    2.354224         8.253499  0.000000e+00  6.412519e+06
gross_option_trades   2.145489         5.345669  0.000000e+00  1.578750e+05
gross_trades_value    2.336678         8.116444  0.000000e+00  6.412519e+06
stock_trading_costs   2.354224         8.253499  0.000000e+00  6.412519e+02
option_trading_costs  2.145489         5.345669  0.000000e+00  1.578750e+01
net_trading_costs     2.336678         8.116444  0.000000e+00  6.412519e+02
stock_pos_value       0.024513         2.181142 -5.886089e+06  6.684704e+06
option_pos_value      0.253853         0.655672 -6.711300e+05  5.873630e+05
gross_pos_value       0.121650         2.502866 -5.520087e+06  7.148315e+06
stock_PL             -0.071932        -0.170702 -6.388745e+05  5.163709e+05
option_PL             0.588947         0.600919 -3.638743e+05  7.433197e+05
net_PL                0.777775        -0.103997 -9.694342e+04  4.269232e+05
start_cash            0.799383        -0.138466  9.169981e+05  1.443109e+06
initial_kapital       0.797592        -0.139962  9.169759e+05  1.443100e+06
short_fee             3.887240        18.033096 -1.268325e+00  2.428192e+02
initial_cash          1.840538         4.178353  0.000000e+00  6.659374e+06
interest              2.462929         7.910559 -2.087234e+01  3.149349e+02
lever_cash            3.781740        16.880801  0.000000e+00  5.974028e+06
leverage_fee          6.241189        46.327317  0.000000e+00  4.837435e+02
end_kapital           0.797723        -0.139504  9.169981e+05  1.443109e+06
net_short_fees       -0.174843        -0.515759  0.000000e+00  1.354508e+04
net_interest_paid    -0.833472        -0.245736  2.958465e+01  3.872824e+04
net_interest_earned   2.236608         6.514927  0.000000e+00  1.298386e+04
net_pos_value         0.779850        -0.142445  8.685793e+05  1.419346e+06
tot_cash              0.007592         2.500485  2.987330e+06  1.562085e+07
daily_option_PL      -1.022962        10.837477 -5.005651e+04  6.995727e+04
daily_stock_PL        1.725971        18.123452 -6.006872e+04  7.029373e+04
daily_net_PL         -0.987223        13.598898 -3.578368e+04  3.236006e+04

                      Max Drawdown
gross_stock_trades        -1.000000
gross_option_trades       -0.999994
gross_trades_value        -1.000000
stock_trading_costs       -0.998443
option_trading_costs      -0.940432
net_trading_costs         -0.998443
```

stock_pos_value	-5.052143
option_pos_value	-107839.000000
gross_pos_value	-39687.059976
stock_PL	-352.069659
option_PL	-29.182400
net_PL	-381.252059
start_cash	-0.295621
initial_kapital	-0.295611
short_fee	-1.001101
initial_cash	-1.000000
interest	-1.083401
lever_cash	-1.000000
leverage_fee	-0.997937
end_kapital	-0.295621
net_short_fees	-0.000169
net_interest_paid	-0.000797
net_interest_earned	0.000000
net_pos_value	-0.304238
tot_cash	-0.802107
daily_option_PL	-6.703200
daily_stock_PL	-80.140810
daily_net_PL	-80.140810

Trading Strategy 1 Summary Stats (Model Free IV vs BS IV):

Gross Stock Trades show substantial trading activity with a mean significantly higher than the median, which indicates a skewed distribution with some exceptionally large stock trades. The zero minimum and the high maximum further confirm a wide range of trade values. Gross Option Trades, while lower on average than stock trades (as indicated by the mean), still show significant activity. The difference between the mean and median is less pronounced than for stock trades, but still suggests right-skewed data, pointing to fewer but larger outlier trades driving up the average. Gross Trades Value consolidates the total value from both stocks and options, revealing high trading activity overall. The mean is larger than the median, suggesting a right-skewed distribution typical for financial data where a few high-value trades increase the average trade value.

Stock_PL indicates a loss on average (negative mean), suggesting that stock trades have generally not been profitable. The negative skewness indicates that there are more losses piling up on the higher end (left side of the distribution). Option_PL, in contrast, shows a positive mean, indicating overall profitability in option trading. This suggests that while stock trading was not profitable on average, option trading appears to have offset some of those losses. A positive mean for Net_PL suggests that despite losses in stock trading, the total trading activities (including options) have been generally profitable. Cash Reserves:

Tot_Cash represents the total available cash, with a mean significantly higher than the median, again indicating a right-skewed distribution. This suggests that while the typical (median) cash reserve is lower, there are instances of significantly higher cash reserves, likely reflecting successful trades or the accumulation of profits over time. Overall, the trading strategy seems to have sufficient liquidity as well.

[8]:
```
performance_summary(PL_trade_2)
```

[8]:

	Mean	Median	Volatility	Sharpe Ratio
gross_stock_trades	1.933879e+05	0.000000e+00	609598.390241	0.317238
gross_option_trades	5.317485e+03	0.000000e+00	19896.957856	0.267251
gross_trades_value	1.987054e+05	0.000000e+00	618058.226745	0.321500
stock_trading_costs	1.933879e+01	0.000000e+00	60.959839	0.317238
option_trading_costs	5.317485e-01	0.000000e+00	1.989696	0.267251
net_trading_costs	1.987054e+01	0.000000e+00	61.805823	0.321500
stock_pos_value	-4.745100e+04	0.000000e+00	969208.000600	-0.048959
option_pos_value	4.250401e+04	0.000000e+00	111077.523390	0.382652
gross_pos_value	-4.946988e+03	0.000000e+00	969267.911742	-0.005104
stock_PL	3.694258e+05	1.126285e+05	314278.056367	1.175474
option_PL	-5.249225e+05	-1.378639e+05	468552.306903	-1.120307
net_PL	-1.554966e+05	-4.706002e+04	160436.783127	-0.969208
start_cash	8.644422e+05	9.782579e+05	155776.372500	5.549251
initial_kapital	8.641691e+05	9.782560e+05	155802.539865	5.546566
short_fee	3.635975e+00	0.000000e+00	17.188871	0.211531
initial_cash	9.572315e+05	9.782579e+05	687646.847168	1.392039
interest	3.014062e+01	3.349487e+01	30.913563	0.974997
lever_cash	9.023479e+04	0.000000e+00	556606.755466	0.162116
leverage_fee	9.724585e-01	0.000000e+00	5.716310	0.170120
end_kapital	8.641983e+05	9.782569e+05	155811.821466	5.546423
net_short_fees	3.129886e+03	3.493760e+03	1561.184468	2.004815
net_interest_paid	2.351500e+04	2.930935e+04	10123.778714	2.322750
net_interest_earned	6.901988e+02	3.907693e+02	422.725771	1.632734
net_pos_value	8.620789e+05	9.782434e+05	156272.602776	5.516507
tot_cash	9.824506e+06	9.924143e+06	979489.191186	10.030234
daily_option_PL	-8.836072e+02	0.000000e+00	6242.512891	-0.141547
daily_stock_PL	6.141553e+02	0.000000e+00	5674.511433	0.108231
daily_net_PL	-2.694520e+02	0.000000e+00	3918.606039	-0.068762

	Skewness	Excess Kurtosis	Min	Max
gross_stock_trades	4.527659	25.512258	0.000000e+00	6.412519e+06
gross_option_trades	3.985601	15.929008	0.000000e+00	1.578750e+05
gross_trades_value	4.479469	24.919250	0.000000e+00	6.412519e+06
stock_trading_costs	4.527659	25.512258	0.000000e+00	6.412519e+02
option_trading_costs	3.985601	15.929008	0.000000e+00	1.578750e+01
net_trading_costs	4.479469	24.919250	0.000000e+00	6.412519e+02
stock_pos_value	0.107321	18.130890	-6.050401e+06	6.684704e+06
option_pos_value	3.003672	8.805896	0.000000e+00	6.445940e+05
gross_pos_value	1.127853	19.635929	-5.520087e+06	7.198018e+06
stock_PL	0.328478	-1.711151	-1.211316e+03	7.971735e+05
option_PL	-0.370850	-1.738031	-1.146922e+06	0.000000e+00
net_PL	-0.428780	-1.664026	-4.142224e+05	5.989147e+04
start_cash	-0.442549	-1.645331	6.094263e+05	1.084978e+06
initial_kapital	-0.439247	-1.648369	6.094268e+05	1.085015e+06

short_fee	7.007721	60.483658	-1.867961e+00	2.428192e+02
initial_cash	4.001612	21.396654	0.000000e+00	6.193564e+06
interest	1.109809	2.769934	-2.229330e+01	2.389453e+02
lever_cash	7.655120	63.935040	0.000000e+00	6.479074e+06
leverage_fee	7.487355	66.467590	0.000000e+00	8.246907e+01
end_kapital	-0.439263	-1.648375	6.094263e+05	1.084978e+06
net_short_fees	-0.513733	-1.226650	0.000000e+00	4.719495e+03
net_interest_paid	-0.996940	-0.352847	2.958465e+01	3.912253e+04
net_interest_earned	0.175119	-1.506167	0.000000e+00	1.262251e+03
net_pos_value	-0.415887	-1.666362	5.968101e+05	1.139550e+06
tot_cash	-1.093957	18.163451	2.468238e+06	1.514058e+07
daily_option_PL	-3.213462	43.840489	-5.467579e+04	6.995953e+04
daily_stock_PL	5.732236	78.368809	-6.006872e+04	7.030262e+04
daily_net_PL	-1.765585	45.020162	-4.063736e+04	3.233784e+04

	Max Drawdown
gross_stock_trades	-9.999998e-01
gross_option_trades	-9.999937e-01
gross_trades_value	-9.999998e-01
stock_trading_costs	-9.984430e-01
option_trading_costs	-9.404319e-01
net_trading_costs	-9.984430e-01
stock_pos_value	-1.026891e+01
option_pos_value	-9.999984e-01
gross_pos_value	-4.138909e+00
stock_PL	-1.211316e+03
option_PL	-1.146922e+06
net_PL	-4.869690e+04
start_cash	-4.383051e-01
initial_kapital	-4.383239e-01
short_fee	-1.003560e+00
initial_cash	-9.999998e-01
interest	-1.088742e+00
lever_cash	-9.999998e-01
leverage_fee	-9.880195e-01
end_kapital	-4.383051e-01
net_short_fees	-4.647275e-04
net_interest_paid	-7.548281e-04
net_interest_earned	0.000000e+00
net_pos_value	-4.762751e-01
tot_cash	-8.369786e-01
daily_option_PL	-3.528206e+04
daily_stock_PL	-2.329447e+02
daily_net_PL	-5.649311e+03

Trading Strategy 2 Summary Stats (Long Gamma):

Stock_Pos_Value shows a negative mean, indicating an overall decrease in the value of stock

positions. Option_Pos_Value, on the other hand, presents a positive mean, suggesting that, on average, option positions have increased in value or have been more profitable compared to stock positions. This is further supported by the positive skewness, indicating a distribution leaning towards gains in option values. Gross_Pos_Value combines the values of stock and option positions. The negative mean here suggests that the overall position values, when combined, have decreased, mainly dragged down by the losses in stock positions despite the gains from options.

Stock_PL and Option_PL metrics reflect the cumulative profit and loss from stocks and options, respectively. The positive mean in Stock_PL indicates overall gains in stock trading, whereas a significantly negative mean in Option_PL contradicts the positive option position value. Net_PL has a negative mean here and it indicates that, on average, the total trading activity resulted in a loss, which aligns with the negative gross position value. The infinite maximum drawdowns highlight the potential for catastrophic losses, severely questioning the viability of the strategy under adverse market conditions. This preliminary analysis reveals that this strategy has high risk.

This is again what we expect - we lock in small gains from delta hedging, but the option position usually does not profit relative to the premium paid. The losses are reflected in the data.

[9]:
```
performance_summary(PL_trade_3)
```

[9]:

	Mean	Median	Volatility	Sharpe Ratio	\
gross_stock_trades	5.099952e+05	3.077805e+05	5.973523e+05	0.853759	
gross_option_trades	1.193424e+04	9.756000e+03	1.269503e+04	0.940072	
gross_trades_value	5.219294e+05	3.212479e+05	6.004285e+05	0.869262	
stock_trading_costs	5.099952e+01	3.077805e+01	5.973523e+01	0.853759	
option_trading_costs	1.193424e+00	9.756000e-01	1.269503e+00	0.940072	
net_trading_costs	5.219294e+01	3.212479e+01	6.004285e+01	0.869262	
stock_pos_value	6.295601e+05	3.592170e+05	1.366080e+06	0.460851	
option_pos_value	-1.580316e+05	-1.295520e+05	1.383358e+05	-1.142376	
gross_pos_value	4.715285e+05	2.483664e+05	1.335930e+06	0.352959	
stock_PL	-4.870277e+05	-3.260604e+05	4.295566e+05	-1.133792	
option_PL	8.432022e+05	6.323162e+05	6.959722e+05	1.211546	
net_PL	3.561745e+05	2.843840e+05	3.219589e+05	1.106273	
start_cash	1.367387e+06	1.290608e+06	3.252177e+05	4.204529	
initial_kapital	1.367950e+06	1.299248e+06	3.252429e+05	4.205933	
short_fee	6.787157e+00	0.000000e+00	2.302262e+01	0.294804	
initial_cash	1.089658e+06	1.000458e+06	1.117872e+06	0.974761	
interest	3.133986e+01	3.092063e+00	5.446732e+01	0.575388	
lever_cash	1.891424e+05	0.000000e+00	4.663580e+05	0.405573	
leverage_fee	8.412343e+00	0.000000e+00	3.060027e+01	0.274911	
end_kapital	1.367973e+06	1.299249e+06	3.252398e+05	4.206043	
net_short_fees	2.823143e+03	2.724356e+03	1.941965e+03	1.453756	
net_interest_paid	1.861103e+04	2.201835e+04	8.719365e+03	2.134448	
net_interest_earned	3.989804e+03	4.429460e+03	2.046663e+03	1.949419	
net_pos_value	1.372067e+06	1.346078e+06	3.265734e+05	4.201404	
tot_cash	9.874119e+06	9.997980e+06	1.370007e+06	7.207351	
daily_option_PL	1.884751e+03	0.000000e+00	6.141750e+03	0.306875	
daily_stock_PL	-1.315462e+03	-2.600564e+01	5.998969e+03	-0.219281	

```
daily_net_PL          5.692893e+02 -5.238310e+00  3.307831e+03      0.172104

                     Skewness  Excess Kurtosis           Min           Max  \
gross_stock_trades    1.984503         5.247189  0.000000e+00  4.768780e+06
gross_option_trades   1.256298         2.034144  0.000000e+00  8.294700e+04
gross_trades_value    1.966540         5.168831  0.000000e+00  4.792298e+06
stock_trading_costs   1.984503         5.247189  0.000000e+00  4.768780e+02
option_trading_costs  1.256298         2.034144  0.000000e+00  8.294700e+00
net_trading_costs     1.966540         5.168831  0.000000e+00  4.792298e+02
stock_pos_value       0.210565         0.905196 -4.296727e+06  5.408364e+06
option_pos_value     -0.932048         0.402343 -6.711300e+05  0.000000e+00
gross_pos_value      -0.081621         1.165026 -4.747632e+06  4.981198e+06
stock_PL             -1.450664         1.283994 -1.707469e+06  1.023171e+03
option_PL             0.704176        -0.714034 -1.615640e+01  2.446407e+06
net_PL                0.175024        -1.758702 -2.000261e+04  8.382902e+05
start_cash            0.171141        -1.759839  9.879245e+05  1.852314e+06
initial_kapital       0.168153        -1.761018  9.879361e+05  1.852313e+06
short_fee             5.224135        31.838692  0.000000e+00  2.087994e+02
initial_cash          1.498259         2.594988  0.000000e+00  6.542097e+06
interest              3.141633        12.473001 -6.525747e+00  3.855256e+02
lever_cash            3.084174        10.546752  0.000000e+00  3.318021e+06
leverage_fee          5.964587        45.994124  0.000000e+00  4.045936e+02
end_kapital           0.168168        -1.761030  9.879245e+05  1.852314e+06
net_short_fees        1.030274         1.502672  0.000000e+00  8.809729e+03
net_interest_paid    -0.363402         0.051323  2.958465e+01  4.067914e+04
net_interest_earned   0.191739         0.941216  0.000000e+00  1.091922e+04
net_pos_value         0.152497        -1.759854  9.814521e+05  1.880895e+06
tot_cash              0.463977         1.220143  5.649799e+06  1.551103e+07
daily_option_PL       0.426346         8.039548 -4.236907e+04  4.370388e+04
daily_stock_PL       -0.639158         5.808489 -3.462611e+04  3.266177e+04
daily_net_PL         -0.465936         8.052576 -2.339932e+04  1.835858e+04

                      Max Drawdown
gross_stock_trades        -1.000000
gross_option_trades       -0.999988
gross_trades_value        -1.000000
stock_trading_costs       -0.997082
option_trading_costs      -0.889483
net_trading_costs         -0.996769
stock_pos_value           -5.052143
option_pos_value     -671130.000000
gross_pos_value       -39687.059976
stock_PL               -1668.170888
option_PL                -16.156400
net_PL                  -506.680632
start_cash                -0.106368
initial_kapital           -0.106373
```

```
short_fee                -0.995234
initial_cash             -1.000000
interest                 -1.022907
lever_cash               -1.000000
leverage_fee             -0.997534
end_kapital              -0.106368
net_short_fees            0.000000
net_interest_paid        -0.000294
net_interest_earned       0.000000
net_pos_value            -0.137514
tot_cash                 -0.632859
daily_option_PL          -3.895200
daily_stock_PL         -118.711298
daily_net_PL           -118.711298
```

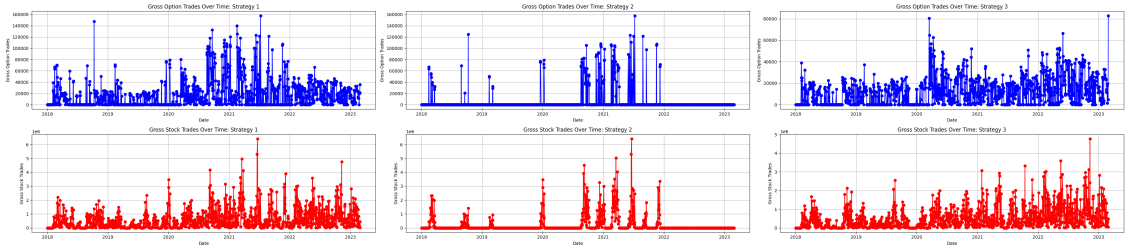
Trading Strategy 3 Summary Stats (Short Gamma):

Gross Stock Trades and Gross Option Trades show significant trading activity, with stock trades having a higher mean value, indicating more substantial volume compared to options. Both distributions show right-skewness, implying that while most of the trades are smaller, there are a few extremely large trades that increase the average trading volume. Gross Trades Value, representing the combined value of stock and option trades, also shows a high mean value with a right-skewed distribution, indicating that total trading activity encompasses a few very high-value trades alongside many smaller ones, typical in varied trading strategies.

Stock_PL indicates a substantial average loss (negative mean), suggesting that stock trading activities have generally resulted in losses. The negative skewness further points towards more significant losses than gains in the stock segment. Option_PL, on the other hand, shows a significant positive mean, indicating profitable outcomes on average from options trading. The positive skewness here suggests that while most option trades are moderately profitable, there are a few outstandingly profitable trades skewing the average upwards. Net_PL indicates that the gains from option trades have been sufficient to offset the losses from stock trades, leading to overall profitability. Yet, the max drawdown figures show significant potential for losses.

This is what we expect from being short gamma: in general, we expect our option positions to profit, while we trade some stock positions at a loss.

[10]:
```
plot_trades_over_time(PL_trade_1, PL_trade_2, PL_trade_3)
```



The plots above show patterns in gross option trades and gross stock trades over time for three different trading strategies.

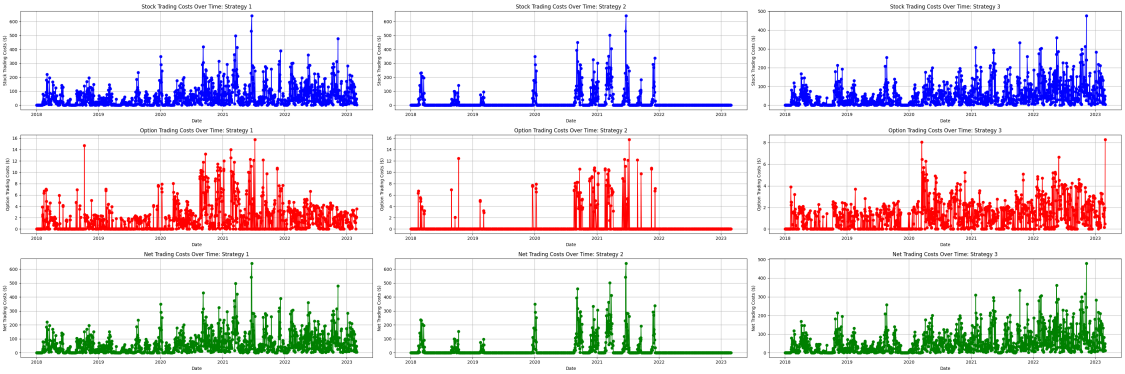
For Strategy 1 and 3, the volume of gross option trades and gross stock trades is quite high with a significant number of spikes, suggesting periods of high trading activity coupled with quieter times. Strategy 2, on the other hand, has significantly fewer spikes in both gross option and stock volume traded over time. For all three strategies, the volume of option trades is significantly higher and more volatile than stock trades, as indicated by the greater frequency and amplitude of peaks in the blue lines.

[11]:
```
plot_position_values_over_time(PL_trade_1, PL_trade_2, PL_trade_3)
```

The plots above illustrate the option and stock position values over time for the 3 trading strategies.

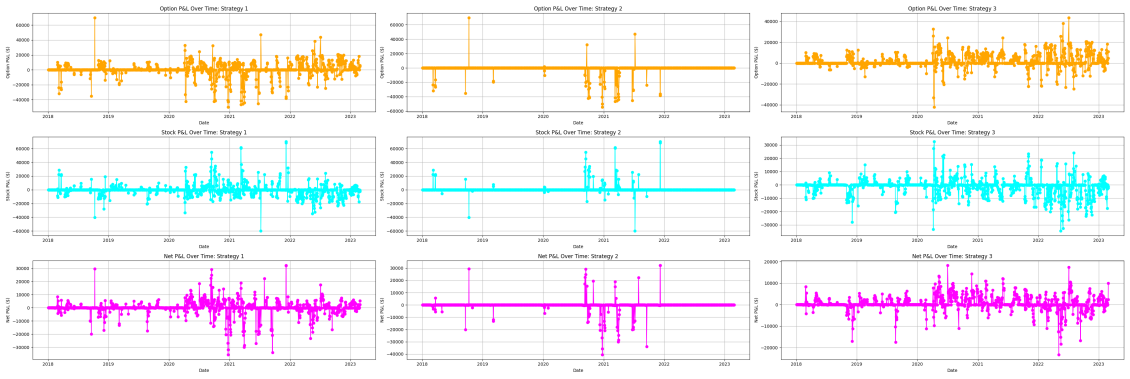
In Strategy 1, there is significant fluctuations in option position value, with some periods showing substantial positive values, especially around 2020 and 2021, suggesting profitable option positions, followed by sharp declines indicating losses which can be attributed to the covid-19 pandemic. The stock position value for Strategy 1, while also volatile, generally oscillates around a narrower range compared to the options, indicating less extreme changes in value but with notable periods of loss. Strategy 3 shows a similar pattern to Strategy 1 in terms of fluctuations. For strategy 2, the option position value always stays positive and the stock position value has minimal deviation from zero. For strategy 3, however, the option position value over time fluctuates below zero while the stock position value oscillates both positive and negative.

[12]:
```
plot_trading_costs_over_time(PL_trade_1, PL_trade_2, PL_trade_3)
```



The plots above show a visual representation of the trading costs associated with all 3 trading strategies.

[13]:
```
plot_pl_over_time(PL_trade_1, PL_trade_2, PL_trade_3)
```

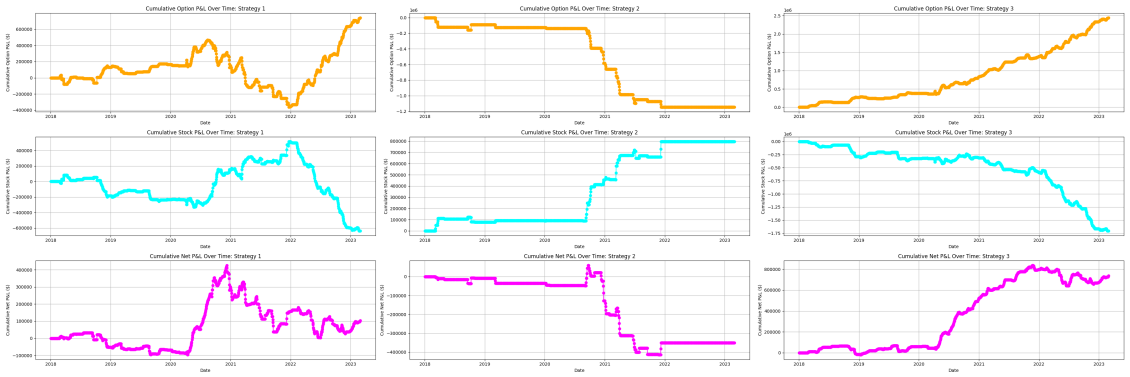


The plots above display the profit and loss (P&L) performance over time for the 3 different trading strategies. Across all strategies, option P&L tends to show greater variability and range compared to stock P&L, suggesting that options trading contributes more significantly to overall P&L fluctuations.

For Strategy 1, there's a consistent pattern of smaller losses and gains in stock trading, with larger outcomes in options trading, leading to an overall net P&L that exhibits a high-risk approach. Strategy 2 exhibits relatively less volatility particularly in the stock pnL, which appears to be slightly more stable. The net P&L for Strategy 2, while also volatile, does not seem to have very high peaks.

Overall, all three strategies demonstrate periods of both profit and loss, with options trading contributing more prominently to the volatility and magnitude of overall results.

[14]:
```
plot_cumulative_pl_over_time(PL_trade_1, PL_trade_2, PL_trade_3)
```



The graphs above show the cumulative profit and loss (P&L) over time for the three different

trading strategies.

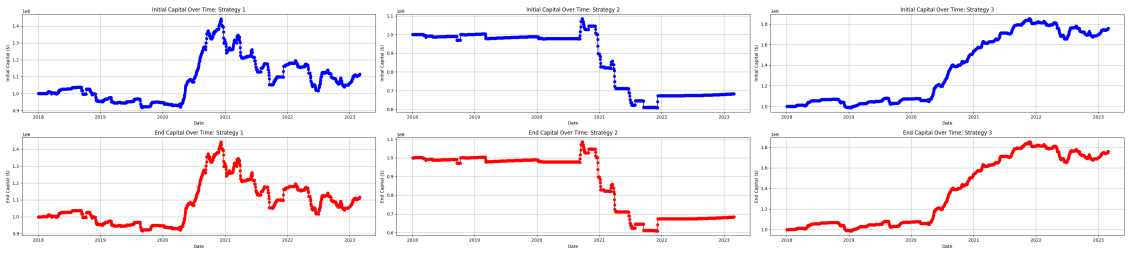
For Strategy 1, the cumulative option P&L shows an overall increasing trend (with a drop between 2020 to 2022), indicating profitable option trading activities by the end of the time period. In contrast, the cumulative stock P&L exhibits a general decline, especially after 2022, suggesting that stock trades were less successful. The net P&L shows fluctuations with a general downward trend until around mid-2020, followed by some recovery till 2021 but still underperformings.

For Strategy 2,the cumulative option P&L is mostly flat but then sharply drops in mid-2021, reflecting significant losses. The stock P&L shows a gradual increase, indicating more consistent gains from stock trading, a contrast to the option results. However, the net P&L mirrors the option performance closely, plunging in 2021, which indicates the losses in options heavily impacted the overall strategy performance.

Strategy 3 reveals continuous growth in option P&L, signifying a consistently profitable option trading strategy over time. The stock P&L, however, declines steadily, suggesting persistent losses in stock trading. The net P&L for Strategy 3 shows improvement and growth, particularly from 2020 onwards, indicating that the gains from options have been sufficient to not only recover from any stock losses but also to generate overall profit.

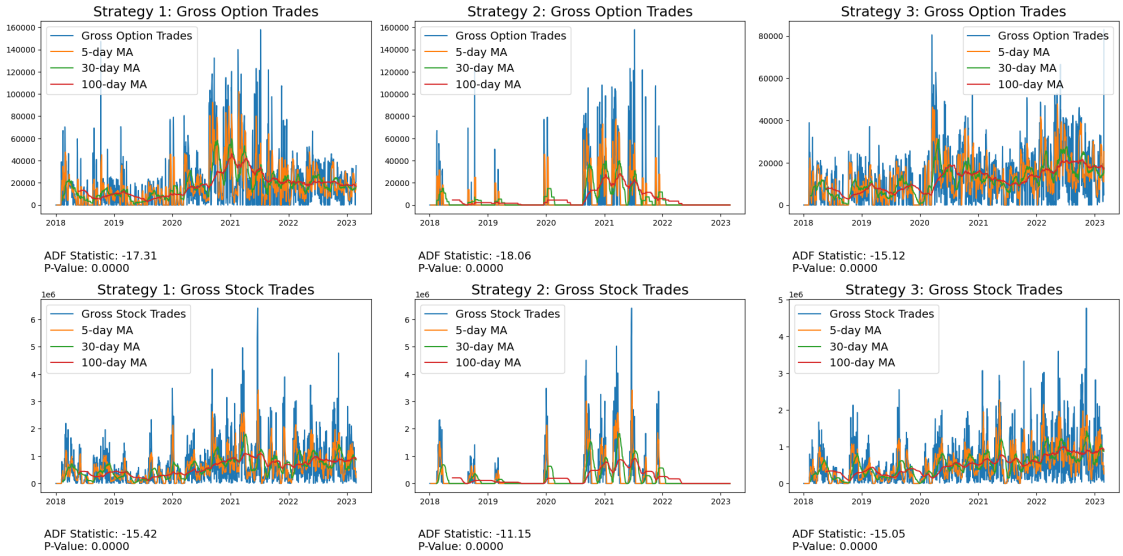
Altogether, this tends to show what one would expect: because options price IV higher than RV, being short gamma is generally a winning strategy, with exceptions occurring with large swings where the trader cannot react to the book in time.

[15]:
```
plot_kapital_over_time(PL_trade_1, PL_trade_2, PL_trade_3)
```



In the plots above, an increase in initial capital until 2021, which sees some decrease. Strategy 2 exhibits a stable initial capital until 2020, then both initial and end capitals plummet significantly with no signs of recovery. Strategy 3 demonstrates consistent growth in both initial and end capitals from 2020 onwards, indicating a successful and effective investment approach. While we do have to treat this with some lookahead bias, it is quite consistent that options are priced with more IV than realized volatility recently, so in general our predictions are logically sound.

[16]:
```
plot_trades_and_test_stationarity(PL_trade_1, PL_trade_2, PL_trade_3)
```



The charts show the gross option and stock trades over time for three different trading strategies, including their 5-day, 30-day, and 100-day moving averages (MAs). The moving averages smooth out short-term fluctuations and help identify longer-term trends in trading activity. The Augmented Dickey-Fuller (ADF) test results provided at the bottom of each graph further tell us about stationarity in the time series data.

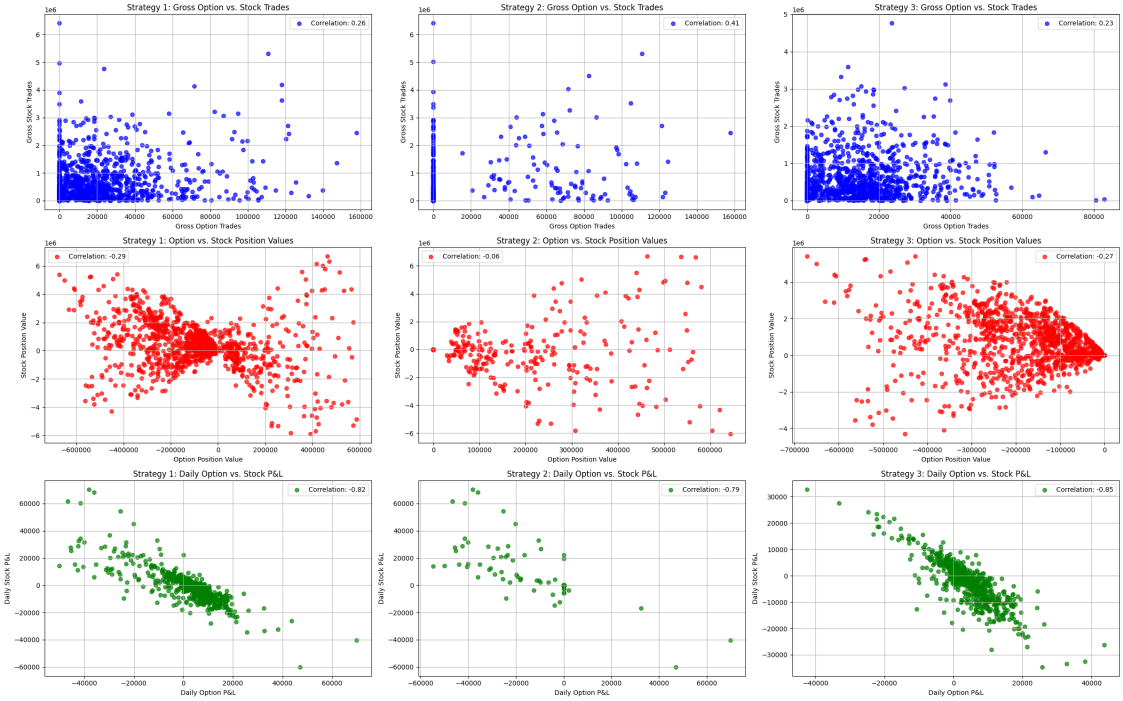
For strategy 1, both gross option trades and gross stock trades have very negative ADF statistic values (-17.31 and -15.42, respectively) with p-values of 0.0000. This suggests strong evidence against the null hypothesis.

For strategy 2, the ADF statistics for gross option trades and gross stock trades are -18.06 and -11.15 respectively. Similar to Strategy 1, these results strongly suggest that the series are stationary as the null hypothesis.

For strategy 3, again, the ADF statistics are -15.12 for gross option trades and -15.05 for gross stock trades, once again indicating that the null hypothesis can be rejected.

The consistency in the stationarity across all strategies for both option and stock trades indicates that these trading behaviors have stable dynamics, which makes them more predictable and relatively more manageable from a risk perspective.

[17]:
```
plot_correlations(PL_trade_1, PL_trade_2, PL_trade_3)
```



The charts display scatter plots with correlation coefficients, comparing Gross Option Trades vs. Stock Trades, Option vs. Stock Position Values, and Daily Option P&L vs. Stock P&L.

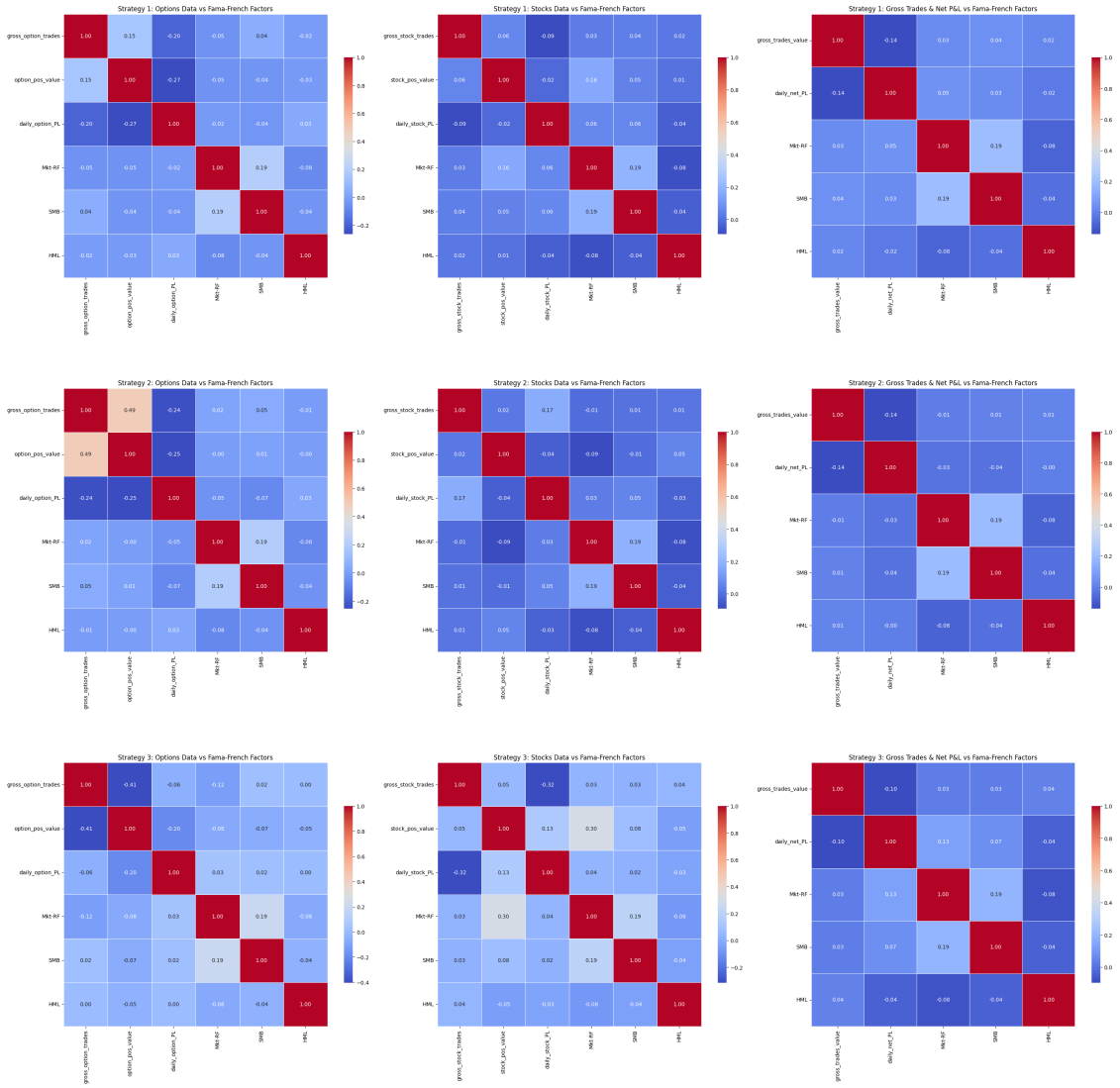
For Gross Option Trades vs. Stock Trades, Strategy 1 has a low positive correlation (0.26), indicating a slight relationship between the volume of option trades and stock trades. The data points are spread out, showing no strong linear relationship. Strategy 2 shows a moderate positive correlation (0.41), suggesting a greater relationship between the volume of options and stock trades compared to Strategy 1. Strategy 3 has a low positive correlation (0.23), similar to Strategy 1, indicating a slight relationship between the volumes.

For Option vs. Stock Position Values, all three strategies show negative correlations: -0.29 for Strategy 1, -0.06 for Strategy 2, and -0.27 for Strategy 3. These correlations suggest that, generally, as the value of option positions increases, the value of stock positions decreases, and the other way around.

For Daily Option P&L vs. Stock P&L, Strategy 1 exhibits a strong negative correlation (-0.82), indicating that on days when options P&L is high, stock P&L tends to be low, and the other way around. Strategy 2 and Strategy 3 both exhibit strong negative correlations as well (-0.79 and -0.85, respectively)

The strong negative correlations between daily option P&L and stock P&L across all strategies indicate a hedging relationship where options offset stock losses and stocks offset options losses, which is what we want - we want to lock in profits as the trading strategy progresses.

[18]:
```
plot_correlation_matrices(PL_trade_1, PL_trade_2, PL_trade_3, fff_data=fff_data)
```



The plots above show correlation matrices between vgross option trades, gross stock trades, daily option P&L, and daily stock P&L and Fama-French factors (market return - Mkt, small minus big - SMB, high minus low - HML, and risk-free rate - RF) for three different strategies.

For strategy 1, gross option trades, stock trades, and daily P&Ls have relatively low to correlations with market returns (Mkt), indicating that these activities are not strongly driven by overall market movements. Similar to Strategy 1, there is similar low correlation between the trading metrics and farma french factors for strategy 2. Stock position value has a correlation of -0.09 with the market factor. For strategy 3, stock position value has a moderate positive correlation of 0.30 with the market factor while the daily net PL has a slightly positive correlation of 0.13 with the market factor and 0.07 with SMB.

In summary, these correlation matrices provide insight into how each strategy's trades and daily performance relate very weakly to broader market and factor behaviors. Given that we are trading a strategy without any particular preference for directional movement, we consider this to be a

success.

We can also relate them to F-F factors - from which we see very little impact (which is good - we should not see any impact from a simple delta-hedging strategy, even with our model-free IV implementation):

[19]:
```
combined_1 = PL_trade_1.merge(fff_data, left_index=True, right_index=True,␣
 ↪how='left')
combined_2 = PL_trade_2.merge(fff_data, left_index=True, right_index=True,␣
 ↪how='left')
combined_3 = PL_trade_3.merge(fff_data, left_index=True, right_index=True,␣
 ↪how='left')
```

[20]:
```
run_regression_option_PL(combined_1, combined_2, combined_3)
```

```
Strategy 1: R-squared of the regression of option_PL on the Fama-French factors:
0.004904

Strategy 1 regression summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:              option_PL   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                  0.003
Method:                 Least Squares   F-statistic:                     2.126
Date:                Fri, 08 Mar 2024   Prob (F-statistic):             0.0952
Time:                        22:40:10   Log-Likelihood:                -17812.
No. Observations:                1298   AIC:                         3.563e+04
Df Residuals:                    1294   BIC:                         3.565e+04
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1.015e+05   6130.440     16.560      0.000    8.95e+04    1.14e+05
Mkt-RF      2552.7593   4478.698      0.570      0.569   -6233.546    1.13e+04
SMB         1.743e+04   8872.607      1.965      0.050      24.997    3.48e+04
HML        -6264.0446   5590.165     -1.121      0.263   -1.72e+04    4702.736
==============================================================================
Omnibus:                       80.328   Durbin-Watson:                   0.012
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               97.083
Skew:                           0.599   Prob(JB):                     8.29e-22
Kurtosis:                       3.600   Cond. No.                         2.06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
--------------------------------------------------------------------------------
```

```
--------------------

Strategy 2: R-squared of the regression of option_PL on the Fama-French factors:
0.003838

Strategy 2 regression summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:              option_PL   R-squared:                       0.004
Model:                            OLS   Adj. R-squared:                  0.002
Method:                 Least Squares   F-statistic:                     1.662
Date:                Fri, 08 Mar 2024   Prob (F-statistic):              0.173
Time:                        22:40:10   Log-Likelihood:                -18787.
No. Observations:                1298   AIC:                         3.758e+04
Df Residuals:                    1294   BIC:                         3.760e+04
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -5.253e+05    1.3e+04    -40.403      0.000   -5.51e+05      -5e+05
Mkt-RF      4517.8311   9498.065      0.476      0.634   -1.41e+04    2.32e+04
SMB         2882.0575   1.88e+04      0.153      0.878    -3.4e+04    3.98e+04
HML        -2.507e+04   1.19e+04     -2.114      0.035   -4.83e+04   -1810.181
==============================================================================
Omnibus:                     5996.765   Durbin-Watson:                   0.008
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              190.199
Skew:                          -0.373   Prob(JB):                     5.00e-42
Kurtosis:                       1.279   Cond. No.                         2.06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
--------------------------------------------------------------------------------
--------------------

Strategy 3: R-squared of the regression of option_PL on the Fama-French factors:
0.002243

Strategy 3 regression summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:              option_PL   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                 -0.000
Method:                 Least Squares   F-statistic:                    0.9697
Date:                Fri, 08 Mar 2024   Prob (F-statistic):              0.406
Time:                        22:40:10   Log-Likelihood:                -19302.
```

```
No. Observations:                1298   AIC:                          3.861e+04
Df Residuals:                    1294   BIC:                          3.863e+04
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const       8.436e+05   1.93e+04     43.649      0.000    8.06e+05    8.82e+05
Mkt-RF     -5450.4088   1.41e+04     -0.386      0.700   -3.31e+04    2.22e+04
SMB         1.193e+04    2.8e+04      0.427      0.670   -4.29e+04    6.68e+04
HML         2.828e+04   1.76e+04      1.605      0.109   -6295.462    6.29e+04
================================================================================
Omnibus:                      157.202   Durbin-Watson:                   0.004
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              134.842
Skew:                           0.707   Prob(JB):                     5.24e-30
Kurtosis:                       2.296   Cond. No.                         2.06
================================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
--------------------------------------------------------------------------------
--------------------
```

The three regression results that use the Fama-French factors to predict option_PL show very small R^2 values, with the best performing regression being strategy 1 with an R^2 value of 0.005. No factors individually had a significant p-value.

[ ]:
```
run_regression_stock_PL(combined_1, combined_2, combined_3)
```

Very similar to the regression results from option_PL, the three regression results that use the Fama-French factors to predict stock_PL show very small R^2 values, with the best performing regression again being strategy 1 with an R^2 value of 0.005. No factors individually had a significant p-value.

[ ]:
```
run_regression_net_PL(combined_1, combined_2, combined_3)
```

Once again, very similar to the regression results from option_PL and stock_PL, the three regression results that use the Fama-French factors to predict net_PL show very small R^2 values, with the best performing regression again being strategy 1 with an R^2 value of 0.008. Once again, no factors individually had a significant p-value in any of the 3 regressions (although the HML factor was close for strategy 1 and strategy 3).

[ ]:
```
plot_rolling_volatility(combined_1, combined_2, combined_3, window_size=30)
```

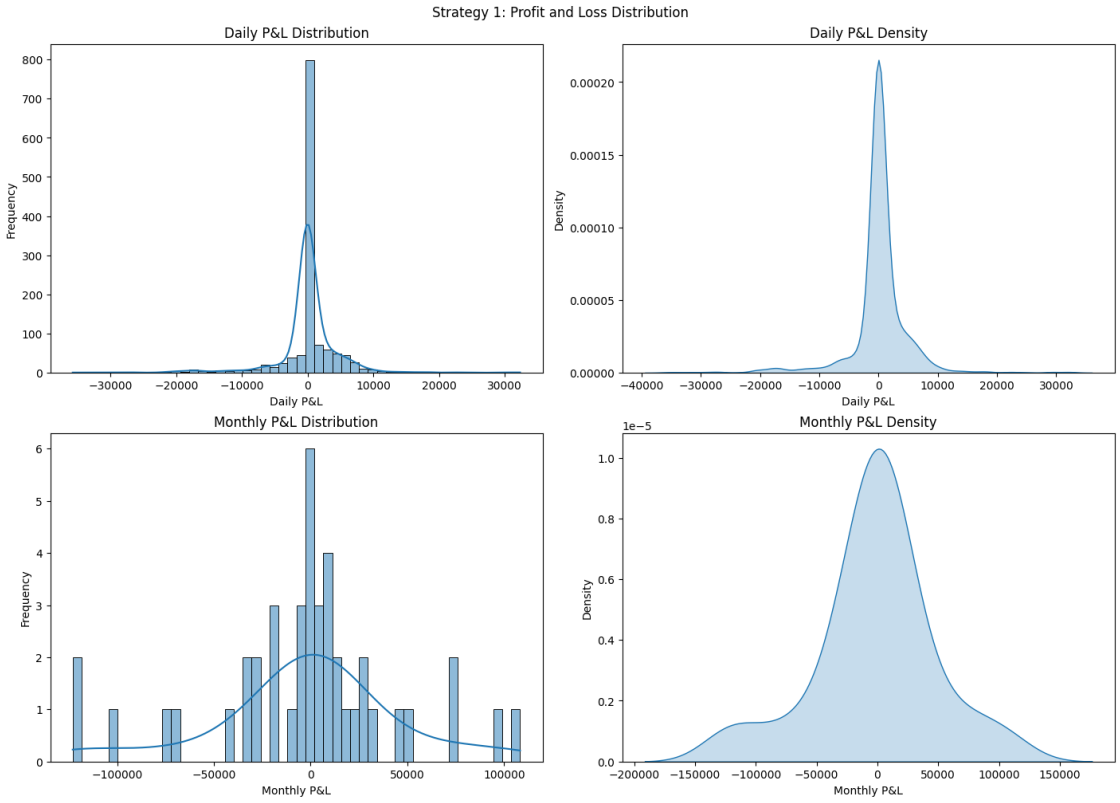
The graphs illustrate the 30-day rolling volatility of returns for the 3 trading strategies.

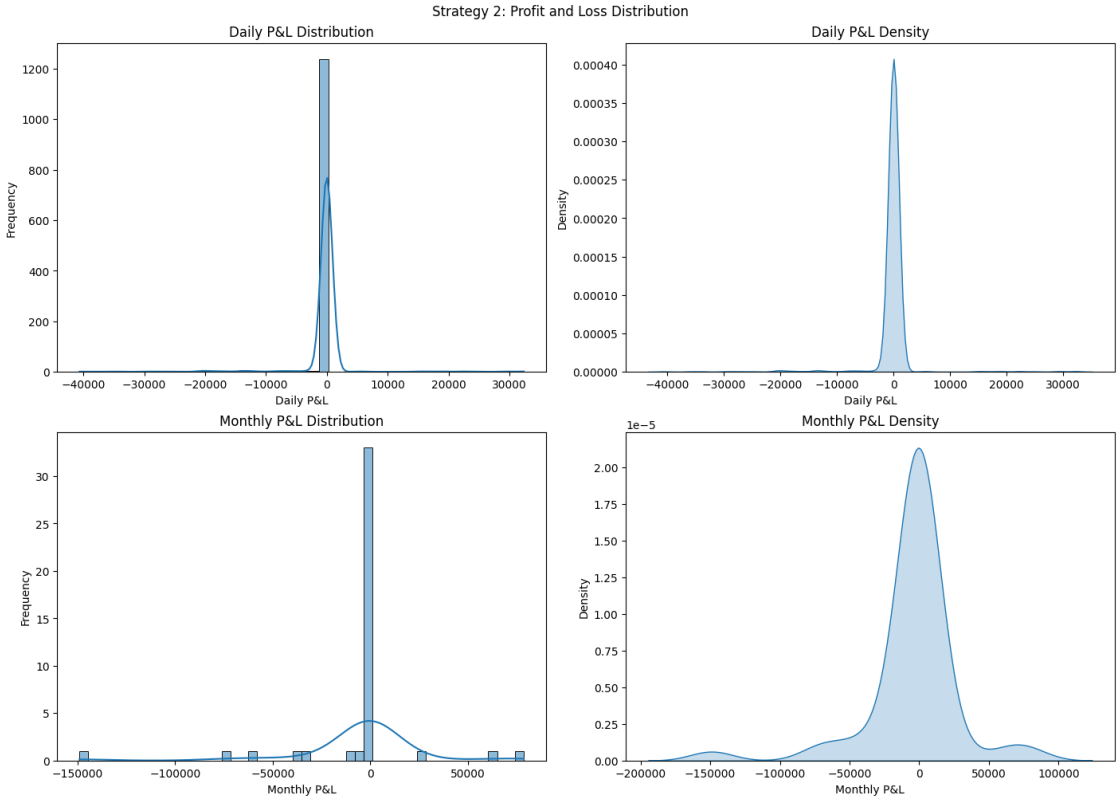
The volatility profile for Strategy 1 shows significant peaks, particularly around early 2019, 2020, and 2022. The volatility profile for strategy 2, on the other hand, is slightly different with major

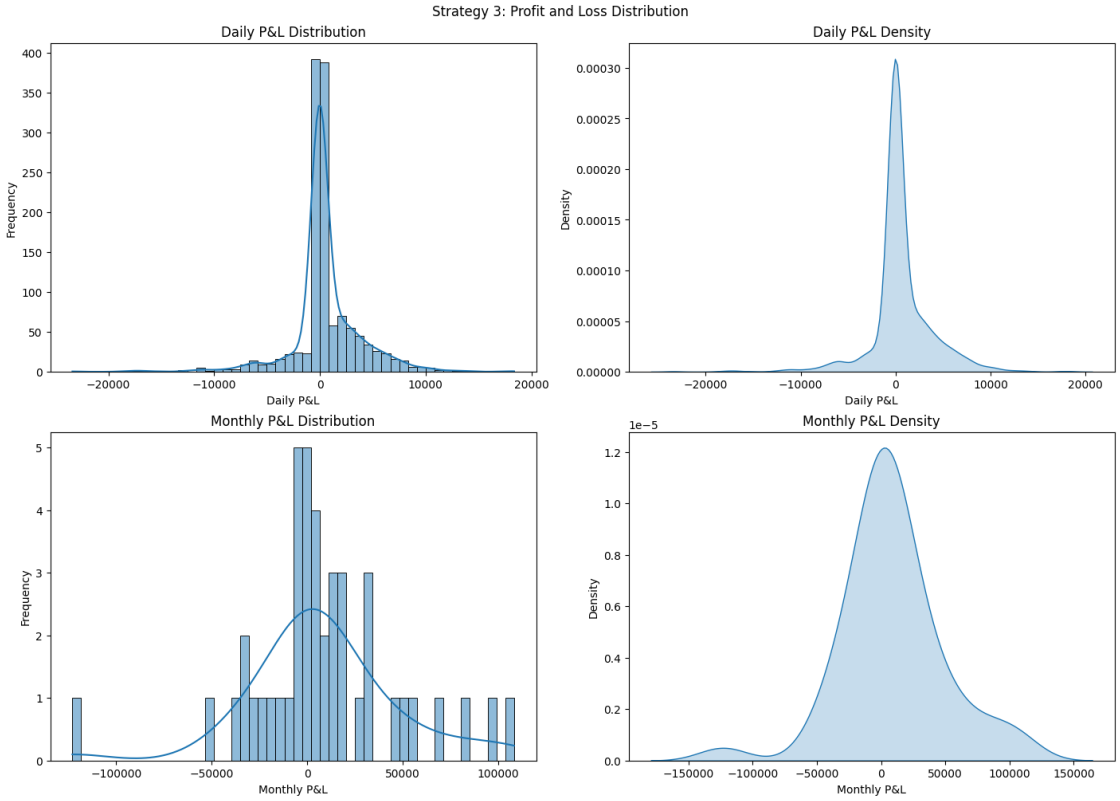
peaks in 2018 and a huge spike in 2020, staying constant otherwise. Strategy 3 also has a very different volatility profile, having elevated spiked from 2018 to 2019, followed by flat rolling vol for the rest of the trading period.

This would lead us to believe that much of the volatility in the strategy stems from long gamma positions, again reinforcing that in general, a short gamma position is more likely to profit.

[24]:
```
plot_pnl_distribution(combined_1, combined_2, combined_3)
```




Strategy 2: Profit and Loss Distribution
Daily P&L Distribution
Frequency
Daily P&L
Daily P&L Density
Density
Daily P&L
Monthly P&L Distribution
Frequency
Monthly P&L
Monthly P&L Density
1e−5
Density
Monthly P&L


Strategy 3: Profit and Loss Distribution
Daily P&L Distribution
Frequency
Daily P&L
Daily P&L Density
Density
Daily P&L
Monthly P&L Distribution
Frequency
Monthly P&L
Monthly P&L Density
1e−5
Density
Monthly P&L

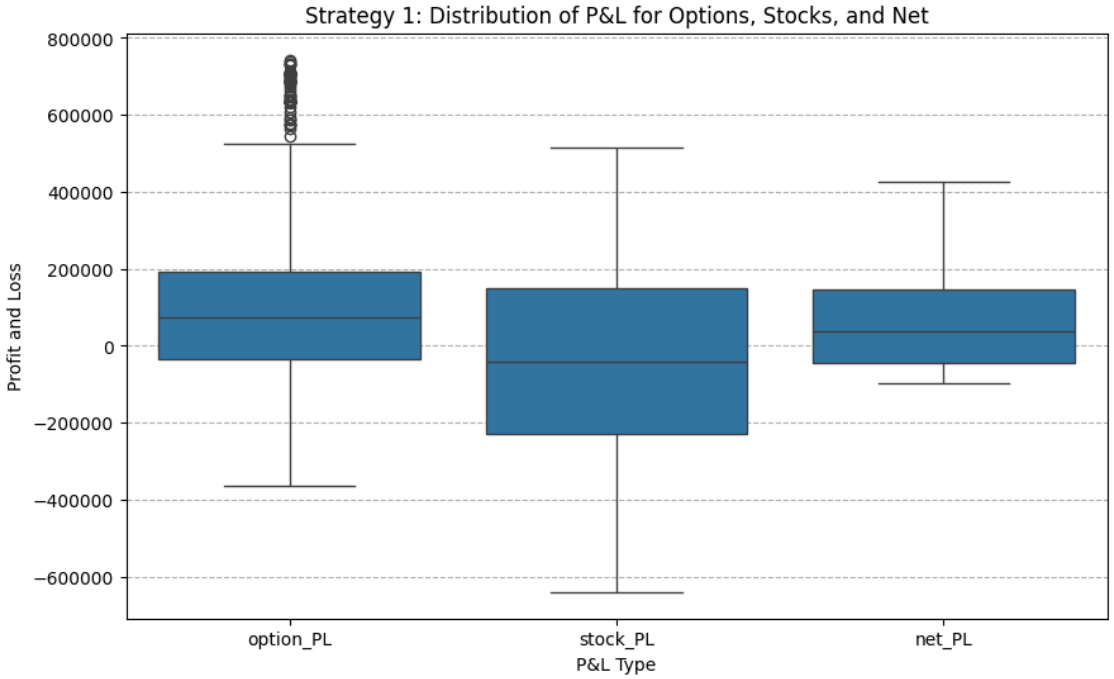
The profit and loss (P&L) distribution for Strategy 1 indicates that on a daily basis, returns are typically close to zero but with a slight skew towards losses, as shown by the sharp peak and longer left tail in the daily distribution plots. In contrast, the monthly P&L exhibits greater variability and a slight positive skew, indicating that while day-to-day results are often negligible or slightly negative, the aggregate monthly outcomes display a wider range of results with potential for profitability. This suggests that Strategy 1 experiences regular minor losses or gains daily but has the capacity for broader, more significant outcomes on a monthly basis, possibly due to cumulative effects of the trading strategy over a longer period.

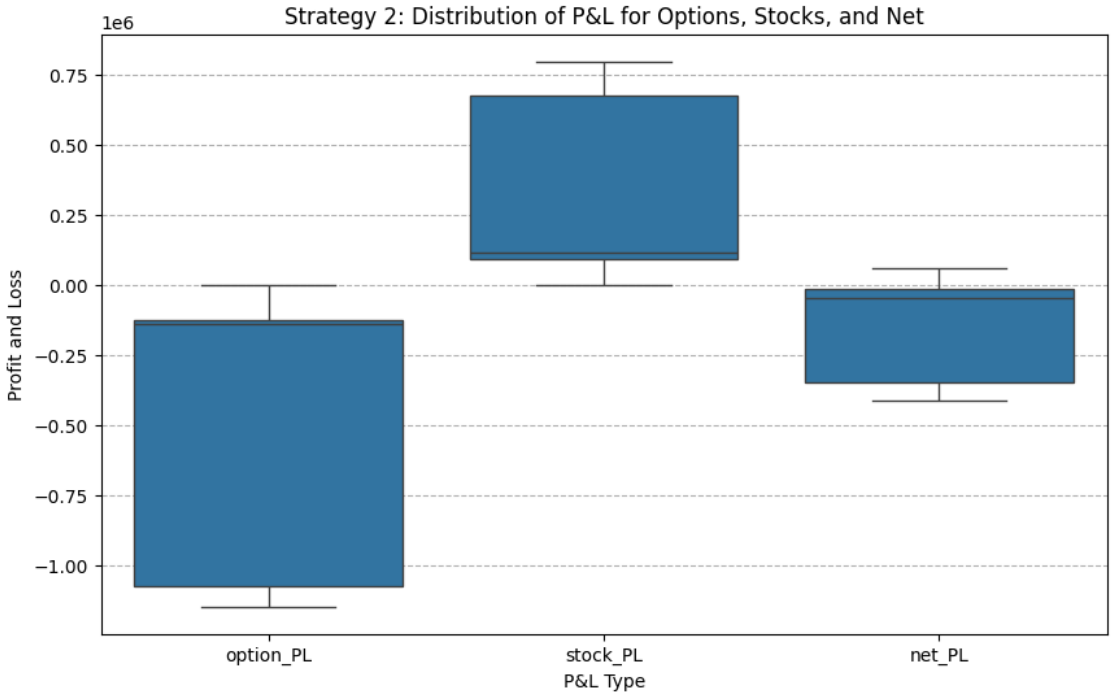
For Strategy 2, the daily P&L distribution and density plot show a very narrow, sharp peak around zero, indicating extremely consistent results on a day-to-day basis with minimal deviation from zero, suggesting very low daily volatility. In contrast, the monthly P&L distribution exhibits a wider range of outcomes with a significant peak at zero but with a notable spread, as seen in the histogram and density plot, suggesting that while daily returns are consistently close to neutral, the cumulative effect over the month can result in a wider range of profit and loss outcomes.

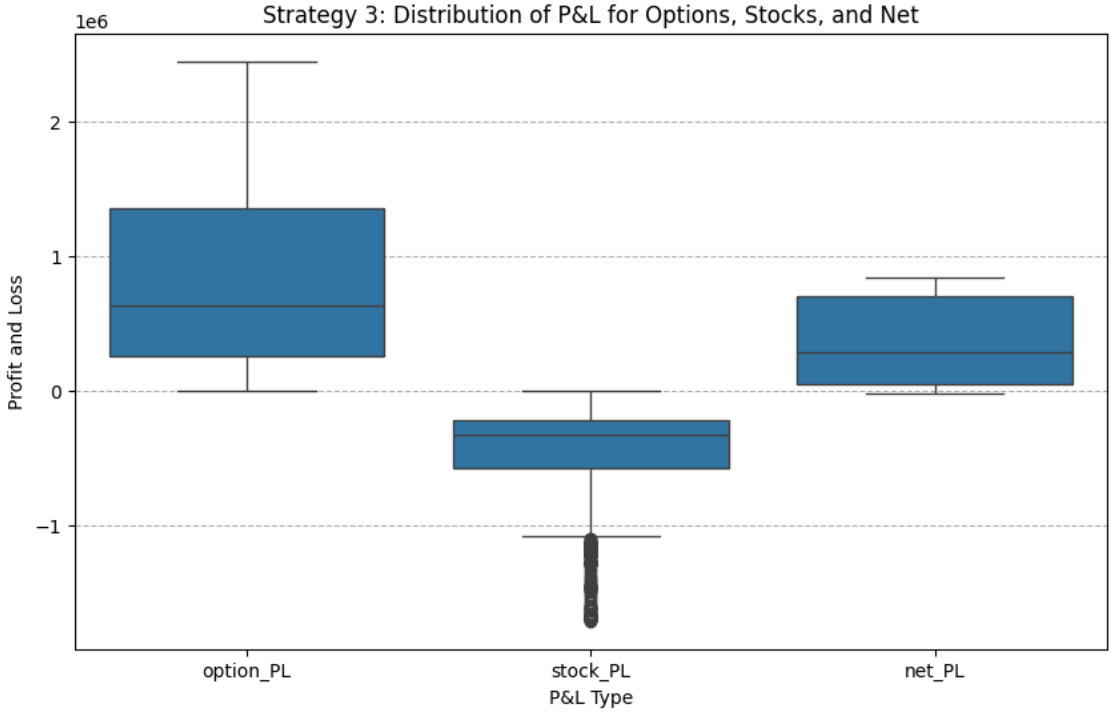
For Strategy 3, the daily P&L distribution again has a sharp peak around zero, indicating that most days result in minimal profit or loss, but with a visible spread indicating occurrences of both significant gains and losses. The density plot supports this with a narrow peak. The monthly P&L distribution and density show a more dispersed range than the daily figures, with a central peak slightly skewed towards the right, leaning towards profitability.

This mostly supports what we observed: short gamma positions generally have resulted in small profits. This is also shown below:

[25]:
```
plot_pl_boxplots(combined_1, combined_2, combined_3)
```




Strategy 2: Distribution of P&L for Options, Stocks, and Net
1e6
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
Profit and Loss
option_PL
stock_PL
net_PL
P&L Type


Strategy 3: Distribution of P&L for Options, Stocks, and Net
1e6
2
1
0
−1
Profit and Loss
option_PL
stock_PL
net_PL
P&L Type

The box plots above show the min, max, median, 1st, and 3rd quartiles of the option, stock, and net PL of all 3 trading strategies. These results were already analyzed with the performance summary above. Nevertheless, they show a visual representation of these statistical parameters. A majority of long option positions are unlikely to profit, which our analysis holds.

It is interesting to note that while the short-only portfolio was more profitable, the IV-comparison (model-free) strategy eliminated many severe outliers; however, this is a bit less interesting when one realizes that the outlying stock losses are generally correlated to strong option profits.

[26]:
```
calculate_profit_factor_analysis(combined_1, combined_2, combined_3)
```

```
Strategy 1: Option Profit Factor: 1.315174804570438
Strategy 1: Stock Profit Factor: 0.7723735545069135

Strategy 2: Option Profit Factor: 0.11664217051956995
Strategy 2: Stock Profit Factor: 4.939689657031665

Strategy 3: Option Profit Factor: 3.6354558279313203
Strategy 3: Stock Profit Factor: 0.4134146298162746
```

The results show the profit factor for options and stocks across the 3 trading strategies. The profit factor is calculated as the total gains divided by the total losses. A profit factor greater than 1 indicates that the strategy is profitable (since total gains exceed total losses), while a profit factor less than 1 indicates a losing strategy.

Strategy 1: Option Profit Factor: 1.31517 - indicates that options trading is profitable, as gains exceed losses. Stock Profit Factor: 0.77237 - indicates that stock trading is not profitable, as losses exceed gains.

A mix of long/short positions is generally more stable, as we expect.

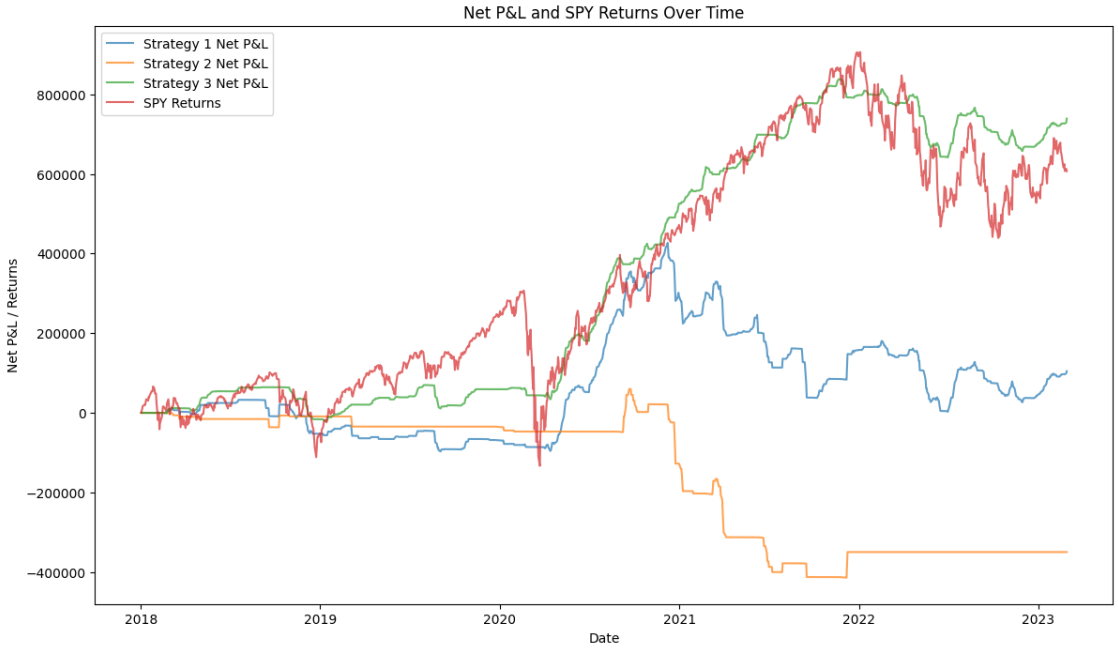
Strategy 2: Option Profit Factor: 0.11664 - indicates that options trading is highly unprofitable, with losses far exceeding gains. Stock Profit Factor: 4.93969 - indicates a highly profitable stock trading approach, with gains significantly outweighing losses.

Long option positions are likely to not be profitable, clearly shown here, where most of the recovered capital is from hedging.

Strategy 3: Option Profit Factor: 3.63546 - indicates that options trading is very profitable. Stock Profit Factor: 0.41341 - indicates that stock trading is not profitable, with losses outpacing gains.

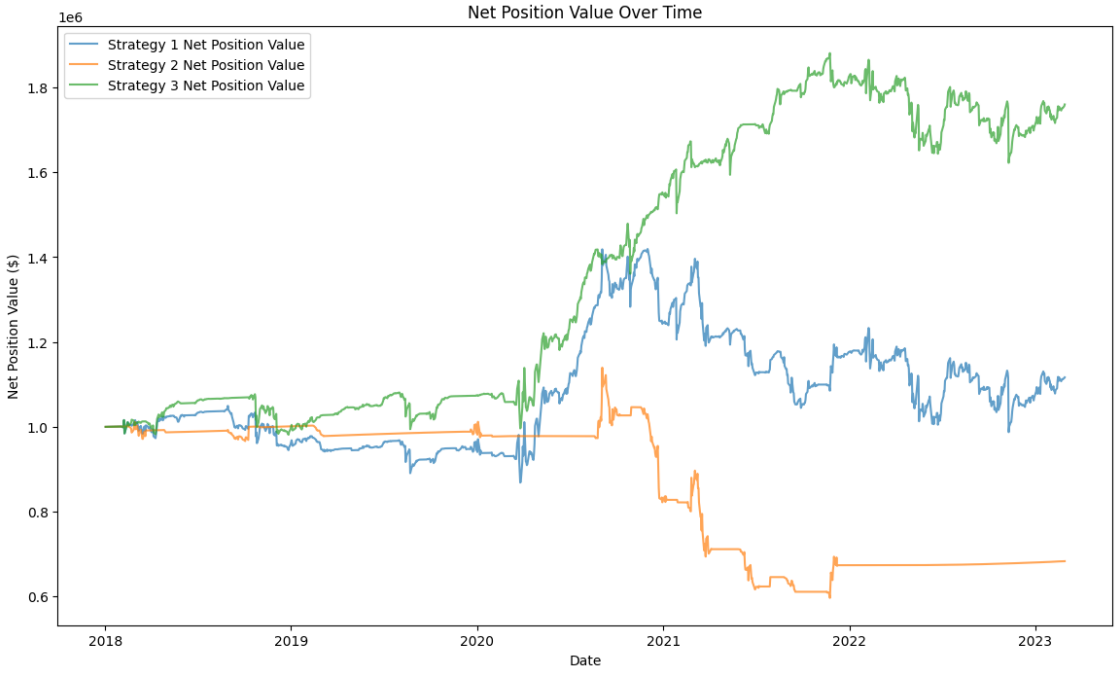
And a short gamma position is profitable as we expect.

[27]:
```
plot_cum_net_pl_and_spy_returns(combined_1, combined_2, combined_3, spydata)
```



The plot above compares the returns for all 3 trading strategies along with excess returns on SPY on a $1,000,000 initial capital.

[28]:
```
plot_net_pos_val(combined_1, combined_2, combined_3)
```



The plot above displays the net position value over time for the 3 different trading strategies. Strategy 1 shows stability until early 2020, after which there's a rapid increase, peaking around mid-2021 / 2022 before it enters a period of volatility and slight decline, yet it remains significantly above its starting value. Strategy 2 maintains a relatively flat line with slight variations, indicating stability but minimal growth, followed by a steep decline towards the end of 2020, bottoming out and remaining flat. Strategy 3 experiences gradual growth until it peaks in early 2022, experiencing volatility towards the end.

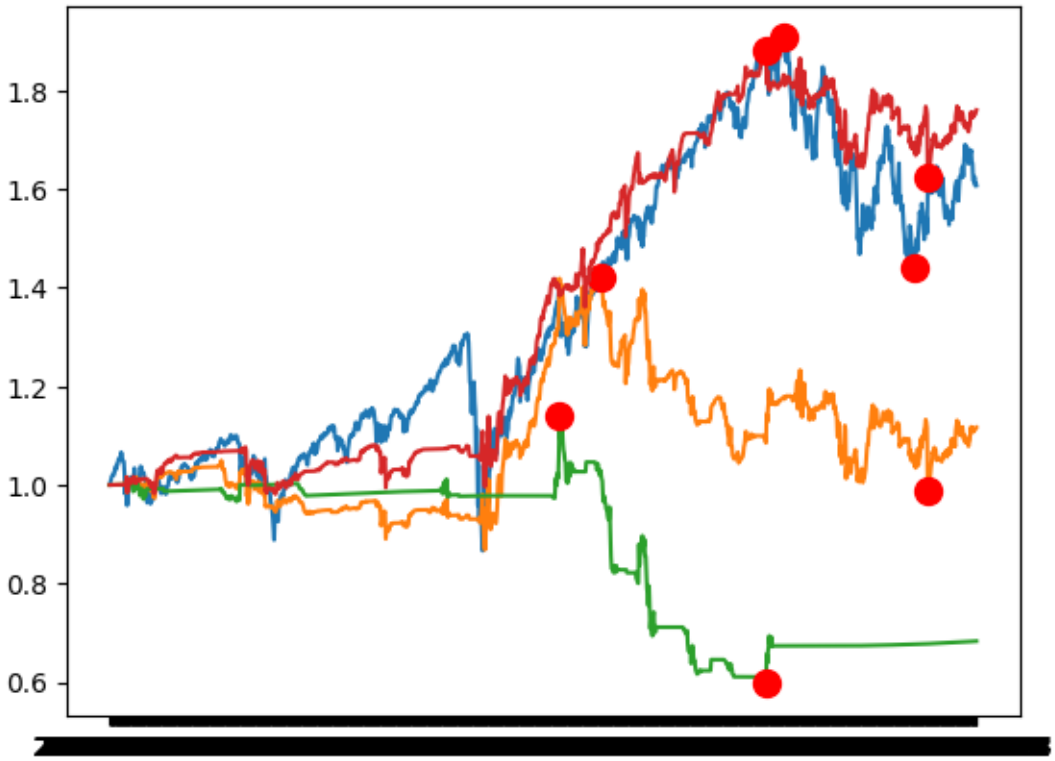
We can also briefly visit the max drawdown metrics, which extends what we see above. We can see visually where these metrics occur:

[29]:
```
long_short = pd.read_csv('simdata/PL_trade_1.csv')[['date','net_pos_value']].
 ↪sort_values(by='date').reset_index(drop=True)
long_only = pd.read_csv('simdata/PL_trade_2.csv')[['date','net_pos_value']].
 ↪sort_values(by='date').reset_index(drop=True)
short_only = pd.read_csv('simdata/PL_trade_3.csv')[['date','net_pos_value']].
 ↪sort_values(by='date').reset_index(drop=True)

long_short['long_short_return'] = long_short['net_pos_value'] / long_short.
 ↪loc[0, 'net_pos_value']
long_only['long_only_return'] = long_only['net_pos_value'] / long_only.loc[0,␣
 ↪'net_pos_value']
short_only['short_only_return'] = short_only['net_pos_value'] / short_only.
 ↪loc[0, 'net_pos_value']
```

[30]:
```
start_date = '2018-01-01'
end_date = '2023-02-28'
spy_data = pd.read_csv('spy_tickerdata.csv')[['date','adj_close']].
 ↪sort_values(by='date').reset_index(drop=True)
spy_data = spy_data.loc[(spy_data['date'] >= start_date) & (spy_data['date'] <=␣
 ↪end_date)].copy().reset_index(drop=True)
spy_data['spy_return'] = spy_data['adj_close'] / spy_data.loc[0, 'adj_close']

ret_data = spy_data[['date', 'spy_return']].copy()
ret_data['long_short_return'] = long_short['long_short_return']
ret_data['long_only_return'] = long_only['long_only_return']
ret_data['short_only_return'] = short_only['short_only_return']
ret_data = ret_data.set_index('date')
```

[31]:
```
for col in ret_data.columns:
    max_dd(ret_data[col])
```

```
0.24497270037076455
0.3042381586224645
0.4762755640185654
0.1375138413928244
```



Also interesting is that if we look at some summary stats, we note that our model-free IV-decided strategy, strategy 1, has a very low R-squared with the market, which is a good sign for separating it from the directional movement of the market. The Sharpe, however, is poor.

Strategy 2 (long gamma only) clearly does not perform well.

Strategy 3, in contrast, seems to be the best performer among the three, with a significant positive annualized return of approximately 11.6%. It is important to note that the annualized volatility is more than the return, however. It is interesting to note that despite being a direction-agnostic strategy, the beta and information ratio is quite high. Alpha is a bit better than the other two implementation.

Strategy 3 appears to be the most successful in terms of both absolute and risk-adjusted return.

[34]:
```
combined_metrics_df = combined_performance_metrics(spydata, combined_1,␣
↪combined_2, combined_3, rfr=0.01)
combined_metrics_df
```

[34]:

	Annualized Return	Annualized Volatility	Sharpe Ratio	Beta	\
Strategy 1	0.021625	0.186944	0.062186	0.221865	
Strategy 2	-0.071188	0.138066	-0.588035	-0.285525	
Strategy 3	0.115873	0.138542	0.764194	0.547836	

	Information Ratio	Alpha	R-squared	Tracking Error

```
Strategy 1           0.034872  0.004964   0.086054        0.142349
Strategy 2          -0.421468 -0.029837   0.386690        0.070793
Strategy 3           0.386764  0.056731   0.350932        0.146681
```

1.12 10. Additional Concluding Thoughts

We've made most of our observations in the simulation and analysis sections, but we can give a few more thoughts: * As we expect, our simulation tends to support long option positions being generally unprofitable on their own * Because of options pricing IV higher than RV (due to high tail risk), we saw short option positions perform as expected * Our risk management decision to close a week before expiry really minimized the tail risk associated with short gamma, even through volatile times such as March 2020 and 2022 bear markets, keeping the maximum drawdown to 14% * Transaction costs are less impactful on the strategy due to daily rebalance outweighing costs, in general * Using model-free IV to decide both long and short positions reduced the overall profitability, but it can be argued that it also removed some outlying performers and underperformers. However, setting a threshold to trade only short gamma positions (and not take positions at all if the threshold is not met, rather than also having model-free IV thresholds on the other side) seems to still outperform.

1.13 Appendix

1.13.1 Simulate and Save

Full Simulation and saving to CSV of all possible position opens.

[ ]:
```
simulations = create_simulations(options, data, dropna_greeks=True)

simulations_long = {date: calculate_realized_PL(df.copy(), long_op=True) for␣
 ↪date, df in simulations.items()}
simulations_short = {date: calculate_realized_PL(df.copy(), long_op=False) for␣
 ↪date, df in simulations.items()}
```

[ ]:
```
os.makedirs('simdata', exist_ok=True)

for date, df_long in simulations_long.items():
    csv_path_long = f'simdata/simulation_long_{date}.csv'
    df_long.to_csv(csv_path_long, index=False)

for date, df_short in simulations_short.items():
    csv_path_short = f'simdata/simulation_short_{date}.csv'
    df_short.to_csv(csv_path_short, index=False)
```