Selling ATM Straddle Strategy before Earnings

Pranav Devarakonda, Junhan Fu, Diana Castellanos Polina, Swaminath Murugadasan, Josh Li, Shrey Jain

Supervised by
Euan Sinclair, Abid Ali

May 2024

1 Data Description

The data for this project is sourced from multiple databases, each providing crucial information for building and testing our strategy. Below is a brief description of each data source, followed by a detailed explanation.

- **ZACKS/FC**: The Zacks Fundamentals Condensed (ZACKS/FC) table in Quandl provides a comprehensive set of over 200 fundamental indicators for more than 19,500 companies, including over 9,000 delisted stocks. These indicators cover a wide range of financial metrics such as revenue, earnings, cash flow, and various financial ratios.
- **Bloomberg**: Bloomberg provides top-quality financial data that seamlessly integrates into the tools your firm uses to make critical decisions
- **OptionMetrics by WRDS**: OptionMetrics is the premier provider of historical options data for use in empirical research and econometric studies. Quantitative researchers and financial professionals leverage OptionMetrics data for purposes such as analyzing market movement before mergers and acquisitions; exploring the relationship between option prices and daily stock return serial correlation; and investigating possible cases of insider trading.
- **CRSP**: CRSP data contains security-level historical descriptive information and market data on more than 32,000 securities for both inactive and active companies from the NYSE, NYSE American, NASDAQ, and NYSE Arca exchanges. range.

1.1 Options and Stock Prices

Options prices are sourced from OptionMetrics, and stock prices are obtained from CRSP. These datasets provide the necessary information to calculate the potential profitability of the trading strategies.

1.1.1 Bloomberg

We download earnings call dates from the Bloomberg terminal for the tickers in our database. Earnings calls are significant events that can lead to substantial movements in stock prices and volatility, making this data essential for timing our straddle strategies. The accuracy and reliability of Bloomberg's data ensure that our models are based on the most current and relevant information available.

1.1.2 OptionMetrics by WRDS

OptionMetrics provides detailed data related to option prices, Option Greeks (Delta, Gamma, Theta, Vega), and other supporting financial metrics for multiple tickers across various sectors from 2018 to 2023. This dataset is pivotal in developing our trading strategy. The Option Greeks, in particular, are vital for understanding the sensitivity of option prices to changes in underlying variables and are crucial inputs for strategy.

1.1.3 CRSP

The Center for Research in Security Prices (CRSP) provides historical stock price data, which is necessary for identifying the strikes that fall into the AtTheMoney (ATM) option range. The CRSP data helps us determine the entry and exit points of our trading strategy and calculate the potential profitability of our trades accurately.

2 Strategy

Using data from Bloomberg, OptionMetrics, and CRSP, we constructed a dataset encompassing 19,476 earnings events from 2018 to 2023. Additionally, we set a criterion that the closing price of the underlying stocks must exceed 20. Our experimental analysis revealed that the realized volatility post-earnings is consistently lower than the volatility implied by at-the-money (ATM) straddles. This observation suggests that buying straddles is generally unattractive.

Consequently, we propose a strategy of selling ATM straddles on the earnings date and covering the positions the following day. Ideally, we would prefer to close the positions at the start of the next trading day. However, due to the unavailability of opening prices, we instead utilize the closing prices of the next day. While this approach aids our research and analysis, it should be noted that it may not accurately reflect real-world trading dynamics. The mean PNL of selling 1000 dollars worth of straddles before earnings and closing then next day across the entire dataset was 1.93 USD (across 4263 data points). For most of this paper, the PNL we analyze is assuming we sell 1000 USD of straddles at close before earnings, and close the position at the next day's close.

The subsequent chapters will delve into an in-depth analysis of the selling straddle strategy, categorized by distinct dimensions: Moments (Vol,Skew,Kurtosis), Sectors, Local Peaks, and Variance of Earnings. Each section will explore how these factors influence the effectiveness of the strategy, providing a comprehensive understanding of its performance across different market conditions.

3 Results by deciles of Volatility,Skew,Kurtosis

We computed implied skew/kurtosis from the implied volatilities of the at the money straddle, 25 delta call, and 25 delta put as described in the paper " The Information Content of Straddles, Risk Reversals and Butterfly Spreads" by Peter Carr and Liueren Wu

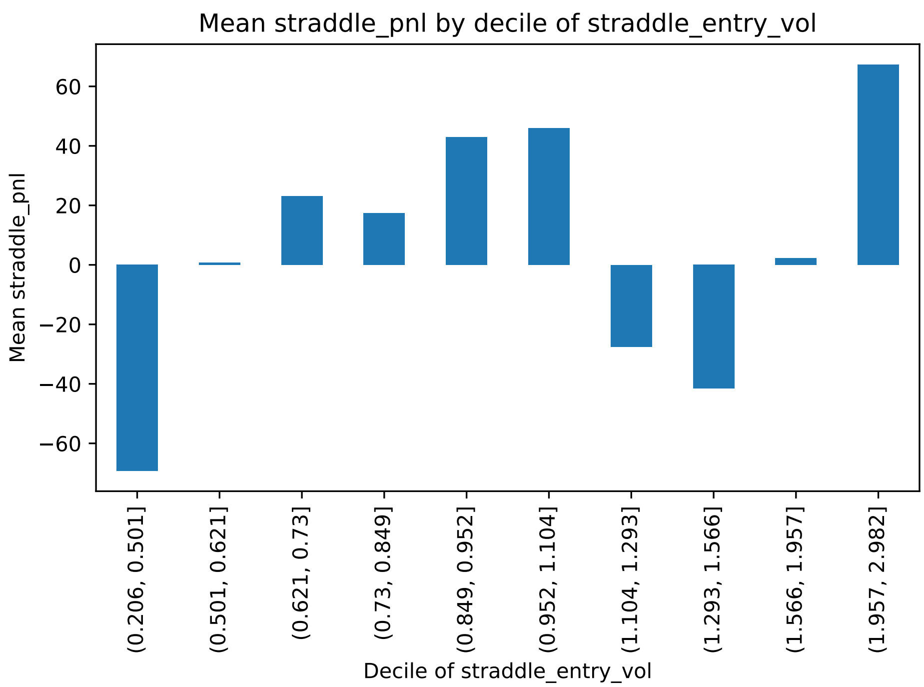


Figure 1: Mean PnL for deciles of ATM volatility

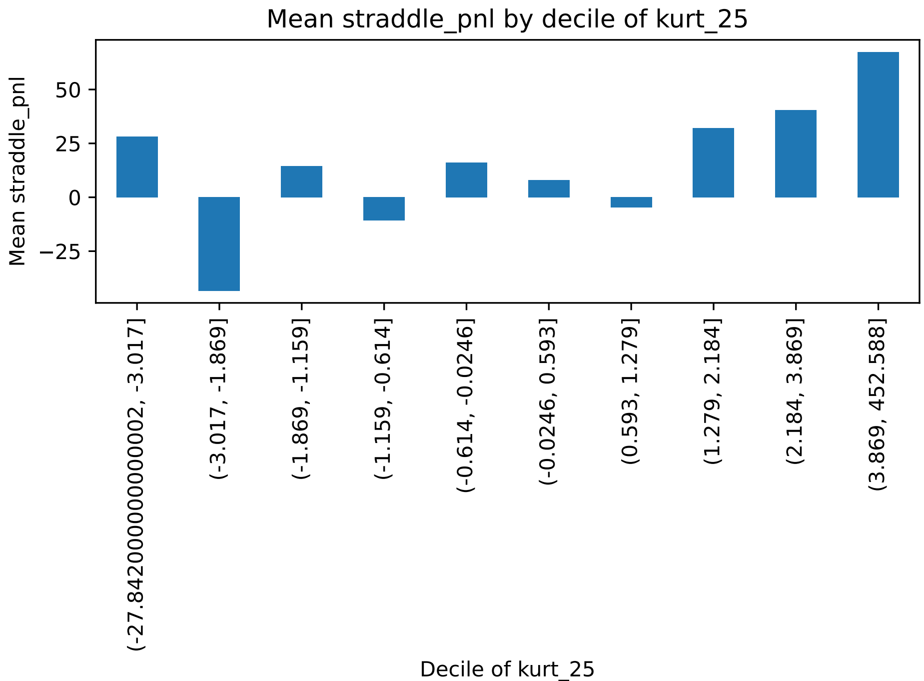


Figure 2: Mean PnL for deciles of Kurtosis

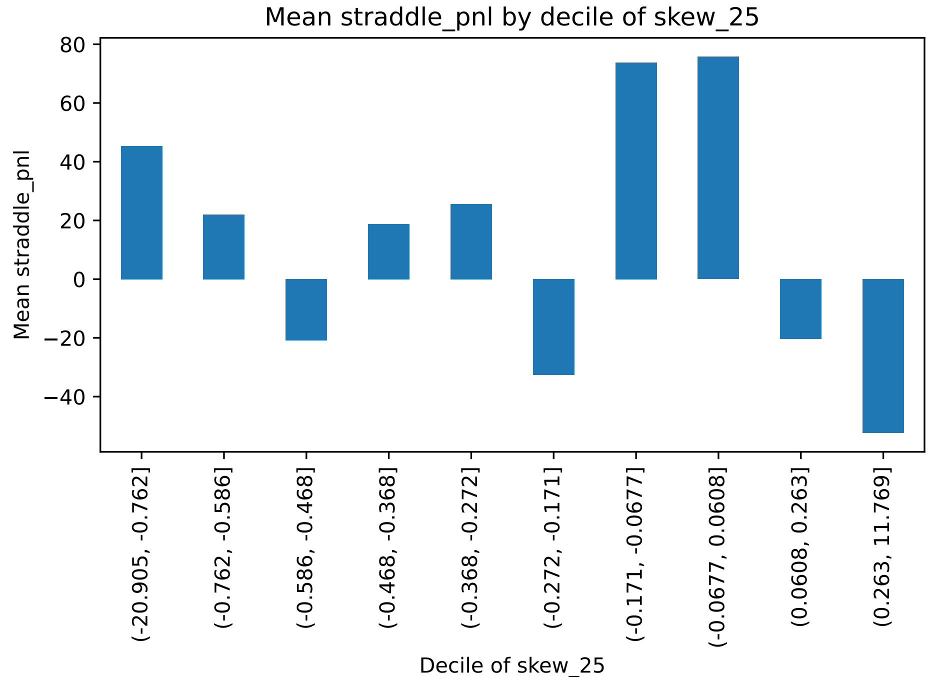


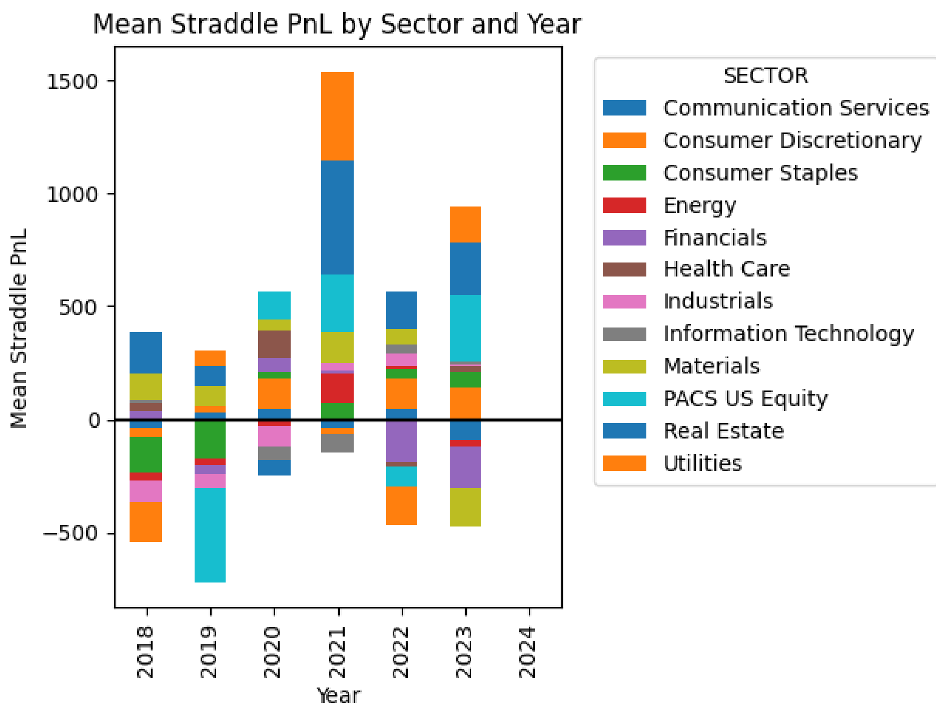
Figure 3: Mean PnL for deciles of Skew

There didn't seem to be any clear trends for grouping by decile of ATM volatility or Skew. For Kurtosis, the top 3 deciles seemed somewhat profitable to sell the straddle. With a mean pnl of 45.86 USD, and a standard deviation of 567.03 USD over 1678 data points in this sample.

4 Results by sectors

In our study, we categorized tickers based on their respective sectors as identified in the Bloomberg database. The sectors considered were: Health Care, Materials, Industrials, Consumer Discretionary, Information Technology, Financials, Consumer Staples, Utilities, PACS US Equity, Communication Services, Real Estate, and Energy. This sector-based classification aimed to explore the influence of specific sectors and different years on the profit and loss (PL) outcomes of our standard investment strategy.

The analysis revealed that the Real Estate and Consumer Discretionary sectors exhibited notably higher profit and loss figures. However, these results do not demonstrate a consistent pattern that would suggest a biased impact on the overall sample outcomes that requires further consideration.



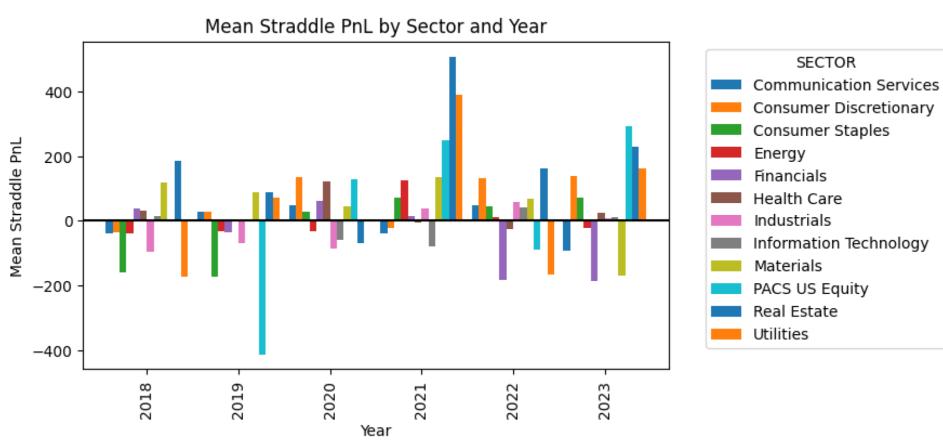


Figure 4: Staddle Profit and Loss (PnL) by sector and year.

5 Results by Debt to Equity Ratio

In our analysis, we try to look for metrics which can explain our Profits and Losses. One such feature is the Debt to Equity ratio, which is obtained from the ZACKS/MT dataframe in QUANDL database. The database provides a numerical value for this metric. We have categorized them into thre classes based on the following criteria.

$$\text{Debt to Equity Ratio} = \begin{cases} \text{High} & \text{if Debt to Equity} > 1.5 \\ \text{Good} & \text{if } 1 < \text{Debt to Equity} \leq 1.5 \\ \text{Low} & \text{if Debt to Equity} \leq 1 \end{cases}$$

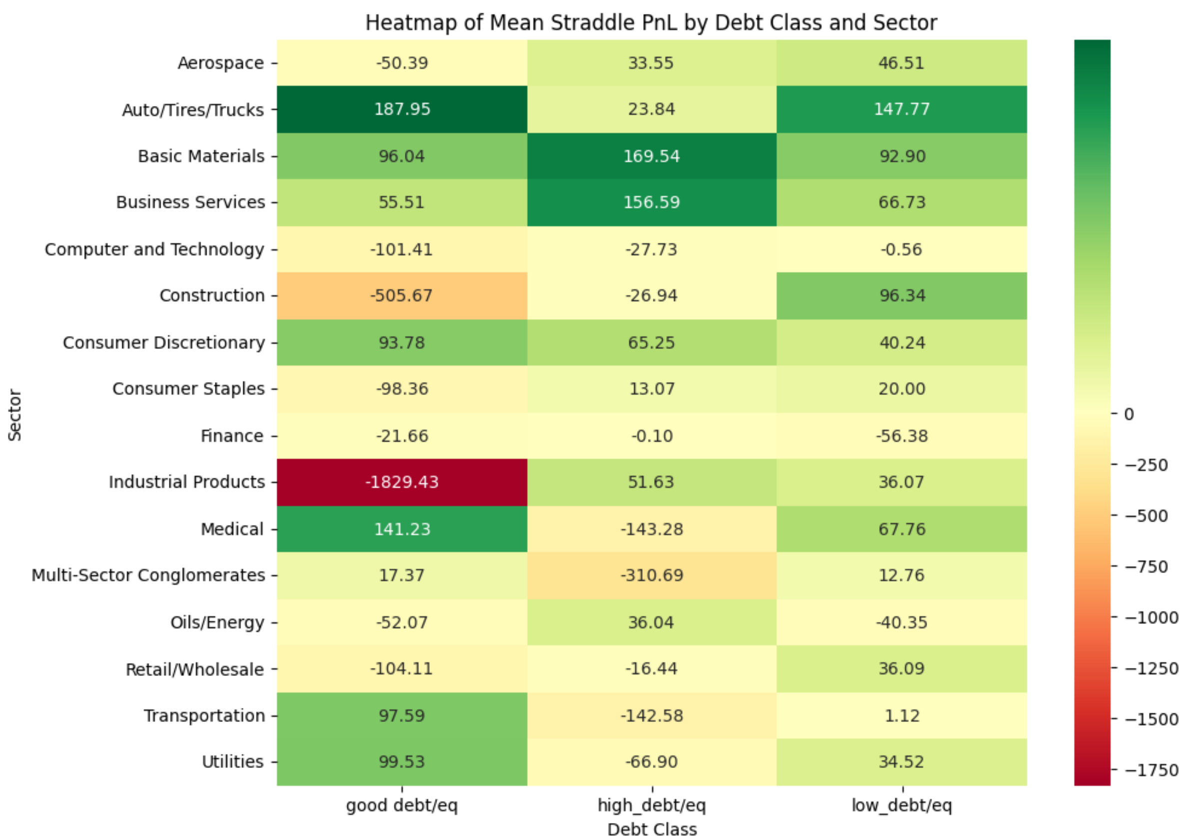


Figure 5: Heatmap of Mean Straddle PnL by Debt class and Sector

Observations

We use the heatmap Figure 5 and the detailed distribution of our straddle PnL Figure 13 for this section.

- **Sectors with High Volatility:** Finance and Industrial Products sectors show high volatility in PnL with high debt/equity ratios.
- **Sectors with Stable PnL:** Auto/Tires/Trucks and Medical sectors with good debt/equity ratios show stable and high average PnL.
- **Risk and Reward:** Computer and Technology sector with low debt/equity ratios shows high variability, indicating higher risk but also potential for significant returns.

6 Results by Local Peaks Analysis

When analyzing options, particularly equity options, the implied volatility (IV) is a critical metric. The IV versus Strike plot is often studied to identify local peaks and troughs in the implied volatility across various strike prices for options of the same maturity.

Local peaks in IV versus strike plots might reflect market expectations of future movements in the underlying asset's price, particularly around specific strike prices. For example, a local peak at a higher strike price in a call option might indicate that the market expects a significant upside movement.

Discrepancies in implied volatility across strike prices can offer arbitrage opportunities. Traders might exploit these by constructing option strategies that involve buying undervalued options and selling overvalued ones, based on their position in the volatility curve.

The function used to count the peaks in the implied volatility is as follows:

$$IV_i > \left(1 + \frac{\text{buffer\_pct}}{100}\right) \times IV_{i-1} \quad \text{and} \quad IV_i > \left(1 + \frac{\text{buffer\_pct}}{100}\right) \times IV_{i+1}$$

- IV_i: Implied Volatility for strike i

- IV_{i-1}: Implied Volatility for strike (i-1)

- IV_{i+1}: Implied Volatility for strike (i+1)

- buffer_pct: we keep a buffer to remove noisy (unnecessary) peaks from analysis

Results for ≥2 peaks with buffer_pct

	10%	**15%**	**20%**	**25%**
count	0.134	0.070	0.047	0.027
mean	13.963	28.452	46.574	128.314
std	640.210	651.689	558.195	496.452
min	-4520.471	-4520.471	-2267.380	-1573.347
25%	-263.731	-240.000	-240.458	-211.930
50%	201.626	226.761	209.877	287.375
75%	433.576	454.836	445.283	508.774
max	918.224	918.224	918.224	886.447

Table 1: Local peaks for Call Strikes

	10%	**15%**	**20%**	**25%**
count	0.126	0.064	0.038	0.024
mean	25.223	23.370	56.305	62.126
std	601.641	567.892	515.700	534.767
min	-3352.655	-2267.380	-1726.550	-1658.537
25%	-243.902	-214.447	-201.117	-90.642
50%	198.370	214.149	226.872	225.760
75%	437.273	404.393	401.361	394.067
max	918.224	918.224	749.016	749.016

Table 2: Local peaks for Put Strikes

An increase in the buffer percentage, which entails the identification of sharper peaks in the implied volatility (IV) distribution, leads to enhanced performance metrics. This enhancement is characterized by a higher mean, and a reduced standard deviation, suggesting more stable strategy.

7 Results by Variance of Earning

7.1 Motivation

Implied volatility often surges before earnings announcements due to the heightened uncertainty and speculation about the financial results a company will report. This phenomenon reflects market participants' anticipation of significant stock price movements based on the forthcoming news. The unpredictability of earnings results—whether they will exceed, meet, or fail to meet analysts' forecasts—increases the demand for options as tools for hedging and speculation, thereby driving up their prices and the associated implied volatility.

Inspired by this observable trend, we developed a model to calculate the "Variance of Earnings" using the implied volatility of ATM straddles. Our model posits that if the "Variance of Earnings" shows an increase in the days leading up to the earnings announcement—despite stable fundamental information—it suggests that the straddle prices are being artificially inflated by market participants. In such scenarios, our strategy leans towards selling the straddle, capitalizing on the elevated premiums before the actual earnings are disclosed.

7.2 Model

For the implied volatility before an earnings event, we postulate that it comprises two components: 1) the base volatility, which excludes the influence of the earnings event; and 2) the variance attributable to the earnings event itself. We further assume that the base volatility for the nearest expiry date is approximately equal to the forward implied volatility spanning from the nearest expiry date to the second nearest expiry date. Our model incorporates the following equations to derive the "Variance of Earning":

$$T_1 \cdot \text{Base IV}^2 + \text{Variance of Earning} = T_1 \cdot \text{IV}_1^2 \tag{1}$$

$$(T_2 - T_1) \cdot \text{Forward IV}^2 + T_1 \cdot \text{IV}_1^2 = T_2 \cdot \text{IV}_2^2 \tag{2}$$

$$\text{Base IV} \approx \text{Forward IV} \tag{3}$$

- T_1, T_2: Time to the closest expiry date, and the second expiry date

- $ForwardIV$: Forward implied volatility from T_1 to T_2

7.3 Results

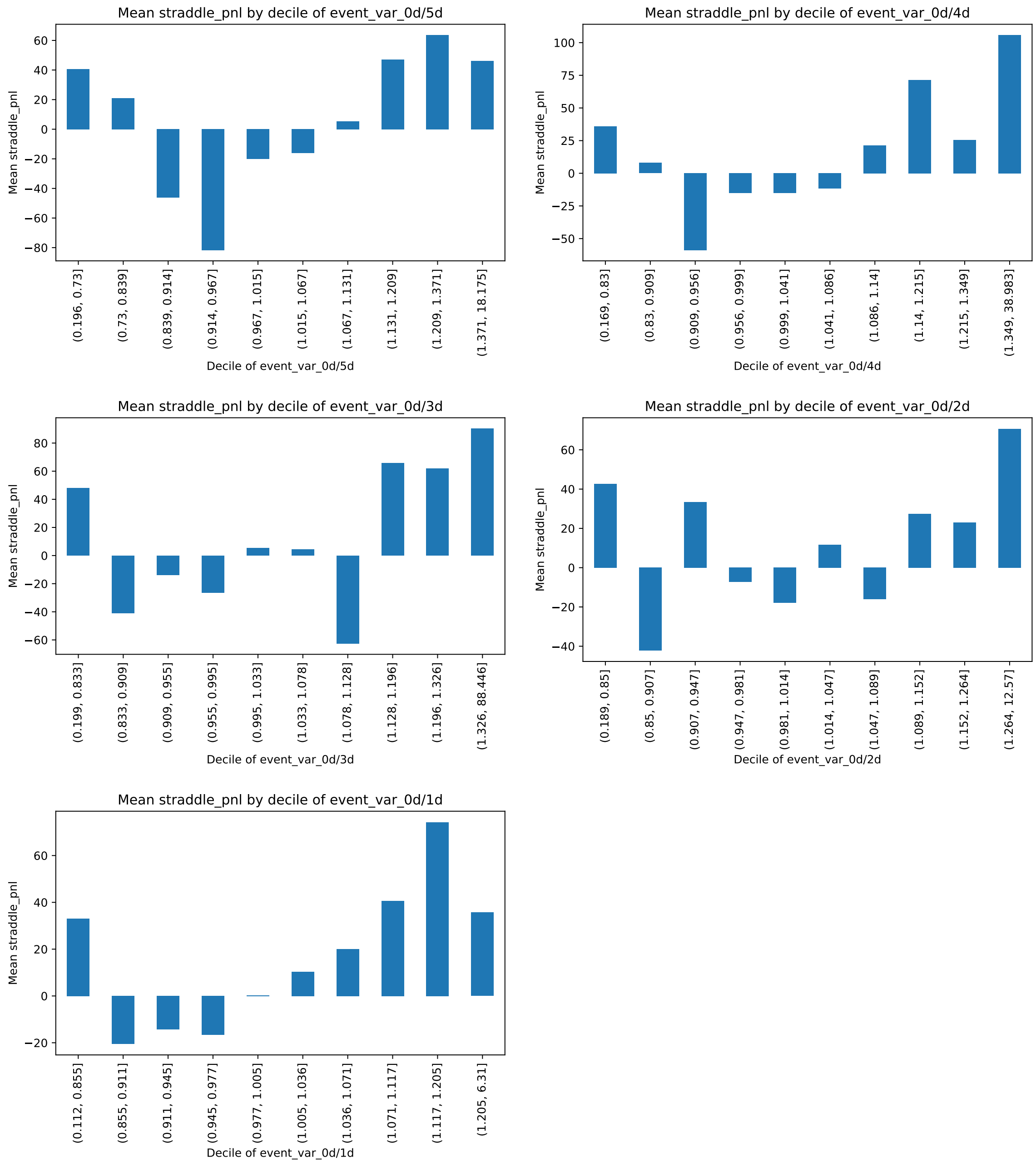


Figure 6: Mean PnL grouped by "Variance of Earning" on earning date / prior i days

According to our model, we calculated the "Variance of Earnings" for the five days leading up to the earnings announcement. We then computed the ratio of the variance on the earnings date to that of i days prior. A ratio exceeding 1 indicates an increase in the "Variance of Earnings" from i days ago, providing a rationale for selling the straddle. We categorized the selling strategy into deciles based on the ratio, observing that the top three deciles consistently showed profitability in selling the straddle. This trend held across each of the days leading up to the earnings, although the increase was not strictly monotonic.

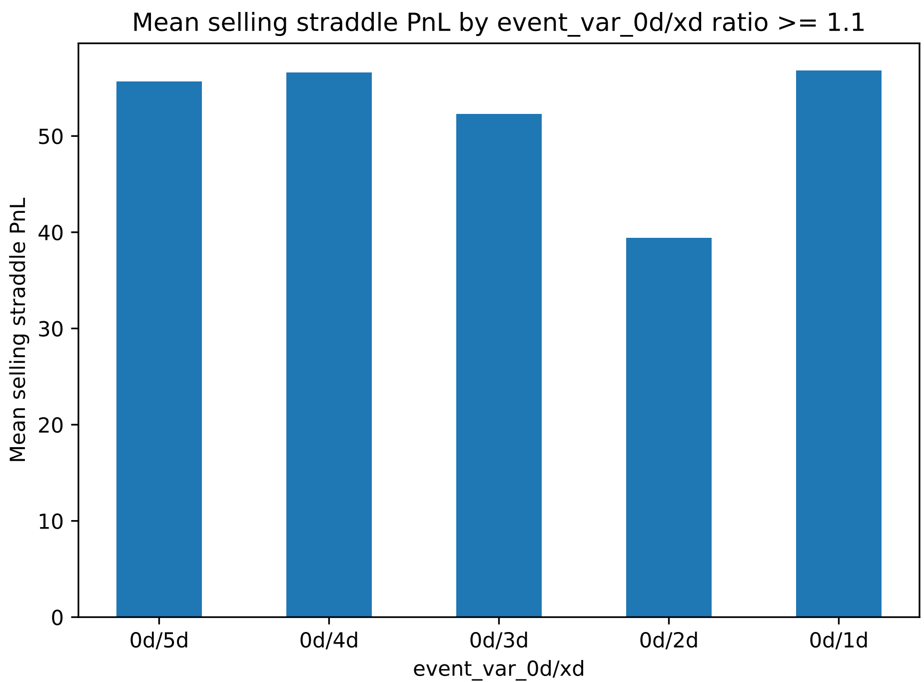


Figure 7: Mean PnL for the cases with variance ratio greater than 1.1

The 3rd highest decile is generally a ratio of approximately 1.1. So, we look at the mean PnL of selling the straddle when the ratio is greater than 1.1 for each of the 5 days before earnings. The graph shows that the mean PnL is around 50 across the prior days. Considering we are selling 1000 straddle for each event, the mean return for using ratio 1.1 as a threshold is around 5%.

7.4 Linear Regression

To better try and combine the 6 days of implied variance of the earnings, we computed a linear regression for each earnings event with at least 4 valid values in the 6 days of implied event variances. The x-values for the regression were the number of days before earning event, and the y-values were the implied earnings volatility.

Then, we first filtered on deciles of slope/intercept for each linear regression. This variable approximately represents what percentage the implied earnings volatility decreases for each day further out from the earnings date. Thus, negative values for this variable indicate the implied event variance has been increasing as we get closer to the earnings date, and positive values indicat the opposite.

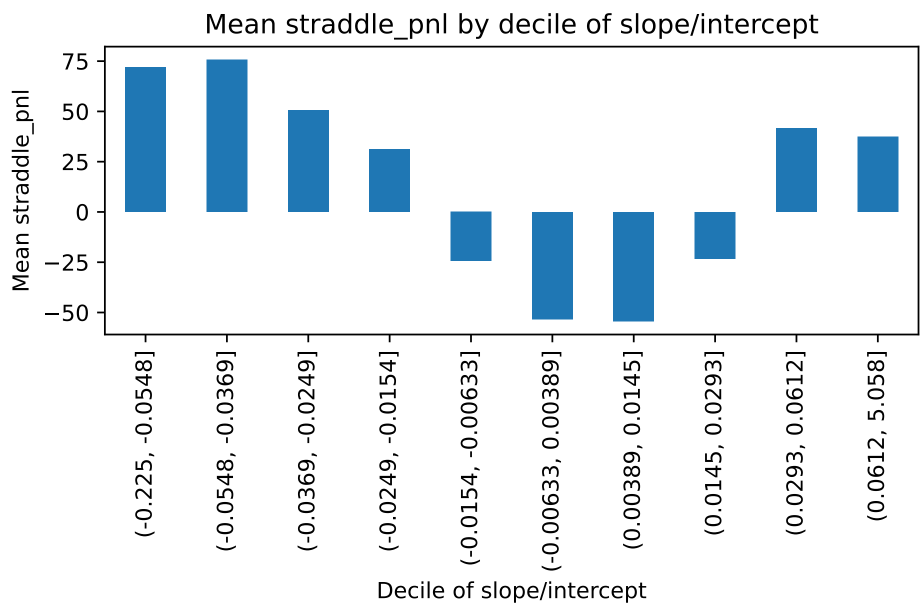


Figure 8: Mean PnL for deciles of slope/intercept

The average PNL for the first 3 deciles are higher than they were when we simply filtered by decile of the ratio of implied event variance 0 days before earnings over the implied event variance 5 days before earnings. It is also worth noting that the top two deciles also had a positive mean PNL. This may be because in those cases, the information from the earnings event may have already been forecasted well in the underlying stock price, and thus market participants are lowering the event volatility as it is too high.

We also filtered on the deciles of the R^2 and R values the regression returned.

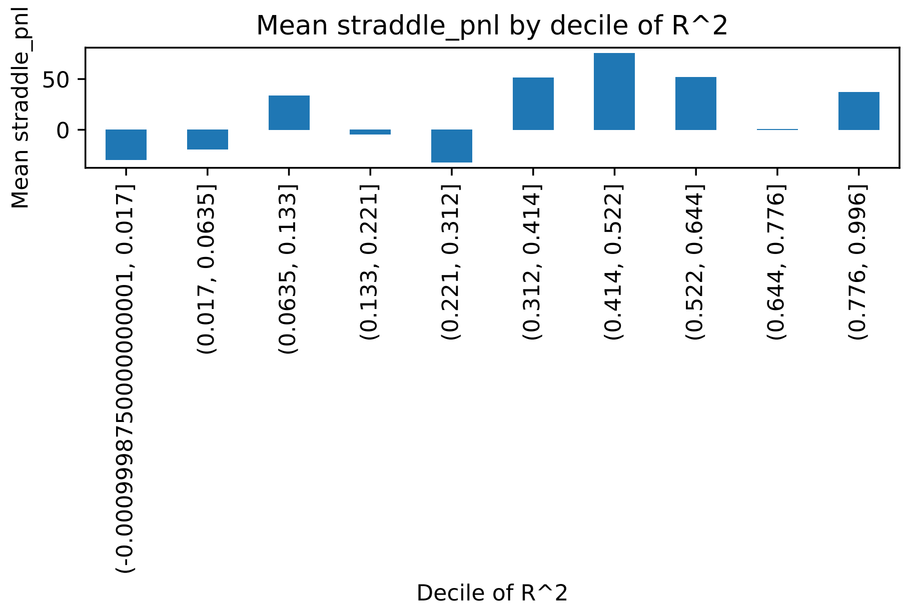


Figure 9: Mean PnL for deciles of R^2

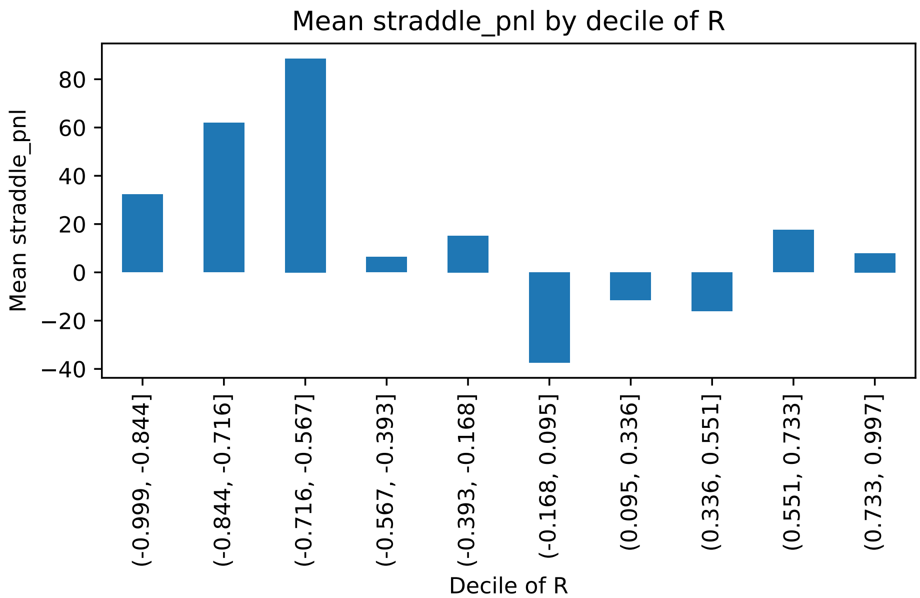


Figure 10: Mean PnL for deciles of R

Higher R^2 values seem to indicate more profitability in selling the straddle. As one may expect, the bottom 3 deciles of the R value indicate profitability in selling the straddle.

Now, we will filter on the cross-quintiles of slope/intercept and R^2 to try and leverage the information provided by both these variables.

R^2_quintile	(-0.0009998750000000001, 0.0635]	(0.0635, 0.221]	(0.221, 0.414]	(0.414, 0.644]	(0.644, 0.996]
slope/intercept_quintile					
(-0.225, -0.0369]	106.1	135.4	126.9	70.32	43.41
(-0.0369, -0.0154]	17.7	46.14	33.74	111.7	-55.02
(-0.0154, 0.00389]	-31.88	-84.3	-67.64	194.2	176.9
(0.00389, 0.0293]	-31.03	-22.14	-108.4	-33.74	34.47
(0.0293, 5.058]	140.9	123.6	10.57	43.28	10.83

Figure 11: slope/intercept and R^2 cross quintile mean

R^2_quintile	(-0.0009998750000000001, 0.0635]	(0.0635, 0.221]	(0.221, 0.414]	(0.414, 0.644]	(0.644, 0.996]
slope/intercept_quintile					
(-0.225, -0.0369]	8	70	141	214	370
(-0.0369, -0.0154]	39	167	208	203	132
(-0.0154, 0.00389]	458	178	68	23	8
(0.00389, 0.0293]	248	239	136	96	48
(0.0293, 5.058]	13	119	225	224	197

Figure 12: slope/intercept and R^2 cross quintile count

There are several buckets of this cross-quintile grouping with a PNL $>$ 100. In particular, very negative or very positive slopes combined with a low R^2 value. The high PNL for the groupings with the middle quintile of slope/intercept and high R^2 may be just noise, as there are only 8 and 23 data points in those 2 buckets.

7.5 Miscellaneous

I also looked at the mean pnl of our strategy when implied event variance has been either monotonically increasing or decreasing every single day before earnings.

When implied earnings volatility has been monotonically increasing, the mean pnl of selling 1000 worth of the straddle is -113. This occurs 427 (8.1 percent) times.

When implied earnings volatility has been monotonically decreasing, the mean pnl of selling 1000 worth of the straddle is -133.43. This occurs 383 (7.2 percent) times.

This indicates that it may be profitable to purchase the straddle right before earnings when the implied event volatility has been either monotonically increasing or decreasing, though we are not sure of any economic rationale for this phenomenon.

Additionally, we computed the realized volatility over the 5 days before earnings. On average (median ratio), the realized volatility was 25 percent higher than the forward vol we computed from the 2 expiries after earnings. This implies there may be a term structure to base volatility, and our approximation of forward volatility = base volatility may be incorrect. Correcting for this in some manner would likely increase the increase in event volatility (which is on average 7 percent using our current calculations).

8 Appendix

8.1 Distribution of PnL's across sectors and debt quality

	('zacks_x_sector_desc', '')	('tot_debt_tot_equity_class',	('straddle_pnl', 'count')	('straddle_pnl', 'mean')	('straddle_pnl', 'std')	('straddle_pnl', 'min')	('straddle_pnl', '25%')	('straddle_pnl', '50%')	('straddle_pnl', '75%')	('straddle_pnl', 'max')
0	Aerospace	good debt/eq	20.0	-50.39	1028.35	-3561.17	-11.22	380.1	459.02	624.45
1	Aerospace	high_debt/eq	23.0	33.55	425.78	-913.37	-105.16	89.49	346.7	650.94
2	Aerospace	low_debt/eq	48.0	46.51	519.43	-1580.95	-121.46	273.1	394.15	652.63
3	Auto/Tires/Trucks	good debt/eq	4.0	187.95	471.62	-371.79	-117.94	271.39	577.29	580.82
4	Auto/Tires/Trucks	high_debt/eq	48.0	23.84	538.17	-1555.56	-250.56	117.97	470.48	729.03
5	Auto/Tires/Trucks	low_debt/eq	29.0	147.77	361.44	-629.82	-89.84	192.77	428.02	705.67
6	Basic Materials	good debt/eq	31.0	96.04	383.06	-607.14	-225.14	119.3	414.18	779.41
7	Basic Materials	high_debt/eq	13.0	169.54	506.18	-1133.93	142.86	280.49	495.24	629.14
8	Basic Materials	low_debt/eq	135.0	92.9	531.69	-2023.74	-98.48	229.41	464.15	666.67
9	Business Services	good debt/eq	21.0	55.51	521.35	-1405.41	-242.52	128.0	497.89	703.2
10	Business Services	high_debt/eq	55.0	156.59	443.49	-1265.07	-109.9	297.62	462.56	900.0
11	Business Services	low_debt/eq	78.0	66.73	570.09	-2460.73	-111.89	218.66	390.8	793.22
12	Computer and Technology	good debt/eq	74.0	-101.41	576.8	-1658.54	-335.5	-50.6	377.92	763.89
13	Computer and Technology	high_debt/eq	175.0	-27.73	642.26	-2640.35	-342.99	102.24	482.91	818.18
14	Computer and Technology	low_debt/eq	479.0	-0.56	681.59	-4520.47	-290.24	189.43	483.86	790.96
15	Construction	good debt/eq	2.0	-505.67	775.95	-1054.35	-780.01	-505.67	-231.33	43.01
16	Construction	high_debt/eq	27.0	-26.94	598.24	-1745.16	-291.59	61.92	430.81	676.08
17	Construction	low_debt/eq	81.0	96.34	462.06	-1637.25	-54.74	200.0	440.53	699.3
18	Consumer Discretionary	good debt/eq	58.0	93.78	561.02	-1665.42	-183.8	282.15	498.7	741.38
19	Consumer Discretionary	high_debt/eq	140.0	65.25	620.04	-3100.0	-215.78	231.25	472.41	886.45
20	Consumer Discretionary	low_debt/eq	139.0	40.24	572.02	-2202.9	-248.86	228.57	462.24	750.51
21	Consumer Staples	good debt/eq	28.0	-98.36	759.73	-2327.59	-489.09	108.98	501.46	677.42
22	Consumer Staples	high_debt/eq	149.0	13.07	541.62	-2723.14	-240.75	135.8	414.63	757.89
23	Consumer Staples	low_debt/eq	128.0	19.99	802.71	-5692.31	-132.51	219.09	476.89	739.58
24	Finance	good debt/eq	85.0	-21.66	552.14	-1846.15	-288.14	119.62	388.89	745.76
25	Finance	high_debt/eq	128.0	-0.1	979.81	-8885.71	-115.67	263.15	428.59	918.22
26	Finance	low_debt/eq	231.0	-56.38	657.3	-5200.0	-313.08	70.31	343.92	850.0
27	Industrial Products	good debt/eq	16.0	-1829.43	4940.7	-17750.0	-899.24	168.44	325.88	687.5
28	Industrial Products	high_debt/eq	64.0	51.63	477.32	-1332.64	-147.93	137.33	388.15	751.53
29	Industrial Products	low_debt/eq	68.0	36.07	529.88	-1670.21	-280.67	162.31	432.18	876.51
30	Medical	good debt/eq	38.0	141.23	377.72	-826.22	-58.8	192.23	406.17	667.55
31	Medical	high_debt/eq	108.0	-143.28	978.54	-6765.91	-447.38	200.86	400.11	830.04
32	Medical	low_debt/eq	325.0	67.76	605.74	-4175.32	-139.66	224.34	451.61	878.9
33	Multi-Sector Conglomerates	good debt/eq	17.0	17.37	550.55	-1410.16	-279.05	248.59	416.23	612.46
34	Multi-Sector Conglomerates	high_debt/eq	7.0	-310.69	1159.08	-2836.25	-244.06	-71.72	310.31	600.67
35	Multi-Sector Conglomerates	low_debt/eq	14.0	12.76	629.53	-1706.9	-250.13	177.2	444.86	612.33
36	Oils/Energy	good debt/eq	36.0	-52.07	996.02	-5303.03	-166.28	226.38	356.77	672.9
37	Oils/Energy	high_debt/eq	39.0	36.04	457.82	-1420.17	-114.69	222.69	340.04	548.15
38	Oils/Energy	low_debt/eq	145.0	-40.35	539.85	-1939.39	-302.47	85.05	327.97	832.3
39	Retail/Wholesale	good debt/eq	51.0	-104.11	800.69	-3059.09	-454.49	12.88	463.95	714.29
40	Retail/Wholesale	high_debt/eq	157.0	-16.44	634.23	-2759.59	-387.34	139.08	462.69	817.65
41	Retail/Wholesale	low_debt/eq	407.0	36.09	636.23	-4375.91	-307.5	219.51	485.49	755.88
42	Transportation	good debt/eq	41.0	97.59	507.9	-1627.87	-192.31	173.08	491.27	706.81
43	Transportation	high_debt/eq	59.0	-142.58	565.72	-1726.55	-437.29	6.67	327.41	575.59
44	Transportation	low_debt/eq	91.0	1.12	527.56	-1628.69	-335.66	143.55	427.02	679.25
45	Utilities	good debt/eq	9.0	99.53	264.5	-349.21	51.95	174.13	248.0	407.51
46	Utilities	high_debt/eq	20.0	-66.9	705.4	-1808.82	-182.31	227.26	386.54	583.33
47	Utilities	low_debt/eq	3.0	34.52	466.76	-480.0	-163.61	152.78	291.77	430.77

Figure 13: Straddle PnL distribution

8.2 Predicting long/short straddles using Machine Learning methods and it's impact on PnL

This section details the implementation of a machine learning-based approach to predict the profitability of long/straddles on the US Equities market using fundamental data. The generated class labels are based on the signs of the resulting PnL (Class 1: Short the straddle, Class 0: Long)

8.2.1 Model Performance Comparison

Table 3 summarizes the key performance metrics for all models.

Table 3: Performance Comparison of Machine Learning Models

Model	**Accuracy**	**Precision** (class 1)	**Recall** (class 1)	**F1-Score** (class 1)
Decision Tree	56.09%	0.64	0.68	0.66
SGD Classifier	61.97%	0.62	0.99	0.76
KNN (k=9)	60.29%	0.62	0.62	0.62
Random Forest	61.97%	0.62	0.97	0.76
MLP Classifier	60.08%	0.62	0.91	0.74
AdaBoost	58.19%	0.62	0.83	0.71

8.2.2 PnL Comparison Table

Table 4 summarizes the initial and adjusted PnLs for each model, along with the difference between these values.

Table 4: PnL Comparison Across Models

Model	**Initial PnL**	**Adjusted PnL**	**Difference**
Decision Tree	-2083.22	8741.87	10825.10
SGD Classifier	-2083.22	-3958.49	-1875.27
KNN (k=9)	-2083.22	-5991.76	-3908.54
Random Forest	-2083.22	1422.39	3505.61
MLP Classifier	-2083.22	-4641.60	-2558.38
AdaBoost	-2083.22	-3832.34	-1749.12