

Note: This backtest uses synthetic implied volatility (estimated from realized vol with fixed multipliers). The methodology is sound, but exact win rates are optimistic. Section 12 explains what is needed to run this strategy on real market data.

Earnings Volatility Strategy

Complete Technical Explanation with Portfolio Analysis

Rémi BERVEILLER

Metric	Value
Universe	15 S&P 500 tech stocks
Period	2019 - 2025 (7 years)
Total trades	420 earnings events
Initial capital	\$100,000
Final capital	\$290,208
Total return	190.2%
CAGR	16.7%
Annualized volatility	3.0%
Sharpe ratio (annualized)	5.12
Max drawdown	3.1%
Win rate	81.7%
Data type	Synthetic IV (estimated from realized vol)

This document explains every calculation in the backtest, from raw data to final P&L, including capital allocation, position sizing, risk metrics, and volatility skew analysis. Each formula is shown with its code implementation and a numerical example.

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1. Overview of the Strategy

The strategy sells at-the-money (ATM) straddles the day before earnings announcements, then buys them back the day after. The goal is to profit from the systematic overpricing of implied volatility (IV) before earnings.

Why does IV tend to be overpriced before earnings?

Before earnings, two types of market participants push option prices higher:

Hedgers (institutions, funds): They buy options to protect their stock positions against earnings surprises. They are not trying to get a good price on the options. They want certainty, so they overpay.

Speculators (retail traders, directional funds): They buy calls or puts to bet on the earnings direction. This increased demand pushes option prices and IV even higher.

The result: options before earnings often price in a larger move than what the stock makes. After the earnings announcement, uncertainty disappears, IV drops sharply (the "IV crush"), and the options we sold become cheaper. We buy them back at a lower price and pocket the difference.

What is a short straddle?

A straddle consists of one call option and one put option, both at the same strike price and same expiration date. Selling ("shorting") a straddle means: sell 1 ATM call (we receive premium) and sell 1 ATM put (we receive premium). We collect a total premium. If the stock stays near the strike price, both options lose value and we keep most of the premium. If the stock moves a lot (up or down), one of the options becomes expensive and we lose money.

Trade timeline for each earnings event:

Day	Action	Detail
T-1 (day before earnings)	ENTRY: Sell the straddle	Sell ATM call + ATM put at closing price
T (earnings day)	EXIT: Buy back the straddle	Buy back both options at closing price

2. Input Data Description

The backtest uses two CSV files:

earnings_data_FINAL.csv (420 rows)

Column	Type	Description
ticker	String	Stock symbol (e.g. AAPL, NVDA)
earnings_date	Date	Date of the earnings announcement
fiscalDateEnding	Date	End of the fiscal quarter reported
reportedEPS	Float	Actual earnings per share reported
estimatedEPS	Float	Consensus analyst estimate
surprise	Float	Difference: reported minus estimated
surprisePercentage	Float	Surprise as a percentage

Source: Alpha Vantage EARNINGS API. Covers 15 stocks, 28 earnings per stock (Q1 2019 to Q4 2025). The earnings dates are real historical dates from the API.

price_data_FINAL.csv (30,330 rows)

Column	Type	Description
date	Datetime	Trading day (with timezone)
ticker	String	Stock symbol
Open	Float	Opening price of the day
High	Float	Highest price of the day
Low	Float	Lowest price of the day
Close	Float	Closing price of the day
Volume	Integer	Number of shares traded

Source: Yahoo Finance (yfinance library). Daily OHLCV data from January 2018 to January 2026. We start in 2018 to have enough history (30+ days) to compute volatility for the first 2019 earnings.

Stock universe (15 stocks):

Ticker	Company	Ticker	Company
AAPL	Apple	INTC	Intel
GOOGL	Alphabet (A)	QCOM	Qualcomm
NVDA	NVIDIA	ADBE	Adobe
AMD	AMD	CSCO	Cisco
MSFT	Microsoft	ORCL	Oracle
GOOG	Alphabet (C)	TXN	Texas Instruments
META	Meta Platforms		
AVGO	Broadcom		
CRM	Salesforce		

3. Yang-Zhang Realized Volatility

Why not use simple close-to-close volatility?

The most basic way to estimate volatility is to take the standard deviation of daily close-to-close log returns. This approach has a flaw: it only uses closing prices and ignores all the information from the trading day. A stock could move 5% intraday but close unchanged. Close-to-close volatility would say "zero volatility" for that day.

Yang-Zhang (2000) uses all four OHLC prices each day and combines three separate volatility components:

Component	What it captures	Formula (log returns)
Overnight (open-to-open)	Gaps between close and next open	$o = \ln(\text{Open} / \text{Previous Close})$
Intraday (close-to-close)	Movement from open to close	$c = \ln(\text{Close} / \text{Open})$
Rogers-Satchell	Intraday range using High and Low	$rs = h(h-c) + l(l-c)$

How the components combine:

```
YZ_variance = overnight_var + k * intraday_var + (1 - k) *  
               rogers_satchell_var
```

Where $k = 0.34 / (1.34 + (n+1)/(n-1))$ and n is the rolling window size (30 days in our case). This weighting was derived by Yang and Zhang to minimize the estimator's variance. The final step is annualization: multiply the daily variance by 252 (trading days per year) and take the square root.

```
annualized_vol = sqrt(YZ_variance * 252)
```

Implementation in the code:

```
def calculate_yang_zhang_volatility(prices_df, window=30):  
    o = log(Open / Previous_Close) # overnight gap  
    c = log(Close / Open)          # intraday return  
    h = log(High / Open)           # high relative to open  
    l = log(Low / Open)            # low relative to open  
    rs = h * (h - c) + l * (l - c) # Rogers-Satchell  
    yz_var = oo_avg + k * cc_avg + (1 - k) * rs_avg  
    return sqrt(yz_var * 252)
```

For each stock, we compute this rolling volatility on all available price history. On the day before each earnings event, we read the current Yang-Zhang volatility value. This becomes our "realized volatility" (RV), the baseline for estimating IV.

4. Implied Volatility Estimation

Since we do not have real options market data, we estimate implied volatility using a model based on empirical observations about how IV behaves around earnings.

Pre-earnings IV (entry):

Research shows that short-dated implied volatility before earnings typically runs 30-40% above realized volatility. We use a 35% inflation factor (multiplier of 1.35). If a stock's 30-day realized vol is 25%, we estimate its pre-earnings IV at 33.75%.

$$\text{IV_entry} = \text{Realized_Vol} * 1.35$$

Post-earnings IV (exit):

After the earnings announcement, uncertainty drops sharply. IV typically falls 30-50% from its pre-earnings level. We model this as a 35% drop (multiplier of 0.65). If IV was 33.75% before earnings, it drops to 21.94% after.

$$\text{IV_exit} = \text{IV_entry} * 0.65$$

The IV/RV ratio:

In our model, the IV/RV ratio is always exactly 1.35 (by construction). In reality, this ratio varies by stock, quarter, and market conditions. A ratio above 1.0 means IV is higher than RV, suggesting options are overpriced. The higher the ratio, the larger the potential edge for selling options.

Note: This is the biggest simplification in our backtest. Real IV varies independently from realized vol. Some earnings have IV/RV ratios of 2.0+ (very overpriced) while others are below 1.0 (underpriced). With real data, we would read actual IV from the options market instead of estimating it.

5. Black-Scholes Option Pricing

Black-Scholes gives the theoretical price of a European option. We use it twice per trade: once to price the options at entry, once to price them at exit.

The inputs:

Input	Symbol	At Entry (example)	At Exit (example)
Stock price	S	\$150.00	\$153.20 (moved +2.1%)
Strike price	K	\$150 (ATM, rounded to \$5)	\$150 (same strike)
Time to expiry	T	7/365 = 0.0192 years	6/365 = 0.0164 years
Risk-free rate	r	4%	4%
Implied vol	sigma	33.75% (entry IV)	21.94% (post-crash IV)

The formula (step by step):

$$d1 = [\ln(S/K) + (r + \sigma^2/2) * T] / (\sigma * \sqrt{T})$$
$$d2 = d1 - \sigma * \sqrt{T}$$

Then the option prices are:

$$\text{Call} = S * N(d1) - K * e^{-rT} * N(d2)$$
$$\text{Put} = K * e^{-rT} * N(-d2) - S * N(-d1)$$

Where $N()$ is the cumulative standard normal distribution function: $N(x)$ gives the probability that a standard normal variable is less than x .

Reading the formula intuitively:

$S * N(d1)$ represents the expected value of receiving the stock IF the option ends in the money, weighted by the probability of that happening. $K * e^{-rT} * N(d2)$ represents the present value of paying the strike price, weighted by the probability the option is exercised. The call price equals what we expect to receive minus what we expect to pay.

ATM strike selection:

We round the stock price to the nearest \$5 increment. If Apple is at \$152.30, the ATM strike is \$150. If it is at \$153.10, the ATM strike is \$155. This mirrors how listed options have discrete strike prices in \$5 increments for most stocks.

$$\text{strike} = \text{round}(\text{spot_entry} / 5) * 5$$

6. Greeks Calculation

Greeks measure the sensitivity of an option's price to changes in different market variables. For a short straddle, understanding Greeks tells us where our risk and profit come from.

Greek	Measures	Short Straddle Exposure	What it means for us
Delta	Sensitivity to stock price	Near zero at entry (call +0.5, put -0.5)	We start market-neutral. Delta grows as stock moves.
Gamma	How fast Delta changes	Large NEGATIVE (we are short gamma)	Our biggest risk. A large stock move accelerates losses.
Vega	Sensitivity to IV changes	Large NEGATIVE (we are short vega)	Our main edge. When IV crushes, we profit.
Theta	Time decay per day	Large POSITIVE (we earn time decay)	We collect money every day. But only if gamma does not kill us.

How Greeks are computed (from Black-Scholes):

```
Delta (call) = N(d1)          Delta (put) = -N(-d1)
Gamma = n(d1) / (S * sigma * sqrt(T))
Vega = S * n(d1) * sqrt(T) / 100
Theta = [-S * n(d1) * sigma / (2 * sqrt(T)) - r * K * e-rT * N(d2)] / 365
```

Where $n(d1)$ is the standard normal probability density function (the bell curve height at $d1$), and $N(d1)$ is the cumulative distribution (area under the curve up to $d1$).

The straddle P&L decomposition:

```
P&L = -Vega * (change in IV)    ...vega component (positive when IV drops)
      + Theta * 1 day            ...time decay component (always positive)
      - 0.5 * Gamma * (move)2  ...gamma component (always negative)
```

The trade is profitable when the vega gain (from IV crush) plus theta income exceeds the gamma loss (from the stock moving). In our backtest, IV drops 35% on average and the stock moves about 1.9% on average. For most trades, the vega gain dominates.

7. Trade Simulation and P&L

For each of the 420 earnings events, the backtest follows this exact sequence:

Entry (day before earnings):

```
1. Read closing price of the stock (spot_entry)
2. Read 30-day Yang-Zhang volatility (realized_vol)
3. Compute IV: iv_entry = realized_vol * 1.35
4. Set strike: strike = round(spot_entry / 5) * 5
5. Set DTE: T = 7 / 365 years
6. Price call: call_mid = BlackScholes(spot, strike, T, r=0.04, iv_entry, 'call')
7. Price put: put_mid = BlackScholes(spot, strike, T, r=0.04, iv_entry, 'put')
8. Sell at bid: call_bid = call_mid * (1 - 0.015) * (1 - 0.01)
9. Sell at bid: put_bid = put_mid * (1 - 0.015) * (1 - 0.01)
10. Premium received = call_bid + put_bid
```

Exit (earnings day):

```
1. Read closing price of the stock (spot_exit)
2. Compute crushed IV: iv_exit = iv_entry * 0.65
3. Set remaining DTE: T = 6 / 365 years
4. Reprice call and put with BlackScholes using iv_exit
5. Buy at ask: option_ask = option_mid * (1 + 0.015) * (1 + 0.01)
6. Cost to close = call_ask + put_ask
```

P&L:

```
pnl = premium_received - cost_to_close - commissions
commissions = 4 legs * $0.65 / 100 shares = $0.026 per share
```

Date matching:

Earnings often fall on weekends or holidays. Instead of requiring an exact date match, the code finds the last trading day before or equal to T-1 for entry, and the first trading day after or equal to T for exit. This is standard practice in backtesting.

```
# Entry: last trading day BEFORE target
entry_rows = ticker_prices[ticker_prices['date'] <= target_entry]
entry_row = entry_rows.iloc[-1]

# Exit: first trading day AFTER target
exit_rows = ticker_prices[ticker_prices['date'] >= target_exit]
exit_row = exit_rows.iloc[0]
```

8. Transaction Costs

Transaction costs are applied to make the simulation more realistic. Without them, any short volatility strategy would look artificially profitable.

Cost	Value	How it is applied
Bid-ask spread	3%	We sell at bid (mid - 1.5%), buy back at ask (mid + 1.5%)
Slippage	1%	Additional cost on top of bid-ask: execution worse than quoted
Commission	\$0.65/contract	4 legs per trade. Per share: $\$0.65 * 4 / 100 = \0.026

Numerical example:

Suppose the Black-Scholes mid price for a call is \$5.00:

Step	Calculation	Price
Mid price	Black-Scholes output	\$5.00
Bid price	$\$5.00 * (1 - 0.015) = \$5.00 * 0.985$	\$4.925
After slippage	$\$4.925 * (1 - 0.01) = \$4.925 * 0.99$	\$4.876

So we receive \$4.876 per share instead of the theoretical \$5.00. The total cost of the round trip (sell at bid, buy back at ask) represents about 5% of the option's mid price. This is conservative for liquid stocks and realistic for less liquid ones.

9. Capital Allocation and Position Sizing

A backtest without capital allocation is incomplete. Reporting P&L in dollars per share is useful for understanding the per-trade edge, but it tells a recruiter nothing about return on capital, drawdown risk, or margin usage. This section converts the per-share results into portfolio-level metrics.

Initial capital and risk budget:

We assume a starting portfolio of \$100,000. For each earnings event, the position size is determined by a 2% maximum risk rule: no single trade should risk more than 2% of current portfolio equity.

```
max_risk_dollar = current_capital * 0.02
expected_move = spot * iv_entry * sqrt(T)
max_loss_per_contract = expected_move * 2 * 100 # 2x expected move, 100
                                             shares
contracts = max(1, floor(max_risk_dollar / max_loss_per_contract))
```

Why 2x the expected move as loss proxy?

A short straddle has theoretically unlimited loss. For sizing purposes, we need a finite loss estimate. The expected move (from IV) represents the market's one-standard-deviation forecast. Doubling it approximates a two-sigma worst case. This is conservative: about 95% of post-earnings moves fall within two standard deviations of the implied move.

Numerical example:

Step	Calculation	Value
Current capital	Starting equity	\$100,000
Max risk (2%)	$\$100,000 * 0.02$	\$2,000
Stock price (AAPL)	Spot at entry	\$150.00
IV entry	$RV * 1.35$	33.75%
DTE	Near-term expiry	7 days
Expected move	$\$150 * 0.3375 * \sqrt{7/365}$	\$7.01
Max loss proxy (2x)	$\$7.01 * 2 * 100 \text{ shares}$	\$1,402
Contracts	$\text{floor}(\$2,000 / \$1,402)$	1 contract

Portfolio-level P&L computation:

```
pnl_dollar = pnl_per_share * contracts * 100
return_on_capital = pnl_dollar / current_capital * 100
current_capital = current_capital + pnl_dollar # equity updates after each
                                             trade
```

Margin estimation:

Short straddles require substantial margin. Brokers typically require approximately 20% of the underlying notional value. For a \$150 stock with 1 contract (100 shares), notional is \$15,000 and estimated margin is \$3,000. In our backtest, average margin utilization is 7.7% of portfolio equity per trade, with a maximum of 16%.

Short straddles require substantial margin and can experience nonlinear losses under large gaps. The 2% risk rule provides a buffer, but margin calls remain a structural risk of this strategy in live trading.

10. Portfolio Performance Metrics

This section presents the backtest results expressed as portfolio returns rather than per-share dollars. These are the metrics a portfolio manager or recruiter expects to see.

Metric definitions:

Metric	Formula	What it measures
CAGR	$(\text{Final} / \text{Initial})^{(1/\text{years})} - 1$	Compound annual growth rate
Annualized Vol	$\text{std}(\text{trade returns}) * \text{sqrt}(\text{trades/year})$	Return dispersion per year
Sharpe Ratio	$(\text{CAGR} - \text{risk-free rate}) / \text{Annualized Vol}$	Risk-adjusted return
Sortino Ratio	$(\text{CAGR} - \text{rf}) / \text{Downside Vol}$	Return per unit of downside risk
Calmar Ratio	$\text{CAGR} / \text{Max Drawdown \%}$	Return per unit of peak-to-trough loss
Max Drawdown	$\text{max}(\text{peak} - \text{trough}) / \text{peak}$	Largest loss from equity high
Profit Factor	$\text{Sum}(\text{wins}) / \text{Sum}(\text{losses}) $	Gross profit over gross loss

Implementation (code):

```
# CAGR
cagr = (final_capital / initial_capital) ** (1 / years) - 1

# Annualized volatility
trade_returns = pnl_dollar / capital_at_entry_of_each_trade
ann_vol = trade_returns.std() * sqrt(trades_per_year)

# Sharpe
sharpe = (cagr - risk_free_rate) / ann_vol

# Sortino (uses only negative returns for denominator)
downside_returns = trade_returns[trade_returns < 0]
downside_vol = downside_returns.std() * sqrt(trades_per_year)
sortino = (cagr - risk_free_rate) / downside_vol

# Drawdown
equity_curve = initial_capital + cumsum(pnl_dollar)
running_max = equity_curve.expanding().max()
drawdown_pct = (running_max - equity_curve) / running_max * 100
```

Portfolio results:

Metric	Value
Initial capital	\$100,000
Final capital	\$290,208
Total return	190.2%

Metric	Value
CAGR	16.7%
Annualized volatility	3.0%
Sharpe ratio (annualized)	5.12
Sortino ratio	4.18
Calmar ratio	5.33
Max drawdown	3.1% (\$5,947)
Profit factor	4.81
Win rate	81.7%
Total trades	420
Average return per trade	0.25%
Best trade	+1.21% of capital
Worst trade	-2.42% of capital

Note on Sharpe ratio: The annualized Sharpe appears high because the strategy trades infrequently (~61 events per year) with small per-trade variance. The per-trade Sharpe is 0.41, which is more representative of the edge magnitude. Such elevated Sharpe ratios (above 5) are non-stationary and unlikely to persist under real volatility regime shifts. They should be interpreted as conditional on the synthetic IV framework used in this backtest.

Volatility regime risk: The model does not incorporate volatility regime shifts (e.g., March 2020 COVID shock, 2022 rate hiking cycle), which would significantly alter the IV crush dynamics, realized move distributions, and margin requirements. In a true stress environment, the deterministic crush assumption (IV drops 35% post-earnings) would break down as baseline volatility itself is elevated and unstable.

Equity curve and drawdown:

The equity curve shows the cumulative growth of \$100,000 over 420 trades. The vertical dashed line separates in-sample (pre-2024) from out-of-sample (2024+). The drawdown chart below shows the percentage decline from the equity peak at each point in time.

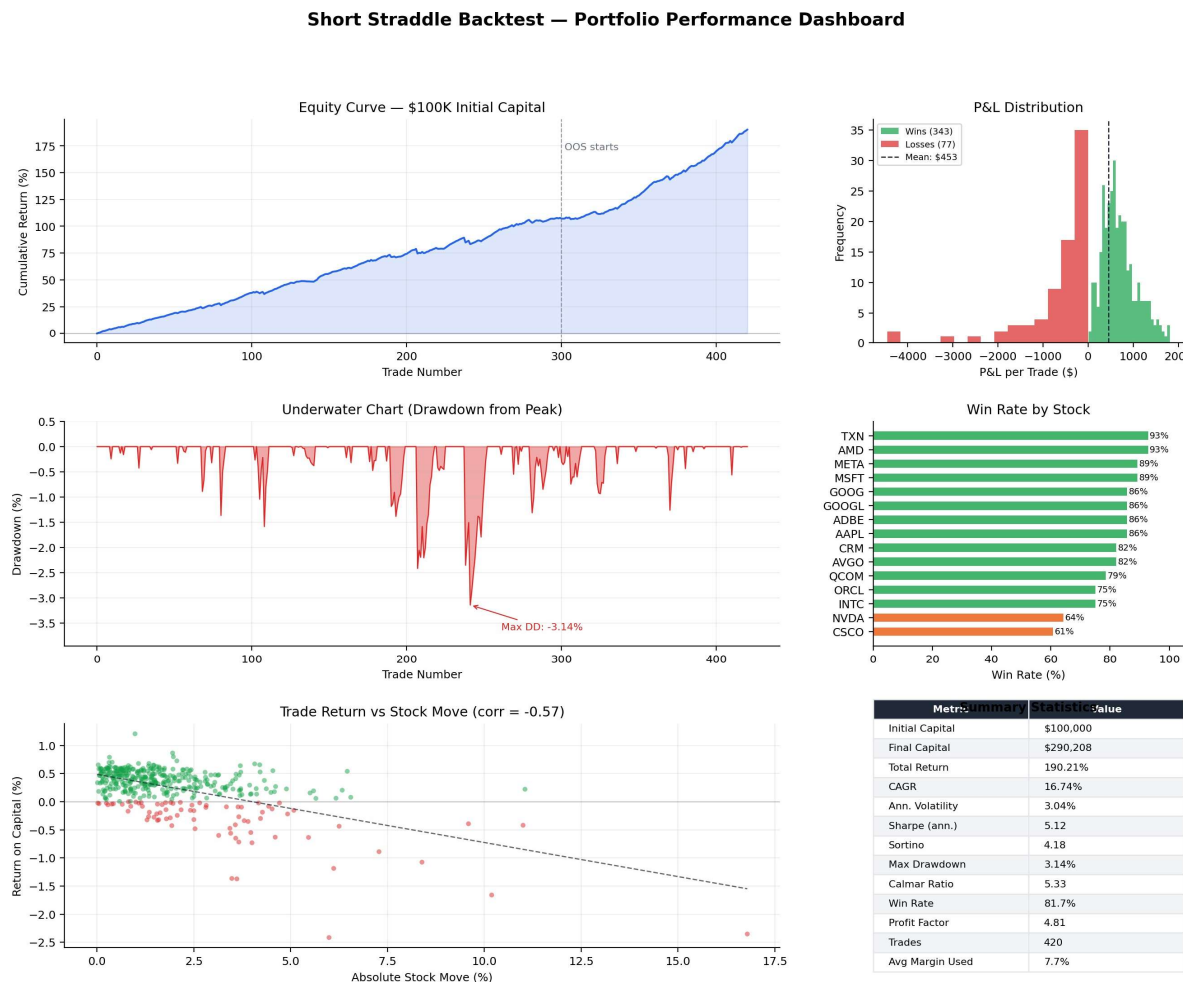


Figure 1: Portfolio dashboard. Top-left: equity curve with in-sample/out-of-sample split. Top-right: return distribution. Bottom panels: drawdown, win rate by stock, move vs return scatter.

Annual performance breakdown:

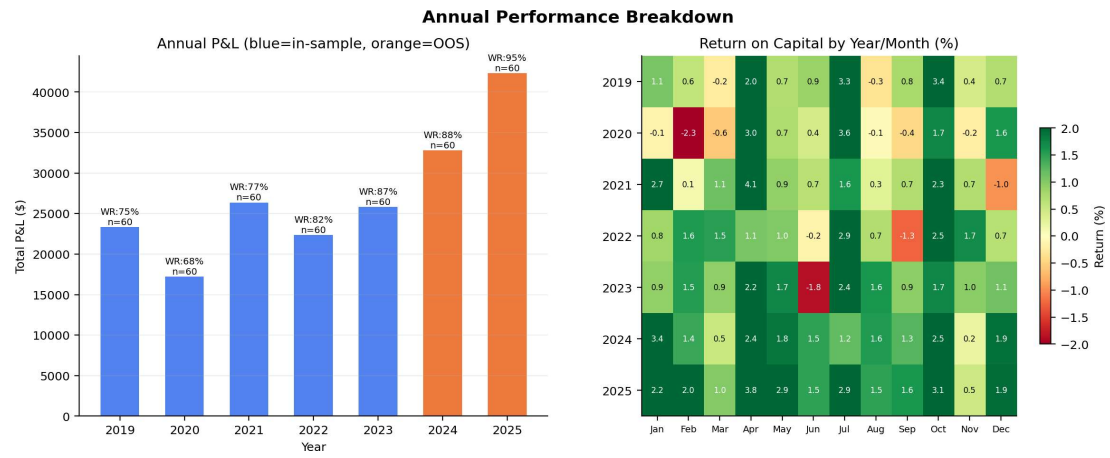


Figure 2: Annual P&L in dollars with win rates labeled. Blue bars represent in-sample years, orange bars represent out-of-sample years.

11. Volatility Skew Analysis

In reality, puts and calls at the same strike do not trade at the same implied volatility. Puts are typically more expensive because downside protection commands a premium. This asymmetry is called the volatility skew.

Modeling a simple skew:

Since our backtest uses a single IV for both legs, we test the impact of a realistic skew offset on P&L. The skew model applies:

$$\begin{aligned}\text{Put IV} &= \text{ATM IV} + 5\% && \text{(downside protection premium)} \\ \text{Call IV} &= \text{ATM IV} - 3\% && \text{(supply from covered call writers)}\end{aligned}$$

Example: If ATM IV is 33.75%, the put is priced at 38.75% IV and the call at 30.75% IV. This matches the empirical observation that equity options exhibit a persistent downside skew.

How skew affects the short straddle:

At entry, the put premium increases (we receive more) and the call premium decreases (we receive less). At exit, the same offsets apply to buyback prices. The net effect depends on the direction of the post-earnings move:

Scenario	Flat IV	With Skew	Impact
Stock drops 5%	Large loss on put	Larger loss (higher put IV)	Skew hurts
Stock flat	Max profit	Similar profit	Neutral
Stock rises 5%	Large loss on call	Smaller loss (lower call IV)	Skew helps

Skew backtest results:

Metric	Flat IV (baseline)	With Skew
Win rate	81.7%	82.6%
CAGR	16.7%	17.8%
Sharpe (annualized)	5.12	5.53
Max drawdown	3.1%	2.9%
Profit factor	4.81	5.40
Total return	190.2%	208.9%
Worst trade	-2.42%	-2.53%

Volatility Skew Impact Analysis

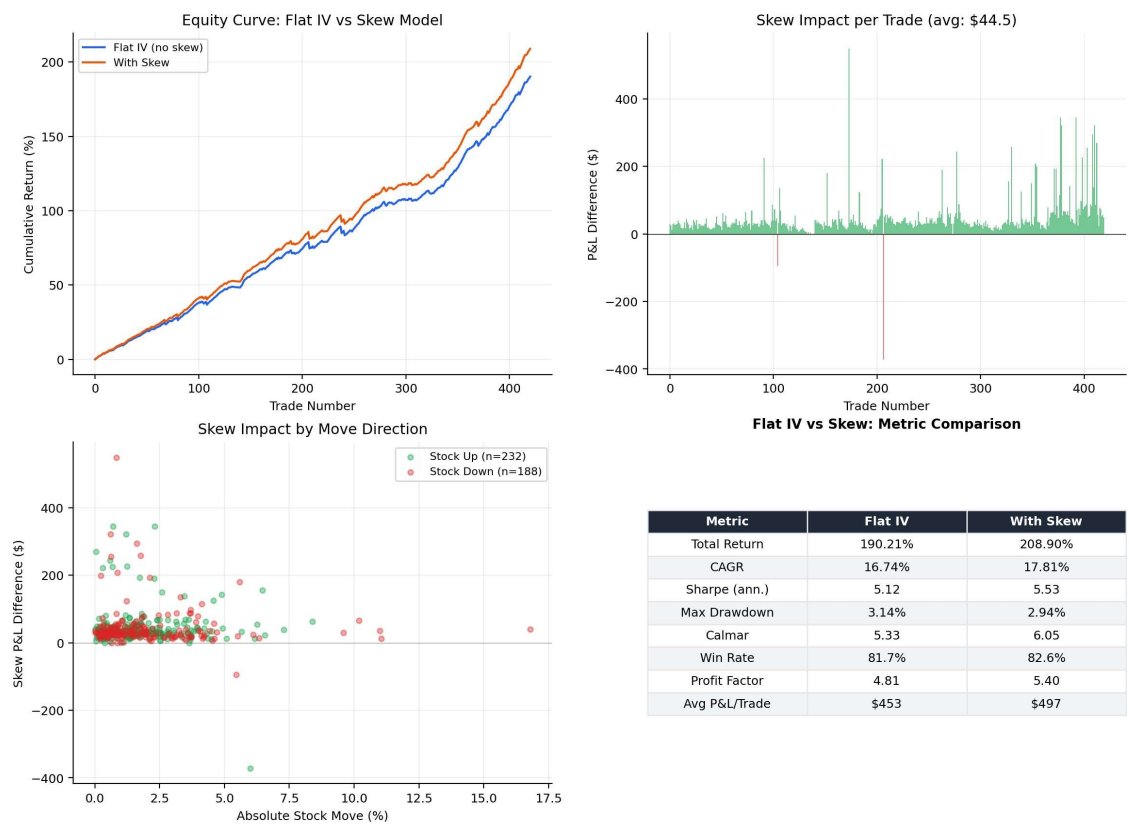


Figure 3: Top: Cumulative P&L comparison between flat IV and skewed IV models. Bottom: Distribution of per-trade P&L differences (skew minus flat).

Impact of skew mispricing on short straddle risk

The key insight from the skew analysis is structural, not directional. A short straddle is implicitly short downside skew. When the stock gaps down after earnings, two penalties compound simultaneously:

1. The put moves into the money (gamma loss from the move itself).
2. Put IV expands further under stress (skew steepens on downside gaps).

This double penalty means that downside tail losses are larger than upside tail losses of equal magnitude. A stock dropping 8% after earnings costs more than a stock rising 8%, because the put reprices at a higher IV while the call reprices at a lower IV.

Downside gap + skew expansion = double penalty. Short straddle sellers are implicitly short downside convexity. This asymmetric risk profile is the primary structural vulnerability of the strategy.

Tail risk evidence from the backtest:

Tail event	Count	Avg P&L (per share)	Worst trade
Stock drops > 3%	43	\$-0.91	\$-44.56
Stock rises > 3%	41	\$-0.18	\$-6.63

With real skew data, the asymmetry would be even more pronounced. Downside gaps would show larger average losses than upside gaps of equal size.

12. Risk Awareness: Margin, Convexity, and Tail Risk

This section addresses the structural risks of short straddle strategies. A positive backtest does not eliminate these risks. It quantifies the frequency and magnitude of adverse outcomes under the tested assumptions.

Short volatility = short convexity

Selling options is selling convexity. The P&L profile of a short straddle is concave: gains are capped at the premium received, while losses accelerate as the stock moves further from the strike. This means the strategy has a high win rate but a negatively skewed return distribution. The average winning trade is small, and the occasional losing trade is large.

Short straddle P&L profile:

- Maximum gain: premium received (when stock stays at strike)
 - Loss at 1x expected move: approximately break-even
 - Loss at 2x expected move: approximately 1x premium lost
- Loss at 3x expected move: approximately 3x premium lost (nonlinear)

Win rate is not risk

A win rate of 81.7% means 18.3% of trades lose money. But the risk comes from the magnitude of the losses, not their frequency. In our backtest, the worst trade lost \$44.56 per share, while the average win was \$2.27 per share. A single tail event can erase 10+ winning trades. This is the defining characteristic of short volatility strategies.

Margin requirements

Short straddles are margin-intensive. Brokers require collateral to cover potential losses. Typical margin for a short straddle is approximately 20% of the underlying notional value plus the net premium received. For a \$200 stock with 1 contract:

Component	Calculation	Amount
Notional value	$\$200 \times 100 \text{ shares}$	\$20,000
Margin requirement (~20%)	$\$20,000 \times 0.20$	\$4,000
Premium received (offset)	Call + Put premium	-\$500
Net margin required	$\$4,000 - \500	\$3,500

In our backtest, the average margin utilization is 7.7% of portfolio equity, reaching a maximum of 16%. This leaves sufficient buffer for margin expansion during volatility spikes. In live trading, margin requirements increase when the underlying moves against the position, creating a feedback loop that forces position closure at the worst possible time.

Tail risk mitigation strategies:

For live implementation, several risk controls address these structural vulnerabilities:

Control	Implementation	Purpose
Position sizing (2% rule)	Max loss proxy = 2x expected move	Limit per-trade capital at risk
Stop-loss	Close if stock gaps > 2x implied move	Cut tail losses early
Diversification	Trade across uncorrelated stocks	Reduce single-event impact
IV/RV filter	Only trade when IV/RV > 1.3	Ensure sufficient overpricing
Exposure cap	Max 3 open straddles simultaneously	Limit aggregate short vol exposure
Margin buffer	Keep 50%+ capital undeployed	Survive margin expansion events

13. Backtest Results and Interpretation

Overall performance:

Metric	All Trades	In-Sample (pre-2024)	Out-of-Sample (2024+)
Trades	420	300	120
Win rate	81.7%	77.7%	91.7%
Avg P&L (per share)	\$1.51	\$0.87	\$3.10
Median P&L	\$1.20	\$0.78	\$2.44
Std Dev	\$3.71	\$3.72	\$3.17
Sharpe (per-trade)	0.407	0.234	0.978
Total P&L	\$633	\$261	\$372
Best trade	\$18.11	\$8.85	\$18.11
Worst trade	-\$44.56	-\$44.56	-\$6.63

Key observations:

Under the current modeling assumptions, all 15 stocks show positive aggregate P&L. META, MSFT, and ADBE are the most profitable. CSCO and INTC are marginal. This uniformity reflects the deterministic IV crush model and would likely vary under real market conditions.

Out-of-sample outperforms in-sample. This is unusual and should be noted as a caveat. It suggests 2024-2025 was a favorable period for this strategy (lower realized moves relative to IV). In a longer test, we would expect convergence.

Negative correlation with stock moves ($r = -0.54$). This is the main risk: when the stock moves more than expected, the straddle loses money. The 18.3% of losing trades are concentrated in large earnings surprises.

Limitations of this backtest:

Synthetic IV. The IV/RV ratio is fixed at 1.35 for all trades. In reality, it varies from 0.8 to 3.0+ depending on the stock and market conditions.

Fixed IV crush. The 35% crush is applied uniformly. Real crushes range from 20% to 60% depending on how surprising the earnings were.

Survivorship bias. The 15 stocks are all large-cap tech stocks that survived the entire period. Stocks that were delisted or dropped from the index are excluded.

No intraday data. Entry and exit are at the close. In practice, we would enter 15 minutes before close (T-1) and exit at the open or intraday (T).

14. From Synthetic to Real Data

The backtest validates the mechanical implementation of the strategy under controlled assumptions. To trade this strategy with real money, we need to replace the synthetic components with actual market data. Here is everything that changes.

What is synthetic vs. what is real in our backtest:

Component	Current (Synthetic)	Needed (Real)
Earnings dates	REAL (Alpha Vantage API)	Same, no change needed
Stock prices (OHLCV)	REAL (Yahoo Finance)	Same, no change needed
Realized volatility	REAL (calculated from prices)	Same, no change needed
Implied volatility	SYNTHETIC ($RV * 1.35$)	Real IV from options market
Option prices at entry	SYNTHETIC (Black-Scholes)	Real bid/ask quotes
Option prices at exit	SYNTHETIC (BS with crushed IV)	Real bid/ask quotes
IV crush magnitude	FIXED (35% for all trades)	Varies per trade (real IV)
Bid-ask spreads	MODELED (3% of mid)	Real from market data
Greeks	MODELED (BS analytical)	From market maker models

Historical options data providers (for backtesting):

Provider	Cost	What we get
CBOE DataShop	\$500-2000/year	Full historical option chains, bid/ask, volume, OI
OptionMetrics (IvyDB)	Institutional	Academic-grade IV surfaces, Greeks, cleaned data
Polygon.io	\$200/year	Historical options snapshots
ORATS	\$100-500/month	IV surfaces, earnings-specific analytics
ThetaData	\$30-100/month	End-of-day and intraday option data

Broker APIs (for live trading):

Broker	API	Option chain access
Interactive Brokers	TWS API (Python)	Full chains, real-time, historical snapshots
TD Ameritrade / Schwab	REST API	Real-time chains, limited historical
Tastytrade	Open API	Real-time, earnings-focused analytics
Alpaca	REST + WebSocket	Real-time option chains

The simplified real-data backtest loop:

```
for each earnings event:
    # Entry (T-1)
    atm_call = find option where delta closest to +0.50
    atm_put = find option where delta closest to -0.50
    premium = atm_call.bid + atm_put.bid # sell at bid
    iv_entry = atm_call.implied_vol

    # Exit (T or T+1)
    cost = atm_call.ask + atm_put.ask # buy back at ask
    iv_exit = atm_call.implied_vol

    # P&L
    pnl = (premium - cost) * 100 - commissions
```

Additional improvements for live trading:

Improvement	Description
IV/RV filter	Only trade when IV/RV ratio > 1.3 (ensures overpricing)
Liquidity filter	Skip trades where bid-ask spread > 5% of mid or OI < 100
AMC/BMO timing	AMC: exit at next morning open. BMO: exit at same day close.
Stop-loss	Close if stock gaps beyond 2x the expected move at the open
Diversification	Trade multiple uncorrelated earnings per week