A Scenario-Weighted Tariff Shock Model for Constructing a 30-Day Options Hedge on SMH

Report with Mathematical Derivations and Optimisation

Project Report

January 18, 2026

Abstract

This report develops a systematic derivatives strategy that translates tariff-related political uncertainty into an actionable 30-day options position on the VanEck Semiconductor ETF (SMH). The framework combines: (i) a discrete scenario model for tariff-policy outcomes, (ii) robust calibration of short-horizon drift and volatility from historical data, (iii) Monte Carlo simulation of a scenario-weighted terminal price distribution, and (iv) an optimisation procedure that selects an options structure whose payoff best approximates a desired downside hedge profile. Using the available SMH options chain, the optimal structure identified is a debit put spread: long the 385 put and short the 350 put, with a premium of \$577 per spread. Under the scenario-weighted distribution, the trade exhibits a maximum loss of \$577, maximum profit of \$2923, a breakeven price of 379.23, and an estimated expected value of \$87.28.

Contents

1 Introduction

Tariff policy is a macro-political risk factor capable of producing rapid repricing in equity markets. Semiconductor supply chains are globally integrated, with production, assembly, and distribution spanning multiple jurisdictions. As a result, the semiconductor sector is particularly sensitive to tariff escalation, export restrictions, and retaliatory measures.

The objective of this project is to construct a data-driven options position that hedges downside risk in the VanEck Semiconductor ETF (SMH) over a short horizon of approximately 30 days. The strategy is designed to:

- quantify uncertainty using a probabilistic scenario model rather than a single deterministic shock,
- translate scenario uncertainty into a distribution over terminal prices,
- define a target payoff shape consistent with a downside hedge thesis,
- select a real, liquid listed options structure that best matches this target payoff.

The final output is a transparent, reproducible pipeline suitable for portfolio presentation and for extension into more advanced research settings.

2 Data and Instruments

2.1 Underlying Asset

The underlying instrument is the VanEck Semiconductor ETF (ticker: SMH). Let S_t denote the adjusted close price at time t. The strategy is constructed at time $t = 0$ with observed spot price:

$$S_0 = 400.39.$$

2.2 Options Contracts

Let T denote the maturity date of the options. The strategy targets the nearest expiry approximately 30 calendar days from construction. In this project, the selected expiry was:

$$T = 2026\text{-}02\text{-}13.$$

The available options chain is filtered using basic liquidity constraints (mid-price availability and simple spread/open-interest filters), producing a set of candidate calls and puts for payoff replication.

2.3 Notation

Throughout the report:

- S_0 is the current underlying price.
- S_T is the terminal underlying price at maturity.
- K denotes strike price.
- r_t denotes daily log return.
- $R_{0,T}$ denotes cumulative log return from 0 to T.

3 Return Modelling Framework

3.1 Log Returns and Terminal Price

We model returns using log returns:

$$r_t = \log\left(\frac{S_t}{S_{t-1}}\right).$$

Over a horizon of n trading days (here $n = 30$), the cumulative log return is:

$$R_{0,T} = \sum_{t=1}^{n} r_t.$$

Then the terminal price is:

$$S_T = S_0 \exp(R_{0,T}).$$

3.2 Normality Assumption (Local Approximation)

For short horizons, it is common to approximate cumulative log returns by a normal distribution:

$$R_{0,T} \sim \mathcal{N}(\mu_{30}, \sigma_{30}^2),$$

where μ_{30} and σ_{30} represent the drift and volatility of the 30-day cumulative log return.

This is not a claim that returns are exactly normal, but rather a practical approximation that provides tractability and allows scenario-dependent shifts to be implemented transparently.

4 Scenario Model for Tariff Shocks

4.1 Discrete Scenario Space

We define a discrete set of tariff-policy scenarios indexed by $j \in \{0, 1, 2, 3\}$, representing increasing severity. Each scenario has probability p_j such that:

$$\sum_{j=0}^{3} p_j = 1.$$

An example scenario specification is shown in Table 1. (Probabilities are user-defined and can be updated using polling/news indicators or Bayesian updating.)

Table 1: Tariff shock scenarios and illustrative probabilities.

Scenario	Description	Severity s	Probability p
0	No new measures	0	0.45
1	Mild tariffs / tighter language	1	0.30
2	Aggressive tariffs / restrictions	2	0.20
3	Aggressive + retaliation	3	0.05

4.2 Scenario-Conditional Return Distributions

Each scenario defines a conditional distribution for the cumulative log return:

$$R_{0,T} \mid j \sim \mathcal{N}(\mu_j, \sigma_j^2).$$

Therefore the unconditional distribution is a mixture:

$$R_{0,T} \sim \sum_{j=0}^{3} p_j \cdot \mathcal{N}(\mu_j, \sigma_j^2).$$

Since $S_T = S_0 e^{R_{0,T}}$, the terminal price distribution is a mixture of lognormal distributions:

$$S_T \sim \sum_{j=0}^{3} p_j \cdot \mathrm{LogNormal}(\mu_j, \sigma_j^2).$$

5 Calibration of Baseline Drift and Volatility

5.1 Rolling 30-Day Drift

Define the rolling 30-day cumulative log return:

$$\hat{\mu}_{t,30} = \sum_{i=1}^{30} r_{t-i}.$$

A robust baseline drift estimate is then computed using a trimmed mean:

$$\hat{\mu}_{30} = \mathrm{TrimmedMean}\left(\{\hat{\mu}_{t,30}\}\right),$$

which reduces sensitivity to extreme market moves.

5.2 Rolling 30-Day Volatility

Similarly, define the rolling 30-day standard deviation of cumulative returns (or equivalently an aggregated measure from daily returns). A robust baseline volatility estimate can be defined as:

$$\hat{\sigma}_{30} = \mathrm{Median}\left(\{\hat{\sigma}_{t,30}\}\right).$$

In this project the calibrated baseline volatility was approximately:

$$\hat{\sigma}_{30} \approx 0.1075.$$

5.3 Scenario Mapping

Scenario severity is mapped to drift penalties and volatility multipliers:

$$\mu_s = \hat{\mu}_{30} + \Delta\mu_s, \qquad \sigma_s = \hat{\sigma}_{30} \cdot m_s,$$

where $\Delta\mu_s \leq 0$ captures negative expected impact of tariffs and $m_s \geq 1$ captures increased uncertainty.

6 Monte Carlo Simulation

6.1 Algorithm

To simulate N terminal prices:

1. Sample scenario index $j \sim \mathrm{Categorical}(p_0, \ldots, p_3)$.
2. Sample cumulative return:
$$R^{(i)} \sim \mathcal{N}(\mu_j, \sigma_j^2).$$
3. Compute terminal price:
$$S_T^{(i)} = S_0 \exp(R^{(i)}).$$

6.2 Empirical Quantiles

From simulation, the terminal price quantiles obtained were:

Quantile	S_T
1%	285.46
5%	326.45
50%	413.62
95%	512.72
99%	567.79

6.3 Interpretation

The distribution exhibits meaningful downside tail risk (e.g. 5% quantile around 326.45) and upside potential, consistent with an event-driven volatility regime. This distribution forms the basis for defining a hedge objective.

7 Target Payoff Construction

7.1 Downside Hedge Objective

The desired hedge should:

- pay approximately zero if SMH ends above S_0,
- increase as S_T declines below S_0,
- saturate (cap) once a sufficiently large decline occurs.

7.2 Piecewise Linear Target

We define a scaled target payoff $g(S_T) \in [0, 1]$:

$$g(S_T) = \begin{cases} 1, & S_T \le 0.85S_0, \\ \frac{S_0 - S_T}{S_0 - 0.85S_0}, & 0.85S_0 < S_T < S_0, \\ 0, & S_T \ge S_0. \end{cases}$$

This form is chosen for interpretability and ease of replication using vanilla options.

8 Options Payoffs

8.1 Put Option Payoff

A put option payoff at maturity is:

$$\Pi_{\text{put}}(S_T; K) = \max(K - S_T, 0).$$

8.2 Debit Put Spread Payoff

A debit put spread consists of:

- long put with strike K_1,
- short put with strike $K_2 < K_1$.

Its payoff is:

$$\Pi_{\text{spread}}(S_T) = \max(K_1 - S_T, 0) - \max(K_2 - S_T, 0).$$

The maximum payoff is bounded:

$$\max \Pi_{\text{spread}} = K_1 - K_2.$$

8.3 Scaling for Payoff Matching

To compare against the target payoff $g(S_T)$, we scale the spread payoff:

$$\tilde{\Pi}_{\text{spread}}(S_T) = \frac{\Pi_{\text{spread}}(S_T)}{K_1 - K_2}.$$

This ensures $\tilde{\Pi}_{\text{spread}}(S_T) \in [0, 1]$, allowing meaningful MSE comparisons.

9 Optimisation Method

9.1 Grid Approximation

We evaluate payoffs on a grid of terminal prices $\{S_m\}_{m=1}^{M}$ spanning a plausible range around S_0:

$$S_m \in [0.6S_0, 1.4S_0].$$

9.2 Objective Function

We select (K_1, K_2) to minimise mean squared error:

$$\text{MSE}(K_1, K_2) = \frac{1}{M} \sum_{m=1}^{M} \left(\tilde{\Pi}_{\text{spread}}(S_m) - g(S_m) \right)^2, \quad \text{subject to } K_1 > K_2.$$

A brute-force search over feasible put spreads in the filtered universe yields the best-fitting structure.

9.3 Optimal Spread

The optimal spread identified was:

$$K_1 = 385, \qquad K_2 = 350,$$

with premium paid:

$$\text{Premium} = \$577 \quad \text{per spread}.$$

10 Trade Summary and Risk Metrics

10.1 Payoff and Profit

Let the contract multiplier be 100. The terminal dollar payoff of the spread is:

$$\text{Payoff}_{\$}(S_T) = 100 \cdot \Pi_{\text{spread}}(S_T).$$

The profit is payoff minus premium:

$$\text{P\&L}(S_T) = \text{Payoff}_{\$}(S_T) - 577.$$

10.2 Maximum Loss

For a debit spread, maximum loss equals the premium:

$$L_{\max} = 577.$$

10.3 Maximum Profit

Maximum payoff is $(K_1 - K_2) \cdot 100$, so maximum profit is:

$$G_{\max} = (K_1 - K_2) \cdot 100 - 577 = 35 \cdot 100 - 577 = 2923.$$

10.4 Breakeven

Breakeven occurs when intrinsic value of the long put equals premium per share:

$$S^* = K_1 - \frac{577}{100} = 385 - 5.77 = 379.23.$$

10.5 Numerical Summary

Metric	Value
Underlying S_0	400.39
Expiry	2026-02-13
Structure	Long 385 put / Short 350 put
Premium	\$577
Max loss	\$577
Max profit	\$2923
Breakeven	379.23

11 Expected Value Under the Scenario-Weighted Distribution

Using Monte Carlo draws $S_T^{(i)}$ from the scenario-weighted distribution, we estimate:

$$\widehat{\mathbb{E}}[\text{P\&L}] = \frac{1}{N} \sum_{i=1}^{N} \text{P\&L}(S_T^{(i)}).$$

The empirical results were:

$$\widehat{\mathbb{E}}[\text{P\&L}] \approx \$87.28, \qquad \widehat{\mathbb{P}}(\text{P\&L} > 0) \approx 25.17\%.$$

This is consistent with a convex hedge profile: frequent small losses and occasional large gains.

12 Figures

12.1 Payoff Diagram

Figure 1 shows the terminal P&L at expiry for the selected debit put spread.

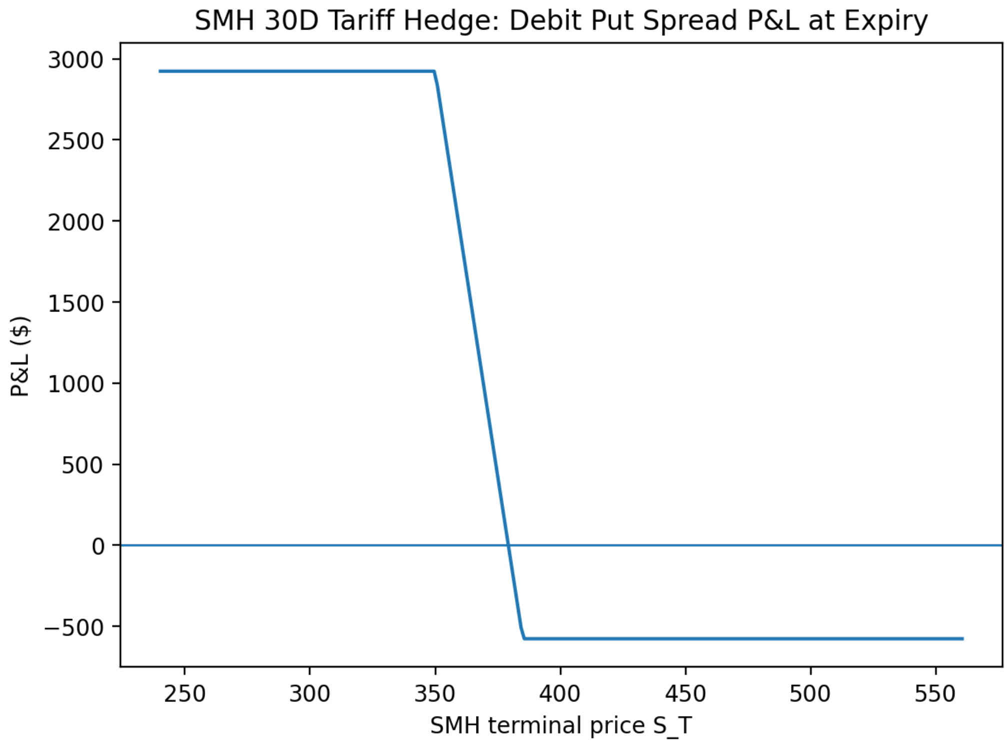
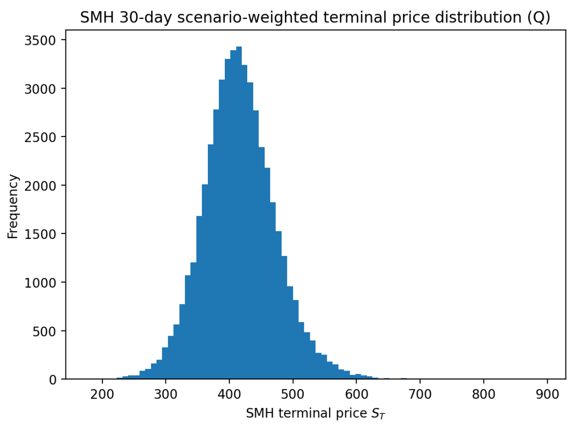
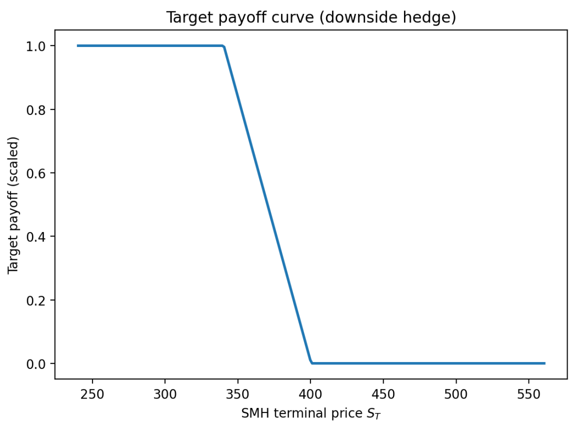


Figure 1: Terminal P&L at expiry for the SMH 385/350 debit put spread.

12.2 Additional Figures



(a) Scenario-weighted terminal price distribution.



(b) Target downside hedge payoff curve.

Figure 2: Figures for the modelling and target payoff design.

13 Discussion

The strategy construction process can be interpreted as a mapping:

Policy uncertainty $\rightarrow$ distribution over S_T $\rightarrow$ desired payoff shape $\rightarrow$ tradable options structure.

The final debit put spread provides:

- limited and known downside cost (premium),

- convex protection against moderate-to-large declines,
- capped upside due to short put leg (cost reduction),
- an interpretable structure suitable for a hedge narrative.

The low profit probability ($\approx 25\%$) is not a flaw; it is characteristic of convex hedges. The positive expected value arises from the large payoff in tail outcomes under the scenario-weighted distribution.

14 Limitations and Extensions

14.1 Limitations

- **Scenario probabilities are subjective:** probabilities could be updated dynamically using Bayesian inference or news-derived indicators.
- **Implied volatility dynamics are not modelled:** mid prices are used directly; a more advanced framework would incorporate the volatility surface and skew.
- **American exercise is ignored:** intrinsic payoff at maturity is correct, but early exercise considerations are not explicitly modelled.
- **Transaction costs and slippage:** bid-ask spreads and execution impact are simplified via mid prices and basic filters.

14.2 Extensions

- **Bayesian updating of scenario probabilities:** incorporate real-time news or macro indicators to update p_j.
- **Multi-leg optimisation:** allow additional legs (e.g. call overwrite) to reduce premium while preserving downside convexity.
- **Risk-neutral calibration:** calibrate to implied volatility and recover a risk-neutral distribution for pricing-consistent comparisons.
- **Backtesting framework:** evaluate performance across historical tariff-like shock windows.

15 Conclusion

This report presented a full end-to-end pipeline for translating tariff-policy uncertainty into a systematic options hedge on SMH. The project integrates scenario modelling, robust calibration, Monte Carlo simulation, and payoff-shape optimisation to select a tradable options structure. The final output (SMH 385/350 debit put spread) is interpretable, bounded-risk, and aligned with a downside hedge thesis.

Final Trade Summary:

- Underlying: SMH
- Expiry: 2026-02-13
- Structure: Long 385 put / Short 350 put
- Premium: $577

- Max loss: \$577
- Max profit: \$2923
- Breakeven: 379.23
- Estimated EV: \$87.28
- Estimated $\mathbb{P}(\text{P\&L} > 0)$: 25.17%

A Appendix A: Pseudocode for the Full Pipeline

A.1 Scenario-Weighted Simulation

```
Input: S0, scenarios {p_j, mu_j, sigma_j}, N simulations
For i = 1 to N:
    Sample scenario j ~ Categorical(p_0,...,p_3)
    Sample return R ~ Normal(mu_j, sigma_j)
    Compute ST = S0 * exp(R)
Output: {ST_i}
```

A.2 Payoff Target and Put Spread Search

```
Input: price grid {S_m}, target payoff g(S_m), put strikes {K}
For each K_long in strikes:
    For each K_short in strikes with K_short < K_long:
        Compute spread payoff across grid
        Scale payoff by (K_long - K_short)
        Compute MSE vs target payoff
Choose spread with minimal MSE
```

B Appendix B: Key Mathematical Objects

B.1 Put Spread Payoff (Piecewise Form)

For $K_1 > K_2$:

$$\Pi_{\text{spread}}(S_T) = \begin{cases} K_1 - K_2, & S_T \leq K_2, \\ K_1 - S_T, & K_2 < S_T < K_1, \\ 0, & S_T \geq K_1. \end{cases}$$

This piecewise structure explains the capped payoff and convex downside protection.

C Appendix C: Implementation Notes (Python)

The implementation was modularised into:

- `data/market_data.py`: price and options chain retrieval
- `modeling/calibration.py`: robust drift/vol calibration
- `modeling/distribution.py`: scenario-weighted simulation
- `trading/target_payoff.py`: hedge payoff design
- `trading/put_spread_search.py`: brute-force spread search
- `trading/trade_summary.py`: risk metrics and P&L evaluation