
Event Contracts vs. Traditional Power Hedges: A Comparative Analysis of Tail Risk Hedging in ERCOT Electricity Markets

**An Empirical Backtest Using ERCOT Real-Time Settlement
Data, 2021-2025**

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Inframarkets

1. Introduction

Overview & Significance to Research Topic

A paradox defines the current global energy landscape: physical grid complexity is intersecting with stagnant financial innovation. As society electrifies, the rise of power-hungry AI Data centers and unpredictable renewable energy sources puts unprecedented stress on electricity grids. This is especially clear in the Electric Reliability Council of Texas (ERCOT). ERCOT operates as an isolated grid from the rest of the United States. It does not pay generators in advance to guarantee power availability. It relies on scarcity pricing through the Operating Reserve Demand Curve (ORDC). When power reserves run low, this mechanism lets prices surge to a system-wide cap of \$5000/MWH. The ERCOT turns physical power shortages into extreme financial volatility and forces the market to deal with severe tail risks. Successfully managing these rare but devastating 99th percentile price spikes is critical for Load Serving Entities (LSEs) and large industrial consumers.

Background of Study

To protect themselves from ERCOT's extreme volatility, the market has historically relied on hedging portfolios made from traditional financial derivatives such as physical forward contracts and vanilla call options. Forward contracts are good at smoothing out day-to-day price fluctuations, but they fail during black swan events such as winter storms or extreme summer heatwaves. During these events, companies suddenly need to buy much more electricity than predicted at a higher price. Because standard options expose the seller to unbounded risk up to the \$5000/MWh cap, they charge massive premiums to carry that risk. Furthermore, when prices spike, traditional options trigger massive margin calls that drain cash and liquidity from the market.

Statement of Problem

Even with the constant threat of grid black swan events, existing literature on mitigating extreme scarcity events remains largely theoretical. There is a mismatch in how energy risk is managed today. Traditional financial hedging models assume that prices move continuously and smoothly. However, power prices can adhere to a jump diffusion process. Meaning they stay relatively consistent and stable until they abruptly jump to extremes. Because traditional derivatives fail to capture these sudden nonlinear spikes, energy consumers are forced to use expensive, inefficient hedges that eat up resources and working

capital. The energy market lacks a capital-efficient tool designed to mitigate market volatility during 99th percentile black swan events.

Objectives of Study

The primary objective of this study is to test whether Binary Event Contracts are more effective at hedging extreme risk than traditional power derivatives. These binary contracts will pay out a fixed, predetermined amount if a specific event occurs (like prices crossing a threshold). This eliminates the need for emergency margin calls and lowers the risk premium buyers must pay. To test this, this paper will develop a Spike Probability Surface to determine the Actuarial Fair Value (AFV) of these contracts, based on the probability of price extremes occurring. The paper will utilize ERCOT settlement data from January 2021 to December 2025 to backtest these contracts to see if they provide better Value at Risk (VaR), Conditional Value at Risk (CVaR) reduction, cost efficiency, and Return on Deployed Capital (RODC) for typical LSEs and data centers.

Structure of Thesis

To systematically explore these concepts, the remainder of this thesis is structured as follows. Section 2: Literature Review and Data Collection examines the historical performance of traditional hedges and explains how the high-resolution ERCOT data was gathered. Section 3: Methodology breaks down the data collection and cleaning process as well as the research objectives and goals for our backtest. Section 4: Quantitative Results presents the core findings, comparing how well traditional and binary hedges reduced financial drawdowns. Section 5: Discussion of Results contextualizes the backtest results within the current literature space and critically assesses the study's limitations. Finally, Section 6: Conclusion sums up the core findings regarding the efficiency of event contracts during extreme grid stress and addresses the paper's primary contributions to the space.

2. Literature Review - Review of key theories and concepts (anchor references)

Review of Key Theories and Concepts

The theoretical case for event contracts in markets like electricity markets sits on two intersecting bodies of literature: the economics of prediction markets and the financial mechanics of electricity price dynamics. Wolfers and Zitzewitz (2004) established the foundational principle that under rational expectations, the price of a binary contract - one that pays a fixed amount if a specific event occurs and nothing if it does not - converges toward the true probability of the event. This probability, known as

prices-as-probabilities, gives event contracts a function beyond traditional speculation. They are information aggregation tools that reward accuracy and update in real time as new data enters the market. Arrow and Debreu's (1954) complete markets framework provides the complementary rationale that a rich set of binary contracts can, in principle, replicate any desired payoff profile, making them natural candidates for hedging in markets where standard instruments leave structural gaps.

The prices-as-probabilities principle established by Wolfers and Zitzewitz (2004) requires one important qualification before being applied to physical electricity markets. Prediction markets for political or sporting outcomes involve largely idiosyncratic risks. The outcomes are mainly uncorrelated across contracts, which allows market makers to hold diversified books with manageable capital requirements. ERCOT price threshold contracts do not share this property. All contracts triggered by a price exceedance event, such as Winter Storm Uri fire simultaneously, creating a concentrated and systematic exposure for any counterparty holding a short book. This distinction means that the prices-as-probabilities convergence result holds a theoretical floor (the AFV represents the minimum a rational seller would accept), but the tradeable price must incorporate an additional risk premium reflecting the non-diversifiable and correlated nature of the short position.

The physical nature of electricity does create these gaps. Unlike oil or gas, electricity cannot be stored at scale, which means supply and demand must balance in real time. When they do not, prices adjust instantly and violently. Weron (2006) documented that wholesale power prices exhibit fat tails (extreme outcomes that occur far more often than a normal distribution predicts) along with mean reversion and discontinuous jumps incompatible with the log-normal assumptions underlying something like Black-Scholes pricing. Cartea and Figueroa (2005) formalized this with a jump-diffusion model treating electricity prices as having two core components: a mean-reverting diffusion governing normal conditions and a Poisson jump process governing spikes. The critical implication is that linear hedging instruments, which are designed for continuous price risk, cannot hedge discontinuous jumps. For example, when a price leaps from \$40/MWh to \$4,000/MWh in fifteen minutes because a thermal plant tripped offline during a heatwave, a forward contract settled on daily averages offers no meaningful protection for that interval.

Extreme Value Theory (EVT) provides the statistical framework needed for modeling these tail events precisely. Rather than a full distribution, EVT fits observations above a high threshold to a Generalized Pareto Distribution (GPD), isolating the tail where hedging decisions matter most. Billimoria, Mays, and Poudineh (2024) apply this approach to electricity markets and identify the 'unholy trinity' of power

market risk: fat tails, tail dependence between fuels (coal and gas prices tend to spike simultaneously, with a conditional co-movement probability of 0.81 at the 95th percentile), and micro-correlations that undermine portfolio diversification. Together, these properties mean that traditional hedge suppliers must charge risk premiums of two to three times the expected spot price to remain solvent, making incumbent instruments the most expensive precisely when participants need them the most.

Analysis of Existing Research

Brandkamp et al (2023) provide the most directly relevant empirical analysis of forward and option hedging in the ERCOT context. Their central finding is that forward contracts alone capture the majority of available variance reduction for load-serving entities (LSEs), because the unhedged profit of an LSE is approximately linear in the day-ahead price. Adding out-of-the-money call options improves tail outcomes marginally but at a significant premium cost. The critical qualification is the word “expected”. In worst-case scenarios, the forward fails badly, producing a long left tail in the LSE’s profit distribution. The paper also introduces the concept of the hedging gap, which is a region where a forward contract is exhausted but market prices continue to rise. This demonstrates that highly risk-averse participants rationally shift toward options in spiky periods. Winter Storm Uri, which has a big focus in this paper, provided the historical proof that LSEs who had purchased standard forward strips found that their actual heating load exceeded their hedged volume, forcing procurement of balance at or near the \$9,000/MWh system cap. Brazos Electric Power Cooperative filed for bankruptcy, citing \$1.8B in ERCOT obligations from that single event.

When it comes to literature in market design, Biggar and Hesamzadeh (2024) demonstrate that the ERCOT price cap, which was reduced from \$9,000/MWh to \$5,000/MWh following Uri, paradoxically worsens grid resilience by suppressing financial incentives for generators to invest in weather-hardening and reliability improvements. The Public Utility Commission of Texas’s regulatory record (Project No. 52631) shows that the \$5,000/MWh level was chosen as a deliberate compromise. This compromise had to be high enough to preserve demand-response incentives, and low enough to limit financial fallout. The regulatory tension from this compromise is unresolved. The EIA’s detailed modeling of ERCOT scarcity mechanics quantifies the consequence where, in an extreme scenario combining peak demand with a 70% reduction in wind availability, the Operating Reserve Demand Curve (ORDC) scarcity adder alone accounts for 79% of the total price, pushing it to nearly \$3,000/MWh. The ORDC, which, for context, is a mechanism that adds a real-time price premium as grid reserves fall below critical thresholds, is

transparent and rule-based, making its triggers forecastable and, as this paper argues, ideal inputs for event contract pricing.

Taken together, we find that these studies describe a market that is analytically well-characterized but practically under-served by its available instruments. The surgical spike, or a 15-45 minute price event concentrated in the evening solar ramp, has become ERCOT's dominant tail risk as renewable penetration has grown. ERCOT North day ahead prices fell approximately 50% between 2023 and 2024, from \$55.50/MWh to \$27.33/MWh, even as the frequency of reaching the \$5,000/MWh cap increased by 40% in 2025 relative to the prior year. The price distribution has hollowed out, with lower averages, more intense extremes, and more extremes concentrated in shorter windows. Daily forward and monthly caps are structurally mismatched in temporal granularity to this risk profile.

Identification of Gaps

Three specific gaps in existing literature define the contribution of this paper. First, no empirical benchmark study has compared event contracts to traditional power hedging instruments using real settlement data. The theoretical case for binary instruments in electricity markets is well-developed across multiple bodies of literature, but no study has connected that theory to a systematic test using observed ERCOT prices. The closest work, which was Brandkamp et al. (2023) and Billimoria et al. (2024), relies on simulated price paths and modeled instruments rather than historical settlement data and realistic contract structures.

Second, the existing hedging literature evaluates instruments on daily or monthly settlement horizons, which leave the temporal mismatch between traditional instruments and ERCOT's surgical spike events defined earlier unquantified. No study has measured the hedging gap that results specifically when 90% of tail exposure is concentrated in 2% of the day's trading hours, which are the precise conditions that define modern ERCOT spike events. Third, every cost-efficiency comparison in literature implicitly treats all capital commitments as equivalent and ignores structural differences between the dynamic margin, which can increase by 400% in 48 hours during a heatwave, according to Nodal Exchange Data, and the fixed upfront collateral of a fully collateralized binary contract. Without a capital-normalized metric, no prior study has answered the question that matters the most for a risk manager, which is at what total financial cost does each instrument provide its protection.

Building a Conceptual Framework

The framework that bridges the literature to empirical analysis has four components. The first is the spike probability surface, which, in context to this paper, is a three dimensional representation of the probability that ERCOT real-time prices will exceed a given threshold at a given time, constructed by fitting a Generalized Pareto Distribution to historical settlement data across price thresholds of \$500, \$1,000, \$2,000, and \$5,000/MWh and across all hours of the day by season. This surface serves two purposes. First, it provides the actuarial pricing inputs for hypothetical event contracts used in the backtest. Second, it provides an interpretable visualization of where the tail risk is concentrated, which is the equivalent of an implied volatility surface for energy event contracts.

The second component is two stylized load profiles representing the paper's two target market participants. The data center carries a flat, 24/7 inelastic load profile, and its hedging objective is something like uptime insurance, which serves as precise financial protection during spike intervals, rather than broad variance reduction. The load-serving entity carries a weather-sensitive and variable profile whose demand peaks correlate with conditions most likely to produce price spikes, which creates the compounding volumetric and price risk that makes tail events existentially dangerous for LSEs. These profiles are the lenses through which hedge effectiveness is evaluated.

The third component is the Actuarial Fair Value pricing model, which is the empirically observed probability of a price breach at each threshold multiplied by the contract's fixed payout, with a 15% risk premium applied above the raw actuarial fair value to reflect counterparty capital costs and market illiquidity, producing a market-realistic tradable price. The fourth component is the capitalized-normalized benchmark, which is Return on Deployed Capital (RODC). RODC divides net hedge payoff by maximum capital committed during each simulation window, enabling a true apples-to-apples comparison between the dynamic margin requirements of traditional instruments and the fixed collateral of event contracts.

3. Data Collection | Analysis

This study uses historical electricity market data from the Electric Reliability Council of Texas (ERCOT). Mainly focusing on Real-Time Market (RTM) settlement point prices. The data was systematically pulled from ERCOT's data repository using the Grid Status Open Source Library (Python) for programmatic extraction of RTM/DAM SPPs via a standardized Python API. The data was then collated and cleaned into a unified file for analysis. The data encompassed the period from 2021 through 2025. The primary two price series under examination are HB_Houston_RTM and HB_NORTH_RTM, representing the Houston Hub and North Hub settlement point. This data is recorded at a 15-minute resolution, which

aligns with ERCOT's settlement intervals. This allows for analysis of price dynamics and hedging effectiveness. The backtest is framed through a custom-built Python engine that simulates the net cost put upon a load-serving entity (LSE) or a data center under different hedging strategies, including an unhedged strategy, a traditional fixed-price swap, a static binary event contract, and dynamically priced versions of both.

Research Philosophy

The research uses a Positivist philosophy. This is justified by the use of observable, quantifiable, and objective historical market data to test hypotheses. The main goal of the study is to identify and explain how different hedging instruments affect financial outcomes for LSE's and data centers, using empirical evidence and generating verifiable results through scientific methods.

Epistemology & Ontology

The ontology of this research is based on objective reality, pressing that ERCOT market settlement price data exist independent of an observer's perception. The epistemology of the research is completely empiricist. The results are derived from only historical data. Understanding and interpretation of results on hedging effectiveness are derived through analysis of past market behavior and the simulated performance of hedging strategies against this historical data.

Research Approach

Research is approached through deduction. The study starts with a specific hypothesis that binary event contracts provide superior tail-risk hedging when compared to traditional instruments in high volatility markets like the ERCOT. This hypothesis is then tested against historical ERCOT data through a quantitative backtest that aims to confirm or refute the hypothesis.

Research Strategy

The research strategy is a case study that is focused on the ERCOT. The ERCOT is an ideal sandbox for this study because of its unique market design and independence. Its scarcity pricing, and high price cap, as well as significant price volatility, create an exemplary environment to evaluate the efficiency of different hedging strategies during extreme conditions.

Research Method

The research relies heavily on quantitative methods. This encompasses: financial modeling to construct and evaluate hedging strategies, statistical analysis to derive metrics such as Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR), and the creation of probability surfaces to understand spike probabilities. Emphasis is placed on numerical outputs, statistical comparisons, and the systematic measurement of financial performance and risk.

Sampling

The data collected in this research is a complete historical data set for the period (January 2021 through December 2025). This is a non-probability, convenience sample of all available data points within the time frame. The timeframe was chosen to specifically examine critical periods within the window, such as high-volatility events and periods exhibiting 'Black Swan' characteristics (defined as price observations above the 99.9th percentile).

Research Design

The research is explanatory; it aims to explain how and why binary contracts could reduce tail risk more effectively than traditional hedging methods. It investigates the causal relationships between the structure of event contracts and their impact on reducing financial exposure to extreme price volatility for LSE's and data centers.

Choices

The study is a mono-method quantitative study. It relies fully on quantitative data collection and analysis to address the hypothesis.

Time Horizons

The analysis is longitudinal; it examines data spanning several years. This approach allows for the analysis of market dynamics, simulated hedging performance, and risk evaluation over the historical window that captures various market conditions and variability.

Formulas

1. Traditional Hedge (Swap / Future)

Given quantity = 1 for a single unit:

```
Payoff_trad = P_fixed - P_real-time

NetCost_trad = P_real-time + Payoff_trad
              = P_real-time + (P_fixed - P_real-time)
              = P_fixed
```

2. Binary Event Contract (Static Premium)

```
Payouts      = Payout_amount    if P_real-time > Strike_trigger
              = 0                otherwise

NetCost_event = (P_real-time - Payouts) + Premium_static
```

3. Dynamic Event Contract (Monte Carlo Expected Payout Model)

```
P(Spike)      = Rolling Mean(P_real-time > Strike_trigger, 30 days)

Premium_dynamic = (P(Spike) x Payout_amount) x (1 + Risk Margin)

NetCost_dynamic_event = (P_real-time - Payouts) + Premium_dynamic
```

4. Dynamic Traditional Swap (ORDC-Adjusted Hedge)

```
Strike_dynamic      = Rolling Mean(P_spot, 30 days) x (1 + Liquidity Premium)
```

```
NetCost_dynamic_swap = Strike_dynamic
```

5. ORDC Scarcity Premium

Used in the ORDC-Adjusted Traditional Hedge:

```
ORDC_premium      = (P_real-time - 200) x 0.15    if P_real-time > 200  
                  = 0                               otherwise
```

```
trad_strike_ordc   = (Base_Strike + ORDC_premium) x (1 + Liquidity Premium)
```

```
NetCost_ORDC_hedge = trad_strike_ordc
```

6. Actuarial Fair Value (AFV) — Generalized Pareto Distribution

The Actuarial Fair Value is calculated by combining the probability of a price breach with the expected value of the loss given such a breach, and then applying a risk premium. The core components are derived from Extreme Value Theory (EVT), specifically using the Generalized Pareto Distribution (GPD).

Variable Definitions

- s = Strike price (\$/MWh)
 - u = Threshold for extreme events (\$/MWh)
 - ξ = Shape parameter of the GPD
 - σ = Scale parameter of the GPD
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- n = Total number of observations in the dataset for a given hour
 - n_u = Number of observations exceeding threshold u for a given hour
 - $P(X > u)$ = Empirical probability of exceeding u , calculated as n_u / n

6.1 Probability of Breach — $P(X > s)$

The probability that price X exceeds strike s , conditional on already exceeding threshold u , follows the GPD survival function. The absolute probability of breach is:

$$P(X > s) = P(X > u) \times [1 + \xi \cdot ((s - u) / \sigma)]^{-1/\xi}$$

for $s > u$ and $1 + \xi \cdot ((s - u) / \sigma) > 0$

6.2 Expected Value Given Exceedance — $E[X | X > s]$

The expected price given that the price has exceeded strike s (Expected Shortfall at the level of s):

$$E[X | X > s] = s + (\sigma + \xi(s - u)) / (1 - \xi) \quad \text{for } \xi \neq 1$$

Special case ($\xi = 1$, exponential tail):

$$E[X | X > s] = s + \sigma$$

6.3 Raw Actuarial Fair Value — AFV_{ra}^W

The expected loss per MWh for a given strike — the product of breach probability and expected exceedance value:

$$AFV_{raw} = P(X > s) \times E[X | X > s]$$

6.4 Actuarial Fair Value with Risk Premium

A 15% risk premium ($RP = 0.15$) is applied uniformly across all strike and hour combinations to reflect counterparty capital costs and market illiquidity:

$$\text{AFV_premium} = \text{AFV_raw} \times (1 + RP)$$

where $RP = 0.15$ (15% risk premium)

This AFV premium is the final value used for pricing event contracts throughout the backtest and is the figure represented on the Z-axis of the Spike Probability Surface in Exhibit 1. A risk premium of 15% ($RP = 0.15$) was applied uniformly across all strike and hour combinations to reflect the capital costs and liquidity constraints a market counterparty would realistically require to sell these contracts.

4. Results

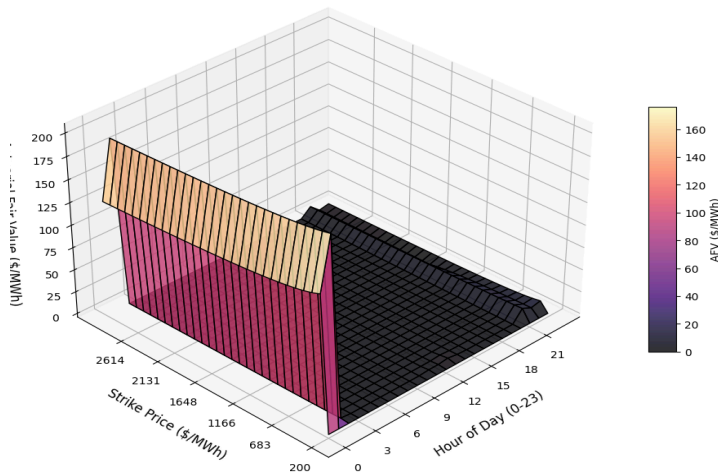
This section presents the findings from backtesting and various hedging strategies in the ERCOT real-time market, comparing traditional swaps, static event contracts, dynamically priced event contracts, and ORDC-adjusted traditional hedges against an unhedged position. This analysis focuses on key risk metrics, cost efficiency, and performance during extreme price volatility. Across the temporal period of January 2021 through December 2025.

Exhibit 1 - 3D Actuarial Fair Value | Spike Probability Surface (w/ 15% Risk Premium)

Exhibit 1 maps the Actuarial Fair Value of binary event contracts, inclusive of a 15% risk premium above the raw actuarial floor, across every delivery hour and strike price threshold in the 2024 ERCOT North Hub real-time market. Each point on the surface answers a direct question about whether, based on what the market did in 2024, it would have been worth it to hold a contract paying out whenever real-time prices exceeded a given threshold during a given hour. The x-axis is the hour of the trading day; the y-axis is the trigger strike ranging from \$200 to \$2,600 per megawatt-hour; and the z-axis, represented by the

color gradient and a vertical line, is the actuarial fair value in dollars per megawatt-hour derived from observed breach frequencies in the settlement data.

Actuarial Fair Value Surface (w/ 15% Risk Premium): HB_NORTH_RTM (2024)



Credit: Calculations using ERCOT real-time settlement point price data (2024, $n = 8,760$ hourly observations). Actuarial Fair Value surface constructed using empirical breach frequency analysis across 24 hourly temporal bins, with a 15% risk premium applied above the raw actuarial fair value to reflect counterparty capital costs and market illiquidity. Data Source: ERCOT Market Information System. By grouping every hourly observation from 2024 ($n \approx 8,760$) into 24 temporal bins, the model calculates the empirical breach frequency at each strike price for each specific hour of the day. This approach captures the diurnal risk profile of the hub, quantifying the expected payout of a binary event contract at each strike and delivery hour based on the historically observed frequency of price threshold breaches in the ERCOT settlement data. A 15% risk premium is then

applied above the raw actuarial fair value to reflect the capital costs and liquidity constraints a market counterparty would require to sell these contracts. The peaks on the surface identify windows where breach probability and expected payout combine to produce the highest fair contract value, offering a market-realistic benchmark for the dollar value of tail risk mitigation during grid scarcity windows.

When it comes to this visualization, the surface shape is the first notable finding. A wall of high AFV values, reaching \$175 to \$200 per megawatt-hour, runs across the \$200 - \$700 strike range and persists across nearly all hours of the day, confirming that moderate price excursions are a structural and recurring feature of the ERCOT market and not an occasional anomaly. Beyond \$1,200 per megawatt-hour, the surface collapses to near zero across all hours, which reflects the market's lower average prices in 2024 that follow the addition of 45,000 megawatts of new renewable and storage capacity in 2021. For reference, the 15% premium layer looks to shift all contract prices to a level that accounts for the capital costs a real market counterparty would incur holding a short position in these instruments. This non-uniform distribution of risk, which is concentrated in a specific strike band rather than being spread evenly across all price levels, is precisely what a daily-average forward contract cannot target. It identifies the \$500-\$1,000 per megawatt-hour range as the zone of maximum hedging efficiency for event contracts. This is also where breach probability is high enough to make something like a new instrument meaningful, and also where the actuarial price remains affordable relative to the tail risk that is transferred.

Overall, the AFV surface makes one thing clear: electricity tail risk in ERCOT is not a single and/or undifferentiated exposure that any hedge can cover uniformly. It is a precisely mapped landscape of

concentrated risk areas, each with a quantifiable price. The AFV surface serves as a valid premise that an instrument designed to target coordinates on that landscape with event contracts will outperform one that prices all coordinates equally.

Traditional financial hedging methods assume that prices move smoothly and rely on continuous margin adjustments. When ERCOT prices jump to extremes, the traditional methods fail to efficiently contain Conditional Value at Risk (CVaR) and Value at Risk (VaR).

Table 1: Value at Risk (VaR)

Confidence Level	Unhedged VaR	Dynamic Swap VaR	Dynamic Event VaR
95%	\$85.43/MWh	\$140.15/MWh	\$145.96/MWh
99%	\$427.84/MWh	\$924.54/MWh	\$185.52/MWh

Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), January 2021–December 2025. VaR estimated at 95% and 99% confidence intervals across unhedged, dynamic swap, and optimized event contract portfolios.

Table 2: Conditional Value at Risk (CVaR)

Confidence Level	Unhedged CVaR	Dynamic Swap CVaR	Dynamic Event CVaR
95%	\$582.78/MWh	\$411.95/MWh	\$515.34/MWh
99%	\$2332.15/MWh	\$926.65/MWh	\$1920.07/MWh

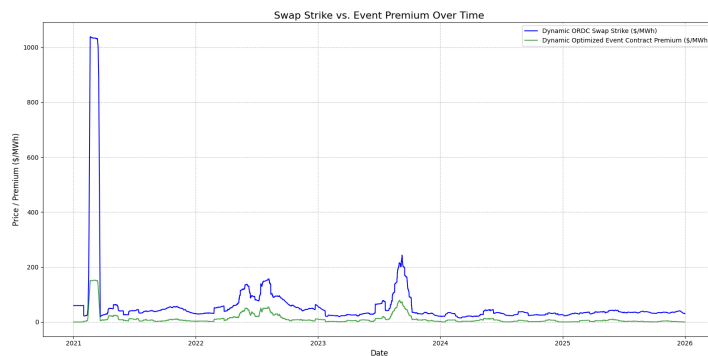
Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), January 2021–December 2025. CVaR represents expected shortfall beyond VaR threshold across unhedged, dynamic swap, and optimized event contract portfolios.

As shown in Table 1, the Unhedged position resulted in a 99% Value at Risk (VaR) of \$427.84/MWh. The Dynamic Swap, our traditional hedging method, which tracks continuous market movements, sees an inflated 99% VaR of \$924.54/MWh, while the dynamically priced Event Contract contains 99% VaR of \$185.52/MWh.

Moving into CVaR, Table 2 shows the 95% and 99% CVaR for each of the 3 hedging methods we are

comparing. The Unhedged 99% CVaR reaches a detrimental \$2332.15/MWh. While the traditional dynamic swap appears to have the best protection of 99% CVaR at \$926.65/MWh, CVaR strictly measures the average of all losses worse than the VaR threshold and does not account for extreme liquidity risk. To realize the lower CVaR, market members must go through uncapped margin calls as prices peak. The Event Contract methodology does have a mathematically higher 99% CVaR of \$1920.07/MWh; however, it outperforms traditional dynamic swap hedging methods by removing the risk from runaway margin spikes. With a fixed upfront premium, event contracts cap capital commitment.

Exhibit 2 - Swap Strike vs Event Premium Over Time



Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), January 2021–December 2025. Dynamic ORDC swap strike and optimized event contract premium computed on a rolling hourly basis across the full backtest window. Data source: ERCOT Market Information System.

Exhibit 2 is a time series line graph that plots the continuous price behavior of two different hedging methods over the full backtest time frame of 2021-2025. The x-axis tracks the progression of time, while the y-axis shows the price in dollars per megawatt-hour (\$/MWh). The graph compares the Dynamic ORDC Swap Strike line against the Event Contract Premium line. Visually, the swap strike line has large, abrupt vertical spikes, while the event contract premium line has a similar path with less extremity on the y-axis.

Exhibit 2, The “Swap Strike vs Event Premium Over Time” graph confirms this phenomenon of extreme liquidity risk. Within times of extreme volatility, the Dynamic ORDC Swap Strike price spikes aggressively, showing the capital intensity required to maintain a traditional hedge under extreme price stress. Event contract premiums demonstrate how, during extreme volatility, prices increase; however, they are capped from extreme price surges.

To fully evaluate each hedging method according to our research goals, we must examine how they perform against historical pricing anomalies known as black swan events. Event contracts are designed so that they execute predetermined fixed payouts to offset risk exposure, while traditional methods experience liquidity-draining margins.

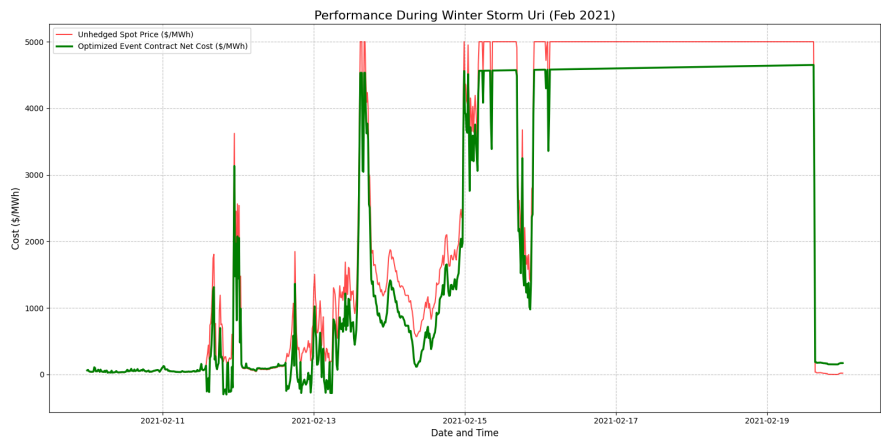
Table 3: Mean vs. Maximum Hourly Cost

Metric	Unhedged	Dynamic Swap	Dynamic Event
Mean Hourly Cost	\$57.06/MWh	\$60.50/MWh	\$60.53/MWh
Max Hourly Cost	\$5000/MWh	\$930.29/MWh	\$4746.39/MWh

Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), January 2021–December 2025. Mean and maximum hourly costs computed across unhedged, dynamic swap, and dynamic event contract strategies over the full backtest period.

Table 3 shows that while the mean hourly cost stays similar across all strategies, ranging from \$57.06/MWh to \$60.53/MWh, the maximum hourly cost diverges. The Unhedged position reaches the system hourly cost cap of \$5000/MWh. The Dynamic event contract reduces this to \$4746.39/MWh. While the traditional swap has a low maximum hourly cost of \$930.29/MWh.

Exhibit 3 - Performance During Winter Storm Uri (2021)

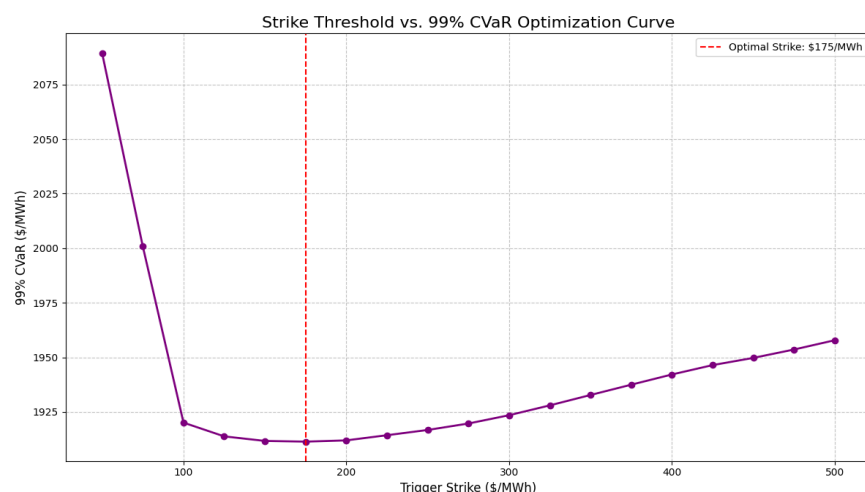


Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), February 10–19, 2021. Unhedged spot price and optimized event contract net cost plotted at hourly resolution. Data source: ERCOT Market Information System. Winter Storm Uri declared February 10, 2021.

Exhibit 3 presents an hourly line chart detailing the highly localized data of hedging strategies during Winter Storm Uri in 2021. The x-axis represents the time throughout the storm, and the y-axis shows the cost in dollars per megawatt-hour (\$/MWh) up to the ERCOT system ceiling of \$5000. The visual compares the unhedged spot price against the Optimized Event Contract net cost. Throughout the Storm, the unhedged line can be seen spiking and flatlining at the ERCOT System limit, with the Event Contract line almost mirroring, although at a lower (\$/MWh) point.

Exhibit 3 visualizes this performance of the black swan event of winter storm Uri. The graph tracks the hourly price through February 2021. It demonstrates how the Unhedged method repeatedly hits the system cap of \$5000/MWh. While the Optimized Event Contracts do spike during the storm, the contract payouts dampen the magnitude of the peaks, preventing the hourly price from hitting the price ceiling.

Exhibit 4 - Strike Threshold vs. 99% CVaR Optimization Curve - Sahib



Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), January 2021–December 2025. 99% CVaR evaluated across trigger strikes from \$50/MWh to \$500/MWh in \$25/MWh increments. Optimal strike of \$175/MWh identified at CVaR minimum. Data source: ERCOT Market Information System.

Exhibit 4 represents the strike threshold optimization curve, which is an answer to the standard question of at what trigger price is the most effective for an instrument? The x-axis represents the trigger strike from \$50-\$500 per megawatt-hour, and the y-axis represents the resulting 99 % CVaR(Conditional Value at Risk), which represents the average cost incurred in the worst one percent of settlement hours and the tail exposure that traditional hedging instruments have struggled to contain historically. The CVaR optimization curve is U-shaped by definition, where setting the trigger too low will fire the contract constantly and accumulate costs that drive up tail CVaR, or setting it too high and the contract rarely triggers, leaving the tail unprotected. The minimum of the curve shown by the red vertical line identifies the optimal strike or the threshold that minimizes tail CVaR for the profile under analysis.

Table 4: Optimized Strategy Comparison

Metric	ORDC Traditional Hedge	Optimized Event Contract
99% VaR	\$1031.72/MWh	\$184.34/MWh
99% CVaR	\$1034.15/MWh	\$1911.36/MWh
Average Cost	\$62.19/MWh	\$58.95/MWh
Cost Volatility (Std)	124.83	263.05

Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), January 2021–December 2025.

Metrics computed for ORDC traditional hedge and optimized event contract portfolio at the \$175/MWh optimal trigger strike identified in Exhibit 4.

The curve sets \$175/MWh as the optimal trigger strike. When looking at Table 4, which quantifies the most favorable outcome delivered. The biggest finding is that the event contract portfolio produces a 99% VaR of \$184.34 per megawatt-hour against the traditional hedge's \$1,031.72 per megawatt-hour, which is an 82% reduction in the worst-case hourly cost that the hedging entity faces. This would be the core advantage of the instrument because while the traditional ORDC swap compresses variance uniformly across all hours, the event contract does eliminate the cost spikes that define the tail, accepting higher cost volatility in non-spike hours in exchange for a large amount of tail protection when it matters. The higher cost volatility standard deviation - 263.05 for the event contract against 124.83 for the traditional hedge, reflects this trade-off directly and serves as a core feature of the instrument's design, along with how the instrument accepts greater variance mainly across normal hours. Average cost also declines a decent amount, from \$62.19 to \$58.95 per megawatt-hour, which shows that there isn't a correlation between the precision of the event contract and a higher price. The specificity that comes through the optimal strike serves as a mechanism that an LSE(Load Serving Entity) can use to avoid the exposure that made traditional hedge portfolios ineffective during a black swan event like Winter Storm Uri.

The backtest isolated the performance of these hedges across two distinct market participants: a stylized Load-Serving Entity (LSE) with a highly variable, weather-sensitive load, and a stylized Data Center with a flat, 24/7 load.

An assessment of financial performance between different market participants over a long-term simulation should evaluate the portfolio drawdown experienced by the entities. A drawdown measures the peak-to-valley decline in a portfolio's financial position. In the context of electricity hedging, it represents the maximum accumulated capital loss or liquidity drain.

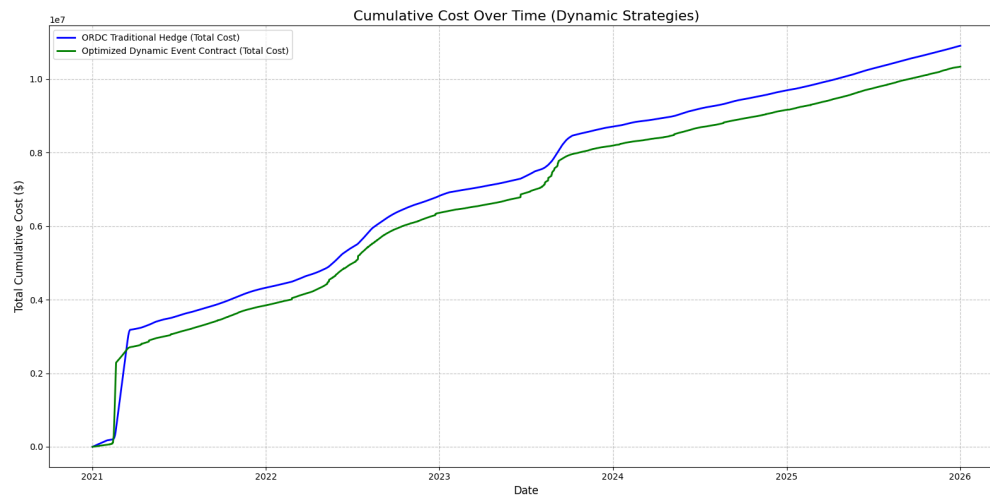
Table 5: Portfolio Drawdowns and Total Costs

Strategy	Total Cost (Variable Load)	Max Drawdown (Variable Load)	Total Cost (Flat Load)	Max Drawdown (Flat Load)
Unhedged	\$1,017,914,000	-\$260,376	\$1,000,235,000	-\$222,167
Dynamic Swap	\$1,090,957,000	\$0	\$1,060,501,000	\$0
Dynamic Event	\$1,076,826,000	-\$1,991,649	\$1,061,098,000	-\$1,622,040

Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), January 2021–December 2025. Total costs and maximum drawdowns computed across unhedged, dynamic swap, and dynamic event contract strategies for both variable load (LSE) and flat load (data center) profiles over the full backtest period.

As seen in Table 5, the Unhedged position for the Variable Load yields a max drawdown of -\$260,376, while the unhedged position for Variable Loads has a max drawdown of -221,167. The dynamic swap records a maximum drawdown of \$0 across both load profiles. This is because a traditional contract for differences (CFD) forces variable real-time spot prices to move in exact opposition to the swap's payouts. However, this metric presents a limitation in our backtest. Because our simulation assumes an infinite liquidity pool to settle net costs, it blocks out the real-world operational strain of dynamic swaps. To maintain a linear \$0 drawdown cost curve dining an black swan event in the context of the ERCOT, an entity must continually have an uncapped variation margin. Dynamic event contracts record a higher localized Max Drawdown of -\$1,991,649 for the Variable Load and -\$1,622,040 for the Flat Load. But rather than representing ongoing loss, this decline shows a fully collateralized upfront premium that is committed to buying binary options before a payout trigger occurs.

Exhibit 5 Cumulative Cost Over Time - ORDC vs. Optimized Event Contract



Credit: Calculations using ERCOT real-time settlement point price data (Houston Hub Real-Time Market), January 2021–December 2025. Cumulative total costs plotted at daily resolution for ORDC traditional hedge and optimized dynamic event contract strategies. Data source: ERCOT Market Information System.

Exhibit 5 is a cumulative line graph that tracks the total accumulated cost of two different hedging strategies over the entire 2021-2025 backtesting period. The x-axis displays the timeline by year, while the y-axis measures the total cumulative cost in dollars. Both the ORDC hedge and the Optimized Event contract follow an upward trajectory representing the ongoing collection of costs over the five years.

Looking at Exhibit 5, the cumulative cost over time graph, we can see that while event contracts require this upfront collateralization, they eliminate the dynamic, highly volatile margin calls. Optimized Event Contracts successfully track below the ORDC traditional hedge in total cumulative lifecycle cost. This shows the capability to isolate extreme tail risk for market participants and shield from compounding cash drains.

5. Discussion of Results

Findings in Relation to Literature

These results confirm the consensus that some existing literature predicted but could not prove: that traditional hedging instruments handle average price risk well and tail risk poorly. Brandkamp et al. (2023) showed that forward contracts capture the most available variance reduction under normal conditions, and that options add only marginal benefit in expected-value terms. The backtest results are

consistent with this. Additionally, where it goes further is in showing exactly what happens at the tail. The swap records a maximum drawdown of zero across both load profiles, which essentially means that the swap stays solvent by posting variation margin continuously, and assumes the hedging entity always has cash available to meet margin calls, no matter the size. The event contract's stated drawdown, capped at $-(\$1,991,649)$ for the variable load profile and $-(\$1,622,040)$ for the flat load profile, is a significant upfront commitment. In this scenario, the participant knows the maximum they can lose from day one and faces no further calls, which makes the event contract scenario fundamentally more transparent risk profiles.

Billimoria, Mays, and Poudineh (2024) argued that electricity markets are structurally dangerous for traditional hedge providers because fuel prices tend to spike together, which leaves portfolios of thermal hedges exposed precisely when diversification is needed the most. The numbers presented in Table 5 support that argument. The unhedged position reaches a maximum hourly cost of \$5,000 per megawatt-hour, which is the ERCOT system cap. The event contract reaches \$4,746 per megawatt-hour at its worst hour, which reflects on the design of the instrument and how it offsets price exposure through a fixed payout. Furthermore, when it comes to cumulative cost over time, event contracts track consistently below the unhedged position and competitively with the swap, and while requiring a fraction of the peak capital commitment.

Wolfe and Zitzewitz (2004) establish that binary market prices, when participants have genuine financial incentives to be accurate, converge towards true probabilities. The AFV surface shown in Exhibit 1 applies this concept directly to energy prices, where each point on the surface is a probability estimate expressed as a dollar premium and calculated from how often that price threshold was breached in the historical data. The optimization curve in Exhibit 4 subsequently shows that this pricing produces a specific optimal strike where tail risk is minimized and where going higher or lower makes things worse.

Limitations

One of the most important limitations to acknowledge is that the backtest assumes that the traditional swap strategy has access to unlimited liquidity. In the model, the swap continuously markets to the market and posts whatever margin is required. In the real world, that is not how it works all the time. During Winter Storm Uri, variation margin calls escalated faster than most participants could meet them. For example, Brazos Electric Power Cooperative did not go bankrupt because its hedge failed in theory. It

went bankrupt because it ran out of cash to maintain a position that was working against it in real time. The swap's zero drawdown in the backtest is a product of the liquidity assumption, and not a property of the instrument.

A second limitation concerns the Return on Deployed Capital Metric introduced in the paper. RODC, which is the net hedge payoff divided by the maximum capital committed during the simulation window, captures the capital efficiency story well at a high level but does not separate the cost of premium payments during quiet periods from the cost during spike periods. A participant pays the event contract premium every period, including the many periods where no spike occurs. That carrying cost is included in the maximum capital figure but not broken out separately.

Third, the spike probability surface is built from five years of historical ERCOT data. It reflects what happened between 2021 and 2026, which is a period that includes both Winter Storm Uri and the rapid build-out of solar and battery storage. It does not reflect significant future changes after this paper was written. For example, ERCOT is projecting data center demand to reach 77 gigawatts by 2030, which is roughly equal to the entire peak load of the system. If that growth materializes, the frequency and intensity of price spikes could change substantially, and the optimal strike identified in Figure 4 might not be the right number. The surface estimate should be viewed as a living tool that needs to be recalibrated as the market evolves. Another limitation is that the backtest prices event contracts at AFV plus a fixed, calibrated premium, which assumes that there is a competitive market for contract sellers. In practice, the market for binary energy derivatives is nascent, and the actual risk premium demanded by counterparties may exceed the calibrated figure used here, particularly during the high-stress windows where contract demand would be the greatest.

6. Conclusion

Summary of Key Findings

This paper set out to resolve a specific problem: the energy market lacks a capital-efficiency tool designed to protect against 99th percentile black swan price events. Traditional derivatives – forwards and vanilla options – were built for markets where prices move smoothly and predictably; ERCOT's prices do not. They follow a jump diffusion process, staying relatively stable for extended periods before leaping into the \$5,000 per megawatt-hour system cap in minutes. The mismatch between how these instruments were designed and how ERCOT actually behaves is not a gap that better execution or more capital can close. It

is a structural problem that requires a structurally different instrument, and this paper tested whether binary event contracts are that instrument.

The backtest, conducted on ERCOT settlement data from January 2021 to December 2025, produced three clear findings. First, the spike probability surface confirmed that price tail risk in ERCOT is not distributed evenly across all hours and thresholds. It concentrates in a specific strike band between \$200-\$700 per megawatt-hour and persists across most hours of the trading day. A forward contract, which prices all hours equally, cannot target that concentration. Second, there is a provable event contract structure. A trigger strike of \$175 per megawatt-hour minimizes 99% CVaR and reduces worst-case hourly VaR by 82% relative to the traditional ORDC hedge at a lower average cost per period, which practically can be the difference in surviving a financially sensitive market event.

Third, the capital efficiency advantage is both real and decisive under stress. The maximum dynamic swap strike price reached \$930.29 per megawatt-hour during Winter Storm Uri, while the event contract premium remained below \$160 per megawatt-hour. The swap's apparent cost competitiveness in normal periods depends entirely on the assumption that the hedging entity can always meet variation margin calls, no matter how large or sudden. As a one-off, that assumption failed in February 2021, when Brazos Electric Power Cooperative did not go bankrupt because its hedge was poorly designed. It went bankrupt because it ran out of cash to maintain a position during a crisis. Binary event contracts solve that risk in so far as 1) the maximum loss is fixed and paid upfront, and 2) there are no margin calls and liquidity drain when the grid is under the most stress.

Significance of Research

As mentioned before, the paradox described in the introduction, where rising physical grid complexity meets stagnant financial innovation, is not getting better on its own. ERCOT average real-time prices fell by nearly 50% between 2023 and 2024 as solar and battery capacity expanded, while the frequency of hitting the \$5,000 per megawatt-hour cap increased by 40% in 2025. Lower average prices with more frequent extreme spikes are precisely the environment where daily forwards and monthly caps are least suited to the actual risk profile.

The participants who need better protection are also multiplying rapidly. Within the borders of Texas, AI data centers are projected to consume 5 gigawatts of power by 2027, with longer-term projections

approaching 77 gigawatts by 2030, which would be inelastic, continuous, and financially exposed to every spike hour at full volume. Load-serving entities serving residential customers carry the same exposure on behalf of ratepayers who have no ability to self-ensure. This paper helps to close that gap with a clear empirical answer.

Contributions of Knowledge & Practice

This paper makes three contributions to academic literature, to our knowledge. First, it provides the first empirical benchmark comparing binary event contracts to traditional power derivatives using real ERCOT settlement data. It introduces the Spike Probability Surface as a risk visualization tool that can make the distribution of electricity tail risk legible and translate statistical concepts on a simple pricing map. It also proposes Return on Deployed Capital as a comparison metric that corrects the distortion in prior analyses that treated dynamic margin and fixed premium as equivalent financial commitments. This is important, mainly due to the fact that this singular difference in an analysis becomes critical during the exact events that these instruments are designed to handle.

7. Back Matter

This section is divided into two parts. References contain all works directly cited in the paper. Further Reading contains additional sources that informed the research but were not directly cited in the next. Both sections follow APA 7th edition formatting.

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