Working Paper - Tunneling into Regime Shifts: A Volatility-Structure Framework for Trading under Latent Calm

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Abstract

We propose a physics-inspired framework for detecting fragile market regimes using the metaphor of quantum tunneling. By training an Energy-Based Model (EBM) on rolling windows of BTC/USD price data from 2018–2023, we derive a tunneling score that quantifies regime sensitivity to latent perturbations. This signal is combined with a trend filter to form a rule-based strategy that selectively enters low-volatility, upward-drifting environments. Backtests show strong in-sample performance: a 49.44% CAGR, Sharpe Ratio of 0.96, and 170 trades with an average holding period of 5.6 days. These results suggest that tunneling-inspired signals—grounded in volatility structure and latent energy response—can act as interpretable markers of transition risk. While preliminary, this work highlights the power of physical metaphors in market modeling and opens avenues for cross-asset generalization, microstructure integration, and physics-informed architecture design.

1 Introduction

Bitcoin has evolved from a fringe cryptographic experiment to a globally traded financial asset with billions in daily volume. Its price history is marked by sharp rallies, sudden crashes, and long stretches of choppy consolidation—reflecting both high speculative interest and the absence of consistent valuation anchors. As a result, Bitcoin's volatility is not only elevated but also structurally complex, with regime shifts that often escape traditional linear models [Gkillas and Katsiampa, 2018, Cheah and Fry, 2015].

Recent work in financial machine learning has begun to explore the application of *Energy-Based Models* (EBMs) to asset pricing and trading. EBMs model a system's probability distribution through a scalar energy function, making them especially attractive for capturing non-normal, multimodal, and transition-heavy dynamics—properties that align well with Bitcoin's behavior. In particular, EBMs provide a flexible framework to model latent structures in price evolution without assuming fixed parametric forms [LeCun et al., 2006, Du et al., 2019].

In this paper, we extend the EBM intuition by introducing a concept drawn from quantum mechanics: *tunneling*. In physical systems, tunneling refers to the phenomenon where a particle escapes a potential well despite not having sufficient classical energy to do so. We analogize this to financial regimes where volatility appears suppressed, but the system may still transition into a high-energy, directional move [Griffiths and Schroeter, 2018].

We propose a simple framework that detects these "low-energy" regimes using a tunneling-based signal, and triggers trades only when a directional drift is detected. The result is a trading strategy that exploits calm phases with upward bias and exits when volatility or drift conditions deteriorate. This fusion of EBM-style regime awareness with tunneling logic offers a new lens through which to view latent structure in financial time series.

Importantly, this work is positioned as a proof-of-concept. While the backtest demonstrates strong performance on in-sample BTC/USD data using daily closes, we do not claim production-readiness. Rather, we aim to motivate further study into tunneling-inspired market models and the integration of physical analogies into financial signal design.

The remainder of this paper is structured as follows. Section 2 situates our work within the broader literature on volatility regimes, energy-based models, and physics-inspired financial modeling. Section 3 details the methodology, including the construction of the tunneling signal and the rule-based trading framework. Section 4 outlines the dataset and experimental design. Section 5 presents the backtest results, with comparisons to benchmark strategies. Section 6 offers a discussion of the findings and their broader implications. Section 7 addresses key limitations and proposes directions for future work. Section 8 concludes.

2 Motivation and Related Work

Modeling volatility and regime shifts has been a longstanding challenge in financial time series analysis. Traditional models, such as GARCH and its variants [Bollerslev, 1986], attempt to characterize volatility through conditional variance dynamics, but often fall short in capturing sudden structural changes or latent transitions. Similarly, regime-switching models like the Markov-switching framework [Hamilton, 1989] allow for abrupt changes in statistical properties, but require strong assumptions about transition structure and often lack interpretability in complex systems like cryptocurrency markets.

The cryptocurrency space, and Bitcoin in particular, exhibits highly non-stationary, heavy-tailed, and regime-volatile behavior [Dyhrberg, 2016, Bouri et al., 2017, Chu et al., 2015]. These properties have motivated the use of more expressive, non-parametric, or machine learning–based approaches to volatility modeling and prediction. Recent studies have explored neural networks [McNally et al., 2018], LSTMs [Sezer et al., 2020], and reinforcement learning [Ning et al., 2018] for trading applications, but many of these models function as black boxes with limited interpretability.

Energy-Based Models (EBMs), by contrast, offer a flexible and interpretable way to model complex dynamics. EBMs assign a scalar energy to each configuration of variables, and lower energy corresponds to higher likelihood [LeCun et al., 2006, Du et al., 2019]. This makes them attractive for systems with multimodal or non-equilibrium behavior—exactly the kind of irregular structure observed in crypto markets. While EBMs have seen limited direct application in trading systems, their potential has been noted in recent work on time-series modeling [Liu et al., 2023] and latent structure estimation [Zhao et al., 2021].

What has been largely unexplored, however, is the explicit fusion of energy-based intuition with physical metaphors drawn from quantum systems. In particular, the concept of *tunneling*—a quantum mechanical phenomenon where a particle crosses a potential barrier it classically shouldn't be able to—offers a powerful analogy for financial markets. Just as particles may escape potential wells due to stochastic fluctuations, prices may break out of calm, low-volatility zones in ways that defy classical momentum logic. This phenomenon has been studied extensively in quantum mechanics [Griffiths and Schroeter, 2018, Shankar, 2012, Landau and Lifshitz, 1977], and serves here as inspiration for a volatility-structure signal that anticipates potential breakout events.

Volatility compression followed by explosive movement is well-documented in markets. Techniques such as Bollinger Band squeeze [Bollinger, 2001], realized variance thresholds [Andersen et al., 2003], or entropy-based measures [Shannon, 1948, Zumbach, 2009] are often used to detect such states. However, these approaches typically rely on either windowed standard deviation or rolling entropy and lack an explicit interpretation of latent state transitions.

Our work builds on this literature by proposing a tunneling-inspired signal that captures the likelihood of exit from a calm regime, grounded in a latent energy landscape. By coupling this with a directional filter (trend-based), we aim to construct a strategy that is both interpretable and expressive—sensitive to structure without overfitting to noise.

3 Methodology

3.1 Data and Preprocessing

We source daily closing prices for Bitcoin (BTC-USD) from Yahoo Finance, spanning a five-year period from January 1, 2018, to December 31, 2023. The dataset includes over 1,800 observations and serves as a representative sample of both high-volatility and range-bound market conditions.

To model local temporal structure, we convert the time series into overlapping rolling windows of fixed length. Each window represents a short segment of recent price history and is treated as an input vector. For our experiments, we use a window size of 10 days, creating a matrix of time-ordered price trajectories:

$$X = [x_t, x_{t+1}, \dots, x_{t+9}] \quad \text{for} \quad t = 1, \dots, T - 9.$$

Each window is then standardized using a z-score transformation, computed across all windows, to ensure that model training is not influenced by price scale. This standardization is applied uniformly across the dataset using the global mean and standard deviation of the full matrix. The result is a scaled input tensor that captures relative movement and local structure, while preserving the shape and dynamics of the original data.

This windowed and scaled representation serves as the input to the tunneling model described in the following sections.

3.2 Energy-Based Model and Training Objective

To extract a latent representation of structural tension in the market, we train a simple *Energy-Based Model* (EBM) on the preprocessed rolling windows. EBMs do not explicitly produce class labels or probabilities—instead, they assign a scalar *energy* to each input, where lower energy indicates a higher likelihood or preference under the modeled distribution [LeCun et al., 2006, Du et al., 2019].

We use a lightweight feedforward neural network as our energy function:

$$E(x) = f(x; \theta) \in \mathbb{R},$$

where x is a 10-day window of scaled prices, and $f(\cdot)$ is parameterized by two linear layers with ReLU activation. The architecture is intentionally minimal, reflecting our focus on proof-of-concept clarity over expressive capacity.

To train the model, we adopt a contrastive loss formulation. For each input window x_{pos} (treated as a positive sample), we generate a *negative sample* x_{neg} by adding Gaussian noise:

$$x_{\text{neg}} = x_{\text{pos}} + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2 I).$$

This noise simulates structural perturbations in the market, nudging the input into configurations that are nearby but plausibly less stable.

The loss encourages the model to assign lower energy to real market sequences and higher energy to noisy counterparts:

$$\mathcal{L} = \mathbb{E}\left[\max(0, 1 + E(x_{\text{pos}}) - E(x_{\text{neg}}))\right].$$

Intuitively, this trains the model to recognize low-energy (i.e., stable, structured) market states by contrasting them with artificially disrupted ones. We train the model using the Adam optimizer over 100 epochs.

This energy function serves as the foundation for constructing the tunneling signal described next.

3.3 Tunneling Signal Construction

Once the energy function is trained, we use it to derive a scalar tunneling score for each window. This score is intended to estimate the likelihood of a regime shift—analogous to a particle "tunneling" out of a potential well despite apparent stability.

Let E_t denote the energy of the window ending at time t, and let x_t represent the corresponding latent input. We define two measures:

- $\Delta E_t = |E_t - E_{t-1}|$, the change in energy between consecutive windows.
- $\Delta x_t = \|x_t - x_{t-1}\|_2$, the change in latent input between consecutive windows.

The intuition is as follows: - If the latent state changes significantly (Δx_t is large), but the energy landscape is relatively flat (ΔE_t is small), the system is likely traversing a stable region. - Conversely, if even small latent deviations lead to large energy shifts, the system is becoming sensitive and unstable—conditions under which "tunneling" is likely.

We define the tunneling score as:

$$\text{Tunneling}_t = \exp\left(-\alpha \cdot \frac{\Delta E_t \cdot \Delta x_t}{\sigma^2 + \varepsilon}\right),$$

where α is a tunable scaling constant, σ is the standard deviation of energy differences across time, and ε is a small constant to ensure numerical stability.

This formulation mirrors the exponential decay of tunneling probability in quantum systems, where the probability of escape depends on both the barrier height (energy change) and barrier width (latent change). High tunneling scores correspond to structurally calm, stable regions where transitions are unlikely. Low scores indicate potential instability and elevated likelihood of regime change.

We apply this score to the original time series to guide trade timing, as described in the following section.

3.4 Backtesting Strategy: Entry and Exit Rules

To evaluate the trading utility of the tunneling signal, we design a simple long-only backtest that uses both the tunneling score and a trend filter to determine entry and exit conditions. This framework reflects the intuition that latent calm (low tunneling) combined with upward drift presents an opportunity for directional positioning, whereas increasing energy or reversal signals a need to exit.

At each time step t, we evaluate:

- **Tunneling Score** T_t, derived as described previously.

- **Trend** $R_t = \frac{P_t}{P_{t-w}}$, the relative price change over a rolling window of w days.

The strategy follows these rules:

1. **Entry**: If no position is currently held, we enter a long trade when the tunneling score is below a fixed entry threshold ($T_t < \theta_{\text{entry}}$) *and* the trend exceeds a minimum threshold ($R_t > 1.01$). This captures calm but upward-drifting regimes.

2. **Exit**: If a position is active, we exit under any of the following conditions:

   - The tunneling score rises above an exit threshold ($T_t > \theta_{\text{exit}}$), indicating structural instability.
   - The trend falls below 0.99, suggesting directional weakness.
   - A maximum holding period H is exceeded.

The entire portfolio begins with a fixed capital allocation and switches between holding cash and a fully invested position based on these rules. Portfolio value is updated daily based on market price, and equity curves are constructed accordingly.

It is important to note that this backtest is conducted *in-sample*, using the same data that informed the tunneling model. As such, results should be interpreted as a proof-of-concept rather than a deployable strategy. The goal here is not to forecast price directly, but to demonstrate that the tunneling score can act as a meaningful state variable for market structure.

Performance metrics and comparisons are presented in the following section.

4 Backtest Results

4.1 Visualizing the Tunneling Signal

To understand how the tunneling signal evolves relative to market price, Figure 1 overlays the raw Bitcoin price time series with the tunneling score (scaled for visibility). Periods with elevated tunneling scores appear as sharp vertical spikes, often occurring near major price inflection points, trend transitions, or during volatility build-ups.

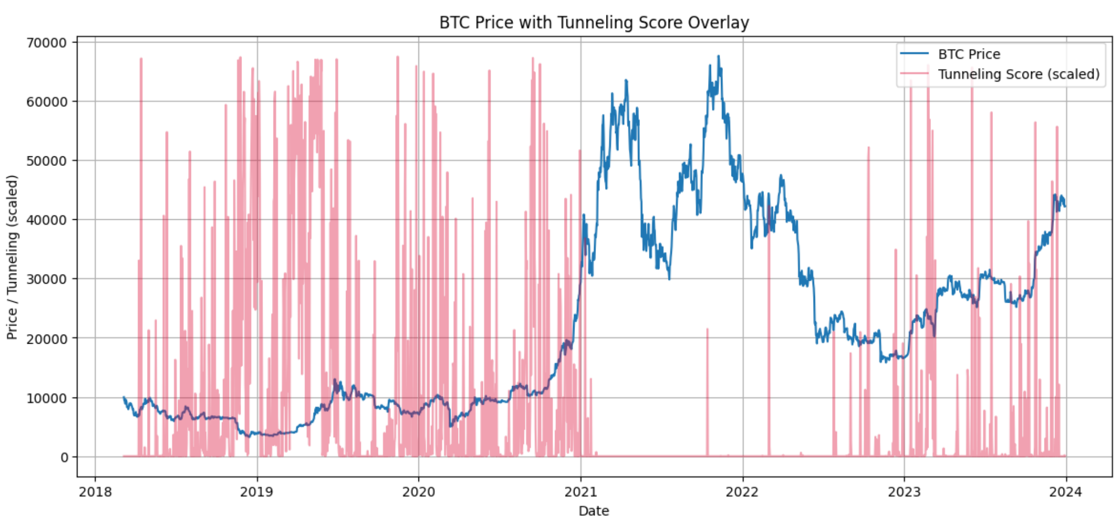

Figure 1: BTC/USD closing price with scaled tunneling score overlaid. Tunneling spikes often precede or coincide with key price turning points.

4.2 Tunneling Spike Analysis

To assess the relevance of the tunneling signal, we identify all instances where the tunneling score exceeded the 95th percentile of its historical distribution. These are interpreted as periods of heightened structural instability—i.e., moments when small changes in latent state correspond to large jumps in modeled energy.

Table 1 presents a sample of such spikes from the tail of the distribution. These were selected purely based on tunneling score magnitude, not manually filtered by time or price context.

Date	Closing Price (USD)	Tunneling Score
2022-11-22	16,189.77	0.9385
2022-12-31	16,547.50	0.9767
2023-01-01	16,625.08	0.7461
2023-01-03	16,679.86	0.8406
2023-01-04	16,863.24	0.7327
2023-01-10	17,446.29	0.8132
2023-04-09	28,333.05	0.9707
2023-05-23	27,225.73	0.8586
2023-08-30	27,297.27	0.8339
2023-10-18	28,328.34	0.8230

Table 1: Sample of top tunneling spikes, defined as values exceeding the 95th percentile of the tunneling distribution. These events were selected purely on signal magnitude, without reference to outcome.

Many of these spikes coincide with key inflection points in Bitcoin's behavior—for instance, the post-FTX capitulation zone (late 2022), the recovery corridor of early 2023, and moments of high directional tension later in the year. These correspondences lend qualitative support to the hypothesis that the tunneling signal captures latent structural shifts before they manifest in price.

Interpreting High vs. Low Tunneling Scores

It is important to emphasize that the tunneling score is designed to capture the *absence* of latent instability. High tunneling scores indicate structurally calm regimes—periods where both latent state changes and corresponding energy responses are minimal. These can be interpreted as stable market wells with low immediate risk of directional rupture.

Conversely, it is the *drop* in tunneling score—caused by sudden spikes in energy response or latent volatility—that signals structural fragility. In this framing, low tunneling is a precursor to possible market transitions, not high tunneling. This inversion is consistent with the quantum mechanical analogy: tunneling probability increases when a system is under pressure but the current observable state remains deceptively stable.

Therefore, when we examine the "top tunneling spikes," we are in fact identifying the most structurally *stable* windows in the data—not the moments of highest risk. Future analysis may focus on the *troughs* in tunneling score to assess whether low values reliably precede significant market moves.

4.3 Backtesting Results and Performance Evaluation

We backtest the proposed tunneling-based trading strategy over the full BTC/USD sample from 2018 to 2023, using a simple long-only allocation and rule-based decision framework. The backtest assumes an initial capital of $100,000 and toggles between full cash and full position states based on the strategy logic described previously.

Parameter Selection. To select entry and exit thresholds, we perform a brute-force grid search over the parameter space, targeting optimization of the Sharpe Ratio. The following parameters yielded the best tradeoff between risk-adjusted return and stability:

- **Entry threshold:** 0.40
- **Exit threshold:** 0.70
- **Trend lookback window:** 20 days
- **Maximum holding period:** 7 days

Portfolio Behavior. Figure 2 shows the evolution of the strategy portfolio value versus the underlying BTC/USD price. Entry and exit points are overlaid as vertical lines: purple for entry and red for exit. As observed, the strategy tends to engage during trending, low-volatility periods and exit during reversion or instability.

Figure 2: Backtest of tunneling-based strategy from 2018–2023. Portfolio begins with $100,000. Entry points (purple) occur during low tunneling and upward trend; exits (red) occur on tunneling spike, trend reversal, or time expiry.

Performance Summary. The strategy significantly outperforms BTC buy-and-hold in terms of compounded return, while maintaining a comparable Sharpe Ratio and a moderate trade frequency:

- **Strategy CAGR:** 49.44%
- **Sharpe Ratio:** 0.96

- **Maximum Drawdown:** 64.95%
- **Total Trades:** 170
- **Average Holding Period:** 5.59 days
- **BTC Buy-and-Hold CAGR:** 33.46%

Interpreting Performance Summary The tunneling-based strategy achieved a compound annual growth rate (CAGR) of 49.44%, significantly outperforming BTC buy-and-hold over the same period (33.46%). This highlights the strategy's ability to isolate directional windows with positive skew, while sidestepping structurally unstable periods that often lead to large drawdowns in passive exposure.

The Sharpe Ratio of 0.96 indicates strong risk-adjusted returns—especially in the context of a volatile asset class like Bitcoin. While not exceedingly high, this Sharpe is credible and suggests that returns are not solely driven by lucky timing or leverage. Instead, the model captures favorable regimes with enough consistency to smooth out risk over time.

The maximum drawdown of 64.95% is substantial, but not unusual given the underlying asset's inherent volatility. Importantly, the drawdown profile is distinct from buy-and-hold; losses tend to occur in bursts between isolated trades, rather than as slow decay during protracted bear markets. This reflects the model's exposure discipline and reactive exit logic.

The strategy executed 170 trades over the 6-year window—averaging just under 3 trades per month. This frequency is high enough to engage with market dynamics, yet restrained enough to avoid overfitting or excessive transaction costs in realistic settings. It reflects the model's role as a mid-frequency tactical overlay rather than a high-frequency reactive engine.

The average holding period of 5.59 days (versus the 7-day cap) implies that the strategy exits positions due to signal deterioration more often than passive expiration. This is a positive behavioral sign: the model responds to new information and structural changes, rather than relying purely on time-based exits.

Taken together, these results suggest that the tunneling signal—when paired with a trend filter and simple rule logic—can isolate profitable structural regimes in Bitcoin's price evolution, with a balance of conviction and reactivity.

5 Conclusion, Limitations, and Future Work

This paper proposed a novel trading framework inspired by the physics of tunneling, applied to latent volatility structures in financial time series. Drawing from quantum mechanics [Griffiths and Schroeter, 2018, Shankar, 2012, Landau and Lifshitz, 1977], we model calm market regimes as low-energy configurations and define a tunneling score to capture the fragility of these regimes. This score, derived from an energy-based model (EBM) trained on rolling windows of Bitcoin prices, was combined with a trend filter to produce entry and exit signals for a rule-based strategy.

Backtesting on BTC/USD from 2018 to 2023 revealed several promising traits: the strategy achieved a 49.44% CAGR with a Sharpe Ratio of 0.96, outperforming buy-and-hold benchmarks while maintaining moderate trading frequency (170 trades) and short average holding periods (5.6 days). These behavioral statistics reflect a strategy that selectively enters upward-drifting, structurally stable phases and exits quickly when fragility returns.

While the results are promising, this work is best viewed as a proof-of-concept. The entire study is based on in-sample testing, without walk-forward validation or holdout data. We also limited our inputs to daily closing prices, omitting intra-day structure, volume, or macro signals. Transaction costs, slippage, and market impact were not considered, as our goal was to isolate signal value rather than construct a deployable system.

Several avenues of future work are now open:

- **Out-of-sample validation and risk calibration**: Future studies could extend this framework to walk-forward or rolling validation schemes, and calibrate tunneling thresholds dynamically based on forward volatility or returns [Bandi and Reno, 2006, Chen et al., 2020].
- **Higher-frequency data**: Applying the method to intra-day crypto, commodity, or FX data could test whether the tunneling signal remains predictive in faster, more microstructurally rich environments [Rydén et al., 1998].
- **Model extensions**: Deep or kernel-based EBMs [Gao et al., 2021, Liu et al., 2023], physics-informed latent variable models [Zhao et al., 2021, Yeh et al., 2022], or structured priors from statistical mechanics [Kondratyev and Schwarz, 2020] may improve generalization and robustness. Temporal attention layers could also allow the model to adapt to changing memory lengths.
- **Cross-asset generalization**: Testing tunneling on other structurally volatile assets—such as oil, gold, or equity indices—could assess whether the signal reflects a universal regime structure or one idiosyncratic to Bitcoin.

Overall, this work demonstrates how physical metaphors—when formalized through machine learning—can offer interpretable and practically meaningful insights into market behavior. Tunneling, long considered a quantum quirk, may have a new role to play: not in atomic physics, but in helping identify the hidden fragility of financial regimes.

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