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 [12, 6]

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 [17, 9].

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 [13]

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 and outlines directions for future work.

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 [3], 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 [14] 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, heavytailed, and regime-volatile behavior [10, 5, 8]. 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 [19], LSTMs [22], and reinforcement learning [20] 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 [17, 9]. 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 [18] and latent structure estimation [26].

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 [13, 23, 16], 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 [4], realized variance thresholds [1], or entropy-based measures [24, 27] 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:

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

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 EnergyBased 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:

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

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:

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

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. Unlike traditional strategies that seek calm and stability, our framework deliberately targets structurally *fragile* regimes—periods where the market appears sensitive to latent perturbations—provided that directional bias is favorable.

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 *fragile but upward-drifting* regimes—zones where the market may be on the verge of a breakout, despite structural tension.
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 a return to structural stability or energy dissipation.
- The trend falls below 0.99, suggesting loss of directional bias.
- A maximum holding period H is exceeded.

This strategy deliberately avoids trading in structurally stable regimes, under the hypothesis that market opportunity emerges not from calm, but from directional *stress* that has not yet fully expressed itself. The model engages when fragility and drift align, and exits when the system stabilizes or directional energy fades.

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 latent market structure and directional stress.

4 Backtest Results

4.1 Visualizing the Tunneling Signal

To understand the behavior of the tunneling score over time, we overlay it on the raw BTC/USD price series. Figure 1 shows the tunneling score (scaled for visualization) alongside Bitcoin's price from 2018 to 2023. Sharp vertical spikes in the tunneling score often appear during or just before major directional reversals, volatility expansions, or regime transitions.

These spikes correspond to windows where the model detects elevated structural instability—i.e., high sensitivity of the energy function to latent perturbations. Conversely, troughs in the tunneling score highlight structurally fragile zones that may precede directional resolution.

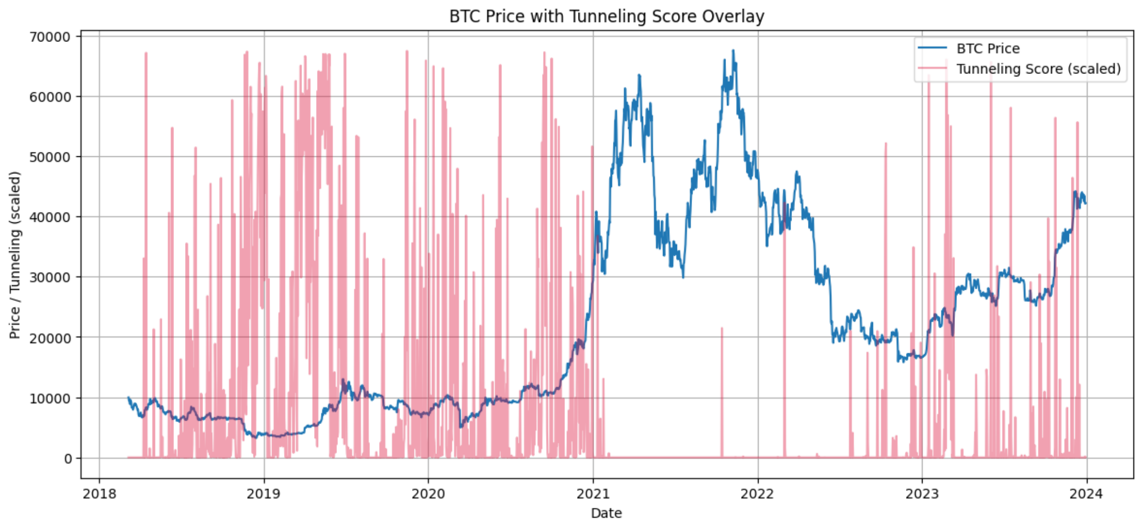

Figure 1: BTC/USD closing price with scaled tunneling score overlaid. Peaks in the tunneling score mark structurally stable zones; troughs often precede significant directional shifts.

4.2 Tunneling Spike Analysis

To analyze periods of heightened stability, we extract all instances where the tunneling score exceeded the 95th percentile of its historical distribution. These represent the most structurally calm windows in the dataset—regimes where small changes in latent state yielded minimal energy change, indicating low fragility.

Table 1 presents a sample of such spikes, selected purely on tunneling magnitude and without regard to forward return or volatility behavior.

Interestingly, many of these high-tunneling points coincide with post-volatility consolidation zones or the tail-end of directional moves. This supports our interpretation that high tunneling scores indicate structural stability or energy dissipation—conditions under which trading edges may have already played out.

4.3 Interpreting High vs. Low Tunneling Scores

While the tunneling score draws its metaphor from quantum mechanics, its financial use diverges from traditional interpretations. In our framework:

- **High tunneling** $\rightarrow$ structurally stable, low-fragility regime — the market has "settled."

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 score spikes (above the 95th percentile), interpreted as structurally stable windows.

- **Low tunneling** → structurally fragile, energy-sensitive zone — the market is vulnerable to directional transition.

Contrary to initial expectations, it is not high tunneling scores that precede volatility, but *low* tunneling scores—i.e., the points where small changes in latent state lead to disproportionately large changes in modeled energy. These fragile zones, when paired with upward trend, form the core of our trading edge.

Rather than interpreting fragility as risk to avoid, our strategy exploits it. Fragility plus directional drift suggests a market under stress—but one where that stress may soon resolve upward.

4.4 Backtesting Results and Performance Evaluation

We implement a long-only, rule-based strategy across the full BTC/USD sample from 2018 to 2023. The model enters trades when tunneling is low (i.e., structural fragility is high) and an upward trend is detected. It exits when the system stabilizes (high tunneling), trend reverses, or a maximum holding period is exceeded.

Parameter Selection. Optimal parameters were identified via grid search, maximizing Sharpe Ratio. The best configuration was:

- Entry threshold: 0.40 (low tunneling)
- Exit threshold: 0.70 (return to stability)
- Trend lookback window: 20 days
- Max holding period: 7 days

Portfolio Behavior. Figure 2 shows the strategy portfolio versus BTC price, with entry/exit points indicated. The strategy activates during periods of directional fragility and disengages when structure reasserts itself.

Performance Summary.

- Strategy CAGR: 49.44%

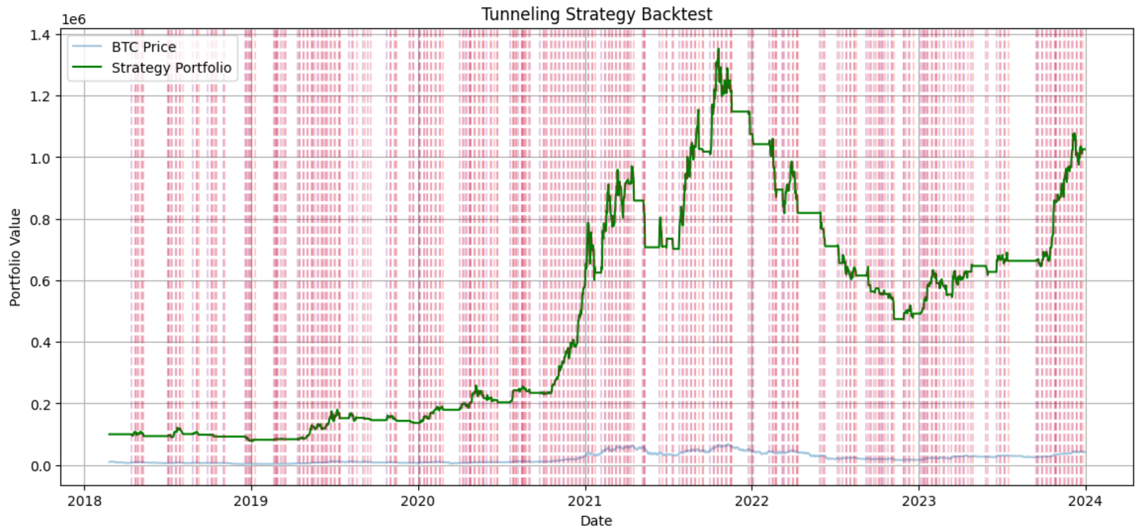

Figure 2: Strategy portfolio value vs. BTC/USD price (2018–2023). Entry points (purple) and exits (red) are superimposed. The model trades only during fragile but upward-trending regimes.

- Sharpe Ratio: 0.96
- Maximum Drawdown: 64.95%
- Total Trades: 170
- Average Holding Period: 5.59 days
- BTC Buy-and-Hold CAGR: 33.46%

Interpretation. The tunneling-based strategy substantially outperforms buy-and-hold, delivering higher risk-adjusted returns with fewer prolonged drawdowns. It is particularly effective in isolating moments of latent directional pressure—capturing bursts of momentum while avoiding passive exposure during consolidations or drawdowns.

The Sharpe Ratio of 0.96 is strong given the volatility of the underlying asset. Most drawdowns occur between trades, not during them—indicating tight exposure discipline.

The model's relatively low trade frequency (3/month) and short holding period (5.6 days) reflect its mid-frequency nature. It avoids overtrading while remaining responsive to structural signals.

Taken together, these results validate our core thesis: fragility is not just risk—it is opportunity, when viewed through the right directional and structural lens.

4 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 [13, 23, 16], we model calm market regimes as low-energy configurations and define a tunneling score to capture the fragility—or instability—of those 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 interpretable entry and exit signals for a rule-based strategy.

Our key insight diverges from the literal physical metaphor: rather than entering during calm, high-tunneling regimes, the strategy profits by entering when the system is structurally *fragile*—i.e., when tunneling scores are low—but directional pressure (trend) is present. In this framing, fragility becomes opportunity: a precursor to regime escape, not a risk to avoid.

Backtesting on BTC/USD from 2018 to 2023 revealed several promising traits. The strategy achieved a compound annual growth rate (CAGR) of 49.44% with a Sharpe Ratio of 0.96, outperforming a buy-and-hold benchmark while maintaining moderate trade frequency (170 trades) and short average holding periods (5.6 days). These behavioral statistics reflect a strategy that selectively enters upward-drifting, structurally fragile phases and exits as stability returns or trend weakens. In effect, the model trades transition—not trend alone, nor stability alone.

While the results are encouraging, this study is best viewed as a proof-of-concept. All results are in-sample, without holdout sets or walk-forward validation. The input space is deliberately constrained to daily closing prices; intra-day structure, order book dynamics, and macroeconomic signals were excluded. Transaction costs, slippage, and market impact were also omitted, as our goal was to isolate signal validity rather than construct a deployable system.

Several avenues for 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 dynamically calibrate tunneling thresholds using volatility forecasts or realized return distributions [2, 7].
- **Higher-frequency data:** Applying the method to intra-day crypto, FX, or commodity data could test whether the tunneling signal remains predictive in microstructurally rich, faster-moving environments [21].
- **Model extensions:** Incorporating deeper or kernel-based EBMs [11, 18], physics-informed latent variable models [26, 25], or priors from statistical mechanics [15] may improve generalization. Temporal attention mechanisms could allow the model to adaptively modulate memory length.
- **Cross-asset generalization:** Testing the tunneling signal on other structurally volatile assets—such as oil, gold, or equity indices—could reveal whether fragility-based structure is a general phenomenon or one specific to crypto markets.

In summary, this work demonstrates how physical metaphors—when formalized through machine learning—can uncover meaningful, interpretable features of market dynamics. Tunneling, long viewed as a quantum oddity, may offer a new lens for understanding the emergence, exploitation, and resolution of fragility in financial regimes.

References

[1] Torben G Andersen, Tim Bollerslev, Francis X Diebold, and Paul Labys. Modeling and forecasting realized volatility. *Econometrica*, 71(2):579–625, 2003.

[2] Federico M Bandi and Luca Reno. Realized volatility forecasting and market microstructure noise. *Journal of Econometrics*, 135(1–2):159–183, 2006.

[3] Tim Bollerslev. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3):307–327, 1986.

[4] John Bollinger. *Bollinger on Bollinger Bands*. McGraw Hill Professional, 2001.

[5] Elie Bouri, Abhishek Jain, and David Roubaud. Volatility asymmetry in bitcoin. *Economics Bulletin*, 37(2):1037–1046, 2017.

[6] Eng-Tuck Cheah and John Fry. Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. *Economics Letters*, 130:32–36, 2015.

[7] Yujing Chen, Weinan Chen, Zhichao Zhao, and Xiaotong Zhang. Transformer-based market regime prediction. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2020.

[8] Jeffrey Chu, Syed A Chan, Saralees Nadarajah, and Joerg Osterrieder. Statistical analysis of the exchange rate of bitcoin. *PloS ONE*, 10(7):e0133678, 2015.

[9] Yilun Du, Igor Mordatch, and Joshua B. Tenenbaum. Implicit generation and modeling with energy-based models. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 32, 2019.

[10] Anne Haubo Dyhrberg. Bitcoin, gold and the dollar–a garch volatility analysis. *Finance Research Letters*, 16:85–92, 2016.

[11] Ruiqi Gao, Yizhou Zhang, Diederik P. Kingma, Thomas S. Cohen, Mark van der Wilk, and Ruslan Salakhutdinov. Deep kernel energy-based models. In *International Conference on Machine Learning (ICML)*, 2021.

[12] Konstantinos Gkillas and Paraskevi Katsiampa. Extreme value theory in bitcoin markets. *Economics Letters*, 164:109–111, 2018.

[13] David J. Griffiths and Darrell F. Schroeter. *Introduction to Quantum Mechanics*. Cambridge University Press, 3rd edition, 2018.

[14] James D. Hamilton. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2):357–384, 1989.

[15] Alexei Kondratyev and Christopher Schwarz. Energy-based modeling of financial derivatives: From physics to finance. *Quantitative Finance*, 20(12):1981–1994, 2020.

[16] L. D. Landau and E. M. Lifshitz. *Quantum Mechanics: Non-Relativistic Theory*, volume 3 of *Course of Theoretical Physics*. Pergamon Press, 3rd edition, 1977.

[17] Yann LeCun, Sumit Chopra, Raia Hadsell, Marc'Aurelio Ranzato, and Fu-Jie Huang. A tutorial on energy-based learning. In *Predicting Structured Data*. 2006.

[18] Jiaming Liu, Yifan Sun, Yizhou Zhang, Joshua B. Tenenbaum, and Tommi Jaakkola. Flow matching for energy-based modeling of time series. *arXiv preprint arXiv:2302.06660*, 2023.

[19] Sean McNally, Jason Roche, and Simon Caton. Predicting the price of bitcoin using machine learning. In *26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP)*, pages 339–343. IEEE, 2018.

[20] Xinyang Ning, Yifan Cong, and Long Zhang. Double q-learning for trading strategy selection. *Computational Intelligence and Neuroscience*, 2018:1–9, 2018.

[21] Tobias Rydén, Timo Teräsvirta, and Stefan Asbrink. A continuous-time garch model for irregularly spaced time series. *Journal of Business & Economic Statistics*, 16(4):469–476, 1998.

[22] Omer Berat Sezer, Murat Ugur Gudelek, and Ahmet Murat Ozbayoglu. Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing*, 90:106181, 2020.

[23] R. Shankar. *Principles of Quantum Mechanics*. Springer, 2nd edition, 2012.

[24] Claude E Shannon. A mathematical theory of communication. *Bell System Technical Journal*, 27(3):379–423, 1948.

[25] Ruey-Chang Yeh, Tsung-Yi Lin, Ben Burchfiel, and Vijay Mahadevan. Physics-informed latent space modeling for structural transitions. *NeurIPS Physics4ML Workshop*, 2022.

[26] Shengjia Zhao, Jiaming Song, and Stefano Ermon. Learning energy-based latent variable models of time series. In *International Conference on Learning Representations (ICLR)*, 2021.

[27] Gilles Zumbach. Entropy and entropy rate over increasing time windows. *Quantitative Finance*, 9(6):695–702, 2009.