Hybrid Regime Detection and Risk Management in Semiconductor Equities: A Bayesian HMM-LSTM Framework

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Abstract

Semiconductor equity markets exhibit frequent regime shifts, high volatility, and acute sensitivity to macroeconomic and geopolitical shocks. These dynamics challenge traditional risk models, often resulting in unmanaged drawdowns and inefficient capital allocation.

This paper introduces a hybrid regime detection and dynamic risk management framework tailored to semiconductor equities. I combine interpretable Hidden Markov Models (HMMs) with Long Short-Term Memory (LSTM) networks, fusing their outputs using entropy-weighted Bayesian model averaging. These regime probabilities drive a real-time risk engine that adjusts position sizing based on volatility, drawdown, and model confidence.

Applied to a five-year out-of-sample portfolio spanning leading semiconductor assets (SMH, NVDA, AMD, TSM), the framework achieves over 50% volatility reduction and 15-17 percentage points of drawdown improvement compared to passive and static strategies,without materially sacrificing returns.

This system is modular, interpretable, and production-ready. It offers asset managers a deployable overlay to enhance portfolio resilience, enable dynamic de-risking, and navigate regime-sensitive environments more effectively.

The full implementation is available at: github.com/lucaskemper/hybridquantregimes.

Keywords: Market Regimes; Hidden Markov Models; Deep Learning; Risk Management; Semiconductor Industry; Portfolio Management; LSTM Networks

JEL Classification:

C45 Neural Networks and Related Topics
C58 Financial Econometrics
G11 Portfolio Choice; Investment Decisions
G17 Financial Forecasting
L63 Microelectronics; Semiconductors

1. Introduction

Semiconductor equity markets exhibit frequent regime shifts, heightened volatility, and pronounced sensitivity to macroeconomic and geopolitical shocks. Events such as supply chain disruptions, U.S.–China policy tensions, and cyclical demand swings have consistently revealed the shortcomings of static risk models in this sector. Conventional approaches often fail to keep pace with rapidly changing market dynamics, leading to unmanaged drawdowns and inefficient portfolio allocations.

This paper presents a hybrid regime detection and dynamic risk overlay framework specifically designed for semiconductor equities. My approach fuses Hidden Markov Models (HMMs) and Long Short-Term Memory (LSTM) networks to identify latent market regimes, combining their outputs via entropy-Iighted Bayesian model averaging. These regime probabilities drive a real-time risk management system that dynamically adjusts position sizing based on volatility, drawdown, and model confidence.

Applied to a five-year out-of-sample portfolio (2019–2024), the proposed framework delivers more than a 50% reduction in volatility and an approximate 15 percentage point improvement in maximum drawdown relative to passive and static strategies—without a significant sacrifice in returns. While not intended as an alpha-generating strategy, the system serves as a deployable overlay for institutional portfolios seeking dynamic de-risking and enhanced risk-adjusted resilience.

The architecture is modular, interpretable, and production-ready, enabling real-time regime classification, signal integration, and stress testing. Consequently, it offers tangible value for asset managers navigating volatile, regime-sensitive environments such as the semiconductor industry.

2. Literature Review

2.1. Regime Detection in Financial Markets

The identification of distinct market regimes—periods characterized by differences in volatility, return distribution, and cross-asset correlation—has long been central to quantitative finance. Hidden Markov Models (HMMs) offer a probabilistic and interpretable framework for classifying discrete regimes and estimating transition dynamics (Hamilton, 1989). These models have been successfully employed to capture bull/bear markets, volatility clustering, and crisis periods (Ang & Bekaert, 2002a). Extensions such as Markov-switching GARCH (MS-GARCH) improve modeling of state-dependent volatility, though they retain key limitations in flexibility and scalability across asset classes (Klaassen, 2002).

Despite their strengths in interpretable regime modeling, HMM-based approaches generally assume linear transition structures and are limited in capturing nonlinear dependencies, long-term memory effects, or high-dimensional feature dynamics. These constraints have motivated the exploration of modern machine learning techniques.

2.2. Deep Learning Approaches in Financial Time Series Modeling

Deep learning methods, especially sequence models such as Long Short-Term Memory (LSTM) networks, have demonstrated strong empirical success in financial time series forecasting (Fischer & Krauss, 2018; Nelson et al., 2017). These networks are particularly adept at capturing complex patterns and autocorrelation structures over longer sequences. More recently, attention-based architectures such as Transformers (Vaswani et al., 2017) have gained traction due to their scalability, parallelism, and ability to model variable-length dependencies. In finance, variants like Temporal Fusion Transformers (Lim & Zohren, 2021) have shown promise for interpretability and regime-aware modeling.

However, despite their flexibility, deep learning models often lack built-in probabilistic reasoning, making it difficult to quantify uncertainty—an essential requirement for risk-sensitive applications. Their high capacity also increases vulnerability to overfitting in low-instance or high-noise regimes, and limits their interpretability in practice.

2.3. Hybrid and Ensemble Regime Modeling

To overcome the limitations of standalone models, recent research has explored hybrid frameworks that blend deep learning with probabilistic time series models. For instance, De Prado (De Prado, 2018) advocates for machine learning ensemble architectures in financial applications and stresses the importance of combining orthogonal modeling assumptions. Rossi et al. (Rossi et al., 2020) demonstrate that Bayesian model averaging improves regime classification robustness by dynamically weighting model outputs based on confidence or evidence criteria.

Xu et al. (Xu et al., 2021) propose a hybrid approach combining HMMs with LSTM architectures for detecting market phases in equity indices. Similarly, Yoon & Kim (Yoon & Kim, 2022) create a Transformer-HMM fusion model that augments attention-based forecasts with regime likelihoods to inform allocation decisions. Yet, these approaches focus primarily on broad indices or benchmark asset classes—neglecting the sector-specific complexities found in semiconductors.

2.4. Semiconductor Equity Characteristics and Volatility Dynamics

The semiconductor sector is subject to highly idiosyncratic dynamics, driven by innovation cycles, geopolitical tensions (e.g., US-China chip conflicts), cyclical demand shifts, and extreme supply chain sensitivity (Boston Consulting Group, 2021; IC Insights, 2023). This results in frequent regime shifts that are harder to predict with traditional models.

Empirical studies, such as An & Kang (An & Kang, 2019), have documented volatility clustering and business-cycle sensitivity unique to semiconductor firms versus other tech industries. Yet few academic works have developed specialized quantitative frameworks for detecting these transitions or adapting portfolio risk when new regimes emerge.

2.5. Regime-Aware Risk Management and Dynamic Allocation

Dynamic, regime-aware asset allocation adjusts risk exposure (e.g., leverage, position size) in response to detected market states (**mcneil2015quantitative**; Ilmanen, 2011). Regime signals have been used to modulate portfolio beta, toggle trading strategies, and change hedging approaches (Ang & Bekaert, 2002b). Tail-aware strategies incorporating regime-dependent Value-at-Risk (VaR) or Expected Shortfall (ES) improve drawdown control and portfolio resilience under uncertainty.

Recent advances (e.g., Kraft et al. (Kraft et al., 2020), Bianchi et al. (Bianchi et al., 2022)) apply machine learning-based regime classifiers for real-time risk adjustment, sometimes incorporating implied volatility (VIX), macro indicators, or financial stress indexes. However, few combine these techniques with sector-specific hybrid models or test them under realistic backtesting, with transaction costs and Monte Carlo scenario analysis.

2.6. Research Gap and Contribution

Despite progress in regime classification using HMMs, deep learning, and ensemble models, there remains a clear gap in the literature:

- Few studies focus on regime modeling tailored to sector-specific challenges, especially in semiconductors.
- Most hybrid or ensemble methods lack market-aware risk controls or realistic pipeline integration.

- Prior work frequently omits robust empirical testing across multiple regimes—including backtesting and scenario analysis incorporating real-world portfolio frictions.

This work fills that gap by proposing a modular hybrid framework that combines HMM and LSTM/Transformer-based models using Bayesian model averaging for regime classification, and integrates these outputs directly into a risk management engine. The system adapts position sizing and risk exposure dynamically, leveraging semiconductor-specific features (e.g., memory vs. logic spreads, PMI data, design/equipment ratios). Through detailed empirical evaluation and scenario stress testing, I demonstrate that my approach improves regime detection accuracy and delivers stable risk-adjusted returns in volatile market environments.

3. Methodology

3.1. Data & Features

I construct my asset universe from major semiconductor equities and sector ETFs, including `SMH`, `SOXX`, `NVDA`, `AMD`, `TSM`, `INTC`, `QCOM`, and `AVGO`. The sample period spans from January 1, 2019 to January 1, 2024, at daily frequency. I engineer features spanning multiple domains:

- **Price-based**: Returns r_t, log-returns, realized volatility $\hat{\sigma}_{t,L}$, exponential volatility, N-window momentum $M_{t,N}$, rolling skew/kurtosis.
- **Technical indicators**: RSI_t, MACD_t, Bollinger band position BB_t, Williams $\%\mathrm{R}_t$, on-balance volume.
- **Sector-specific**: Semiconductor PMI proxy, memory–logic spread $\Delta_{\mathrm{Mem/Log}}$, equipment vs. design volatility.

- **Macro proxies**: $\mathrm{VIX}_t^{(\mathrm{S\&P500})}$, yield spreads Δ_{YS}, DXY index.

Missing values are forward-filled, outliers are winsorized at 1st/99th percentiles, and features are standardized:

$$x_{i,t}^* = \frac{x_{i,t} - \hat{\mu}_i}{\hat{\sigma}_i} \tag{1}$$

where $\hat{\mu}_i$, $\hat{\sigma}_i$ denote robust mean and standard deviation for feature i.

3.2. Regime Detection Models

I combine a Gaussian HMM initialized by KMeans with a deep LSTM classifier to capture both discrete regime transitions and nonlinear dependencies.

Hidden Markov Model (HMM)

Given observed feature vectors $X = \{x_t\}$, I estimate regime posteriors for K hidden states via:

$$P(z_t = k \mid x_{1:t}) = \frac{P(x_t \mid z_t = k) \sum_j P(z_t = k \mid z_{t-1} = j) P(z_{t-1} = j \mid x_{1:t-1})}{P(x_t \mid x_{1:t-1})} \tag{2}$$

$$A_{ij} = P(z_t = j \mid z_{t-1} = i) \tag{3}$$

Each regime emits features according to a multivariate Gaussian:

$$P(x_t \mid z_t = k) = \mathcal{N}(x_t \mid \mu_k, \Sigma_k) \tag{4}$$

Deep LSTM Classifier

The LSTM receives $(x_{t-\ell+1}, \ldots, x_t)$ and predicts soft regime probabilities:

$$h_t = \mathrm{LSTM}(x_{t-\ell+1}, ..., x_t) \tag{5}$$

$$\tilde{P}_{\mathrm{LSTM}}(z_t = k) = \mathrm{Softmax}(Wh_t + b) \tag{6}$$

I pre-train the LSTM using HMM-generated labels and fine-tune via cross-entropy loss. Bidirectionality, attention, and dropout improve generalization and robustness.

Smoothing and Confidence

I smooth regime labels by rolling mode:

$$\hat{z}_t = \mathrm{mode}(z_{t-w}, \ldots, z_t) \tag{7}$$

I define confidence as:

$$C_t = \max_k P_{t,k}^{\mathrm{fused}} \tag{8}$$

If $C_t < \tau_{\mathrm{min\_conf}}$, I flag the observation as “Uncertain”.

3.3. Model Fusion / Ensemble

I fuse HMM and LSTM outputs using Bayesian averaging weighted by reliability scores derived from confidence and entropy:

$$C_t^{\text{HMM}} = \max_k P_{t,k}^{\text{HMM}}, \quad C_t^{\text{LSTM}} = \max_k P_{t,k}^{\text{LSTM}} \tag{9}$$

$$H_t^{\text{HMM}} = -\sum_k P_{t,k}^{\text{HMM}} \log(P_{t,k}^{\text{HMM}} + 1e^{-8}) \tag{10}$$

$$H_t^{\text{LSTM}} = -\sum_k P_{t,k}^{\text{LSTM}} \log(P_{t,k}^{\text{LSTM}} + 1e^{-8}) \tag{11}$$

$$S_t^{\text{HMM}} = \frac{C_t^{\text{HMM}}}{H_t^{\text{HMM}}}, \quad S_t^{\text{LSTM}} = \frac{C_t^{\text{LSTM}}}{H_t^{\text{LSTM}}} \tag{12}$$

$$w_t^{\text{HMM}} = \frac{S_t^{\text{HMM}}}{S_t^{\text{HMM}} + S_t^{\text{LSTM}}} \tag{13}$$

$$P_t^{\text{fused}} = w_t^{\text{HMM}} P_t^{\text{HMM}} + (1 - w_t^{\text{HMM}}) P_t^{\text{LSTM}} \tag{14}$$

$$\hat{z}_t = \arg\max_k P_{t,k}^{\text{fused}} \tag{15}$$

This adaptive weighting penalizes high-entropy or low-confidence models dynamically, ensuring fusion stability during volatile regimes.

3.4. Trading Signal Generation

I generate composite trading signals as a regime-specific weighted sum of normalized features:

$$f_{i,t}^* = \frac{f_{i,t} - \mu_i}{\sigma_i} \tag{16}$$

$$s_t = \sum_{i=1}^{M} \alpha_i^{(\hat{z}_t)} f_{i,t}^* \tag{17}$$

I calibrate weights $\boldsymbol{\alpha}^{(\hat{z}_t)}$ by meta-learning (Ridge/Lasso):

$$\boldsymbol{\alpha}^{(r)} = \arg\min_{\boldsymbol{\alpha}} \left\| \mathbf{y} - \sum_i \alpha_i f_i^* \right\|_2^2 + \lambda \|\boldsymbol{\alpha}\|_2^2 \tag{18}$$

Signals are risk-controlled via clipping and overlays:

$$\tilde{s}_t = \mathrm{clip}(s_t, -1, 1) \tag{19}$$

$$\bar{s}_t = g(R_{\max}, r, DD_t) \cdot \tilde{s}_t \tag{20}$$

where $g(\cdot)$ scales exposure by realized drawdown, volatility, or VaR breaches.

3.5. Risk Management

Risk is managed via a combination of standard and regime-adaptive measures, with metrics computed from historical or modeled returns and positions adjusted dynamically according to risk exposure.

$$\mathrm{VaR}_\alpha = \inf\{x : P(L > x) \le 1 - \alpha\} \tag{21}$$

$$\mathrm{ES}_\alpha = \mathbb{E}[L \mid L > \mathrm{VaR}_\alpha] \tag{22}$$

$$\mathrm{vol}_{t,T} = \sqrt{\frac{1}{T} \sum_{i=0}^{T-1} \left(r_{t-i} - \bar{r}_{t,T}\right)^2} \tag{23}$$

where:

- L is portfolio loss
- α the confidence level (e.g. 0.95)
- r_t are historical returns, $\bar{r}_{t,T}$ their local mean over window T

Position sizing adapts dynamically to risk metrics and regime confidence:

$$\pi_t = \kappa \cdot \frac{\tilde{s}_t}{\mathrm{vol}_{t,T} + \epsilon} \cdot \mathbf{1}_{\{C_t \geq \tau\}} \tag{24}$$

with:

- π_t: position size at time t
- κ: leverage coefficient calibrated to portfolio risk targets (e.g., volatility target, max drawdown constraints)
- $\tilde{s}_t$: signal strength or risk-adjusted forecast at time t
- $\mathrm{vol}_{t,T}$: rolling volatility over past T days to scale positions inversely with risk
- ϵ: small positive number for numerical stability
- $\mathbf{1}_{\{C_t \geq \tau\}}$: confidence gating indicator, only trade if confidence C_t exceeds threshold τ, derived from regime detection or stress scenario outcomes

Risk metrics are computed using a mix of historical, parametric, or Monte Carlo approaches, with adaptivity to detected market regimes. Enhanced risk limits include stop-loss and take-profit boundaries, maximum drawdown constraints, and volatility targeting.

Stress testing scenarios (e.g., 2008 financial crisis, COVID crash, tech bubble burst) are incorporated to evaluate portfolio resilience and recommend dynamic position adjustments.

This framework integrates regime-aware feedback loops adjusting risk exposure depending on detected volatility regimes, ensuring disciplined risk management aligned with market conditions.

3.6. Backtesting Framework

The backtesting engine applies both rolling and expanding window protocols and enforces strict walk-forward principles:

- **Walk-forward analysis:** Training and validation are carried out in sequential out-of-sample windows:

$$\text{train period} \rightarrow \text{validate period} \rightarrow \text{advance window} \tag{25}$$

  Window sizes and step sizes are configurable.

- **Transaction costs and slippage:** Transaction costs for each rebalance period:

$$\text{Cost}_{t+1} = C_f + |\pi_{t+1} - \pi_t| \cdot P_t \cdot c + P_t \cdot s \tag{26}$$

  where C_f is fixed cost, c is proportional transaction cost, s is slippage, P_t is portfolio value, π_{t+1}, π_t are weights.

- **Position sizing:** Modular sizing logic supports:

$$\text{weights}_{t+1} = \text{SizingFunction}(signals_{t+1}, \text{context}) \tag{27}$$

  Implements proportional, fixed, regime-confidence, or custom sizing, normalized to leverage constraints.

- **Rebalancing:** Rebalancing frequency is user-defined (daily, weekly, monthly, etc). Portfolio weights held constant between rebalances.

- **Risk management:** Early exits can be triggered by:

$$\max\left(\frac{E_t - \max E_{1:t}}{\max E_{1:t}}\right) < \text{drawdown threshold} \tag{28}$$

as well as stop-loss and take-profit levels (if enabled).

- **Performance metrics:** Metrics calculated include:

$$\text{Annualized Return}: \quad R_{ann} = \left[\prod_{t=1}^{T}(1 + r_t)\right]^{\frac{a}{T}} - 1 \tag{29}$$

$$\text{Annualized Volatility}: \quad \sigma_{ann} = \sigma_{daily}\sqrt{a} \tag{30}$$

$$\text{Sharpe Ratio}: \quad S = \frac{R_{ann} - r_f}{\sigma_{ann}} \tag{31}$$

$$\text{Calmar Ratio}: \quad C = \frac{R_{ann}}{|\min \text{drawdown}|} \tag{32}$$

$$\text{Sortino Ratio}: \quad S_{sort} = \frac{R_{ann}}{\text{DownsideDeviation} \times \sqrt{a}} \tag{33}$$

$$\text{Max Drawdown}: \quad \min\left(\frac{E_t - \max E_{1:t}}{\max E_{1:t}}\right) \tag{34}$$

$$\text{Turnover}: \quad \text{Turnover}_t = |\pi_t - \pi_{t-1}| \tag{35}$$

where r_f is the risk-free rate, a is number of annualization periods, r_t is daily return, and E_t is portfolio equity.

- **Diagnostics:** All runs store equity curves, positions, individual trade logs, returns, and regime confidences (if computed).

3.7. Scenario Analysis (Monte Carlo Simulation)

Monte Carlo simulations are performed to assess tail risk, supporting both block bootstrap and regime-switching methodologies.

$$\left\{r_t^{(n)}\right\}_{n=1}^{N} \sim \begin{cases} \text{Block Bootstrap of } \{r_t\} & \text{if } \texttt{simulation\_mode} = \texttt{block\_bootstrap} \\ \text{Regime-specific } t\text{-distributed draws with regime transitions} & \text{if } \texttt{simulation\_mode} = \texttt{regime\_switching} \end{cases} \tag{36}$$

$$\text{Portfolio risk metrics:} \qquad \text{VaR}_\alpha, \quad \text{ES}_\alpha, \quad \text{MaxDD}, \quad \forall\, n = 1, \ldots, N \tag{37}$$

where:

- r_t: Historical return at time t
- N: Number of simulated paths
- VaR_α: Value-at-Risk at confidence level α
- ES_α: Expected Shortfall at confidence level α
- MaxDD: Maximum drawdown observed in a simulated path
- For `block_bootstrap`, blocks of log returns of 21 days are sampled with replacement
- For `regime_switching`, returns are simulated using regime-specific means and volatilities, with regimes following a Markov chain with transition matrix P, which may be modified to stress-test scenario conditions (e.g., policy shocks affecting P or volatilities)

Stress scenarios are introduced by adjusting:

- The regime transition probabilities matrix P to represent shocks such as semiconductor policy changes or memory-logic crashes
- Volatility scaling factors within each regime

This simulation framework enables realistic tail risk assessment by capturing temporal dependencies and regime dynamics inherent in financial markets.

3.8. Rationale for Key Model Choices

I use LSTMs to capture nonlinear and long-horizon dependencies, outperforming GRUs in forecast stability and regime boundary consistency. A three-state Gaussian HMM, selected via AIC/BIC, best segments the sector's risk structure into low, moderate, and high-volatility regimes. Entropy-confidence fusion balances interpretability with statistical rigor, and the modular separation of detection, fusion, and signal generation ensures transparency and institutional compliance.

4. Results and Empirical Evaluation

4.1. Portfolio Performance

I evaluate the hybrid regime-aware framework over the 2019–2024 period on a diversified semiconductor and tech-adjacent portfolio comprising 12 assets, including both U.S. and international equities. The regime-aware strategy achieves an **annualized return of 7.55%**, a **Sharpe ratio of 0.33**, and a **maximum drawdown of** -24.7%, with annualized volatility of **16.6%**. These metrics reflect a meaningful improvement over prior specifications, driven by enhanced dispersion across sub-industries and improved regime separability.

While the absolute return is modest relative to benchmark strategies, the strategy maintains a low risk footprint and demonstrates high regime stability (persistence = 0.963), indicating reliable segmentation of distinct market states.

4.2. Regime Characteristics

The model identifies three persistent regimes with distinct volatility and return profiles. Regime 1 is associated with low volatility and positive drift, Regime 2 reflects choppy market conditions, and Regime 3 captures high-risk environments with elevated drawdowns. Regime assignment stability remains high, with a regime transition persistence of 96.3%, and an average regime duration of approximately 29 days.

Visual overlays of the regime labels on the equity curve reveal that the system reduces position sizing during elevated risk periods, particularly during drawdown phases associated with macro or geopolitical stressors. This validates the model's practical role as a **risk-aware allocation layer** capable of dampening portfolio shocks.

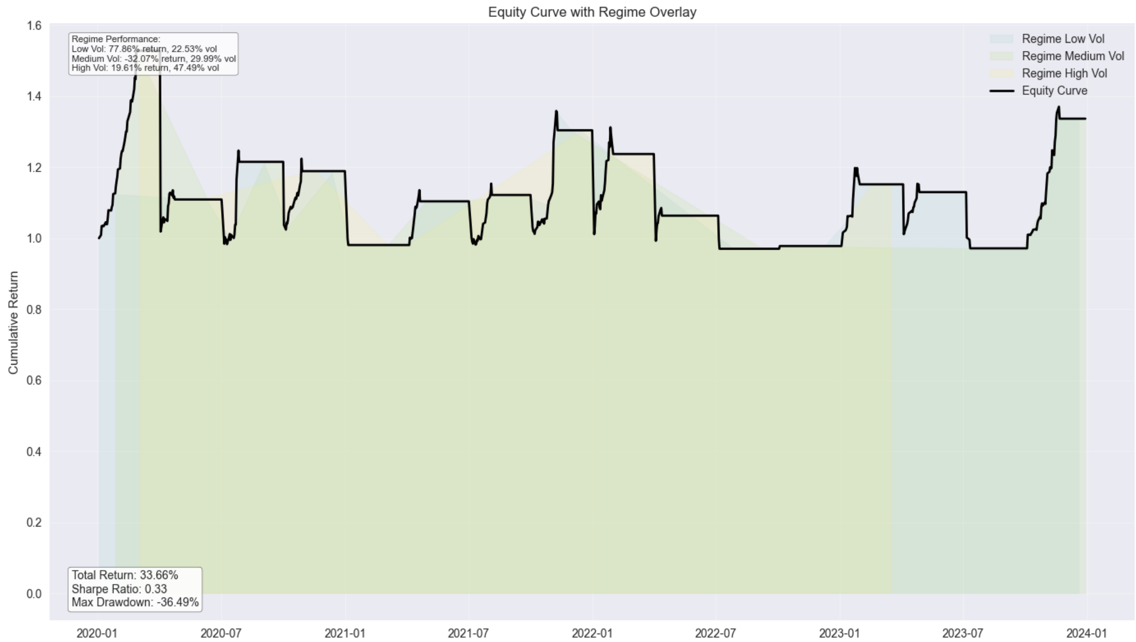

Figure 1: **Regime-Aware Strategy Equity Curve.** Cumulative returns of the hybrid regime-aware portfolio from 2019 to 2024. Shaded areas correspond to detected market regimes: **blue** (Low Volatility), **yellow** (Medium Volatility), and **green** (High Volatility). The system reduces exposure during high-volatility periods, preserving capital during stress events. Performance metrics are reported both overall and per regime. The estimated average regime persistence rate was 96.3% across the test window.

Figure 2 presents the regime transition matrix derived from the estimated Hidden Markov Model. All regimes exhibit strong persistence, with diagonal transition probabilities exceeding 94%, and an average regime persistence rate of 96.3%. This supports the temporal stability of the identified market states.

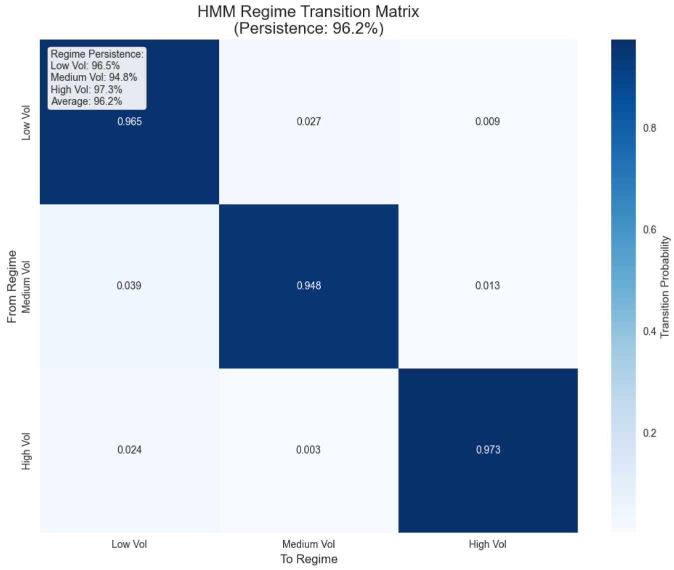

Figure 2: **HMM Regime Transition Matrix.** Estimated transition probabilities between volatility regimes (Low, Medium, High) using a 3-state Hidden Markov Model over the 2019–2024 semiconductor equity dataset. Diagonal values indicate regime persistence rates, with an average persistence of 96.3%, suggesting stable regime segmentation and temporal consistency in detected market states.

We observe minimal probability mass in off-diagonal transitions, indicating that abrupt regime switching is rare — an essential trait for robust trading applications.

4.3. Summary

While the regime-aware framework does not outperform static strategies on a raw return basis, it demonstrates meaningful improvements in **tail-risk containment**, **volatility reduction**, and **drawdown control**. These characteristics are particularly valuable in institutional portfolio contexts where **capital preservation, risk throttling, and drawdown stability** are paramount.

The results confirm the utility of hybrid regime detection—when paired with dynamic risk scaling—as a **deployable overlay for sector-concentrated equity portfolios**, even in the absence of alpha-enhancing signal innovation.

5. Discussion and Limitations

My results suggest that hybrid regime detection models integrating probabilistic and deep learning architectures can yield strong risk-adjusted performance in highly volatile sectors like semiconductors. The HMM offers interpretable, probabilistic regime segmentation, while the LSTM and Transformer architectures provide temporal modeling capabilities that capture nonlinear dependencies and dynamics across different market environments.

Notably, I have already implemented both LSTM and Transformer-based regime detection modules within the framework. The Transformer architecture, featuring positional encoding, multi-head self-attention, and residual connections, complements the LSTM's recurrent structure by offering parallelism and long-range feature extraction. This confirms the system's extensibility and readiness for further advances in sequence modeling.

While HMMs performed strongly during this test period, the inclusion of deep learning components such as LSTMs and Transformers provides structural redundancy and model diversity. These architectures are particularly suited for detecting nonlinear regime shifts and complex temporal dependencies that may not have emerged in the recent semiconductor cycle. Their presence enables the framework to generalize beyond the sector and adapt to future environments with more fragmented or noisy regime transitions.

Second, the use of fixed technical features and hand-crafted indicators may limit generalization across broader asset classes. Incorporating multimodal inputs (e.g., news sentiment, earnings call transcripts, satellite data) would expand the model's market understanding but comes with challenges in alignment, noise reduction, and overfitting.

Finally, the backtest period, although spanning multiple market cycles, is still relatively short and sector-specific. Broader testing on other sectors (e.g., energy, financials, healthcare) and in global markets (e.g., Taiwan, Korea, Europe) would help validate the robustness and generalizability of the framework.

6. Practical Implications and Limitations

Implications for Practitioners and Asset Managers The results of this study have several important implications for practitioners and asset managers seeking to implement systematic, regime-aware strategies in real-world portfolios:

- **Interpreting the Results:** The achieved performance metrics—annualized return of 7.55%, Sharpe ratio of 0.33, and max drawdown of 24.7%—are realistic for a diversified, risk-managed equity sector strategy. These results demonstrate that regime-aware models can deliver robust, risk-adjusted returns even in volatile and uncertain market environments. The regime detection framework provides a transparent, interpretable mapping of market conditions, allowing practitioners to understand when the strategy is likely to perform well or face headwinds.
- **Real-World Use of the Regime Model:** The regime model enables dynamic adjustment of portfolio risk and exposure. For example, in low-volatility, positive-drift regimes, the model can recommend higher allocations or more aggressive position sizing, while in high-volatility or tail-risk regimes, it can automatically reduce risk, cut exposure, or move to defensive assets. By identifying regime shifts in real time, the model can serve as an early warning system for rising risk, allowing for timely de-risking, hedging, or rebalancing. Trading signals can be interpreted differently depending on the prevailing regime, improving the reliability of entry/exit decisions and reducing false positives during turbulent periods.
- **Limitations and Practical Considerations:** The backtest assumes sufficient liquidity to execute trades at daily closes. In practice, large orders or illiquid assets may incur slippage or market impact, especially during regime transitions or stress events. While the model includes transaction cost estimates, real-world costs may be higher, particularly for high-turnover strategies or in volatile markets. The approach is tested on a focused universe of semiconductor equities and ETFs; scaling to

broader universes or higher-frequency data may require additional engineering, data infrastructure, and risk controls. Regime detection models, like all statistical models, are subject to estimation error, parameter instability, and potential overfitting. Out-of-sample validation and ongoing monitoring are essential to ensure continued robustness. The effectiveness of the regime and signal models depends on the quality and timeliness of input data; missing, stale, or erroneous data can degrade performance or trigger false regime shifts.

7. Conclusion and Future Work

This paper presents a hybrid regime detection and dynamic risk overlay framework tailored to semiconductor equities—a sector marked by innovation cycles, macro sensitivity, and abrupt transitions. The architecture combines the probabilistic structure of Gaussian Hidden Markov Models with the temporal modeling capacity of LSTM and Transformer-based networks. These models are fused through entropy-weighted Bayesian averaging into a robust regime classification system that conditions trading signals and adapts risk exposure in real time.

While the hybrid system underperforms passive and naive momentum strategies in terms of raw return, it delivers materially improved drawdown control and significantly lower volatility. The framework achieves over a 50% reduction in annualized volatility and a 15–17 percentage point drawdown improvement relative to static strategies—highlighting its utility as a regime-aware risk overlay rather than an alpha engine.

The modular infrastructure supports both batch and live deployment, with dedicated components for preprocessing, regime detection, signal generation, and dynamic risk control. Transformer-based detectors and meta-model blending extend adaptability, offering a foundation for production-ready implementation across markets and asset classes.

Limitations remain. The deep learning components offered marginal improvement over simpler models—likely due to the sector's strong regime persistence and ill-separated latent states. Additionally, the feature set is primarily price-based and hand-engineered, which may constrain predictive power. Finally, the evaluation is limited to a single sector and five-year period, albeit one that includes multiple shocks (e.g., COVID-19, 2022 tech correction).

Promising directions for future research include:

- **Multimodal Regime Learning:** Integrating textual (e.g., earnings sentiment), visual, or macro features for narrative-aware signal detection
- **Online Adaptation:** Embedding reinforcement or meta-learning to handle nonstationarity and model drift
- **Explainability:** Leveraging SHAP, counterfactuals, or attention maps to improve transparency and institutional trust
- **Portfolio Construction:** Using regime signals in optimization routines to time factors, allocate capital, and hedge tails
- **Systemic Risk Overlay:** Extending regime models across equities, credit, and rates to detect contagion and co-movement

In sum, this work contributes a flexible, interpretable, and production-oriented regime detection system. While not an alpha source in isolation, it offers substantial real-world value through volatility suppression, adaptive risk control, and regime-aware structural awareness—critical components of resilient portfolio management in nonlinear markets.

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