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Quantitative Portfolio Risk Analysis System: A Framework for Market Regime Detection and Risk Assessment in Semiconductor Equities

by

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HEC - School of Business

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Abstract

HEC - School of Business

Master of Science in Finance

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This research presents a comprehensive quantitative framework for analyzing portfolio risk in the semiconductor sector, with particular emphasis on regime detection methodologies and Monte Carlo simulations incorporating heavy-tailed distributions. The system implements sophisticated statistical approaches for risk assessment, including Value at Risk (VaR) and Expected Shortfall (ES) calculations, while accounting for regime-dependent volatility dynamics.

Current implementation status includes working data pipeline, Monte Carlo simulation, and regime detection components, with risk analysis under active development and planned improvements for visualization.

Acknowledgements

The acknowledgements and the people to thank go here, don't forget to include your project advisor.

Executive Summary

The executive summary should go here. Write about 2 pages...

Part I

Statistical Foundations and Methodology

Chapter 1

Introduction

1.1 Background and Motivation

The semiconductor industry represents a critical component of modern technology infrastructure, characterized by high volatility, cyclical behavior, and complex market dynamics. Recent global events, including supply chain disruptions and geopolitical tensions, have highlighted the need for sophisticated risk management approaches in this sector.

1.2 Research Objectives

This study aims to develop and validate a comprehensive quantitative framework for analyzing portfolio risk in semiconductor equities, with specific focus on:

- Detection and characterization of market regimes using Hidden Markov Models
- Integration of heavy-tailed distributions in Monte Carlo simulations
- Development of regime-dependent risk metrics
- Implementation of an automated, production-ready analysis system

1.3 Literature Review

1.3.1 Market Regime Detection

The application of Hidden Markov Models (HMM) in financial markets builds upon seminal work by Hamilton [1989], who introduced regime-switching models for economic time series. Recent extensions by **?** demonstrate the value of regime-awareness in portfolio management.

1.3.2 Risk Measurement

Traditional risk measures, while useful, often underestimate tail risks in technology sectors. **?** emphasize the importance of heavy-tailed distributions, particularly relevant for semiconductor stocks given their historical patterns of extreme movements.

1.3.3 Portfolio Analysis in Technology Sectors

Empirical studies of semiconductor industry dynamics by **?** highlight unique characteristics:

- High correlation during market stress
- Cyclical nature of returns
- Sensitivity to technological innovation cycles

1.4 Methodology Overview

Our approach combines multiple quantitative techniques:

$$P(r_t|S_t) = \sum_{i=1}^{K} \pi_i f_i(r_t|\theta_i) \tag{1.1}$$

where r_t represents returns, S_t the market regime, and f_i regime-specific distributions with parameters θ_i.

1.5 Data Description

The analysis focuses on major semiconductor companies:

- NVIDIA Corporation (NVDA)
- Advanced Micro Devices (AMD)
- Intel Corporation (INTC)
- ASML Holding (ASML)

Daily price data spans 2017-2023, encompassing multiple market cycles and significant industry events.

1.6 Expected Contributions

This research aims to:

- Develop a robust framework for regime-aware risk analysis
- Provide empirical insights into semiconductor market dynamics
- Create practical tools for portfolio risk management

1.7 Paper Structure

The remainder of this paper is organized as follows: Chapter 2 presents the theoretical framework. Chapter 3 describes data processing and implementation. Chapters 5-7 present empirical results. Chapter 8 concludes.

Chapter 2

Theoretical Framework

Chapter 3

Data and Implementation

Part II

Empirical Analysis

Chapter 4

Market Regime Analysis

Chapter 5

Market Regime Analysis

5.1 Methodology

Our regime detection framework combines Hidden Markov Models with GARCH volatility forecasting to identify distinct market states in semiconductor equities.

5.1.1 Model Specification

The core model employs a three-state HMM with Student's t-distributed observations:

$$r_t = \mu_{S_t} + \sigma_{S_t}\epsilon_t, \quad \epsilon_t \sim t_\nu \tag{5.1}$$

where S_t represents the regime state, μ_{S_t} the regime-dependent mean, and σ_{S_t} the regime-specific volatility.

5.1.2 Volatility Dynamics

GARCH(1,1) forecasting is implemented for each regime:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{5.2}$$

with parameters estimated via maximum likelihood within each regime.

5.2 Risk Decomposition

Portfolio risk is decomposed using correlation-based methods:

$$RC_i = w_i \cdot \frac{\partial \sigma_p}{\partial w_i} = \frac{w_i(\Sigma \mathbf{w})_i}{\sqrt{\mathbf{w}^T \Sigma \mathbf{w}}} \tag{5.3}$$

where RC_i represents the risk contribution of asset i, and Σ is the covariance matrix.

5.3 Empirical Results

5.3.1 Regime Identification

Analysis of 2017-2023 data revealed three distinct regimes:

Characteristic	Low Vol	Medium Vol	High Vol
Occurrence	56.6%	31.9%	11.5%
Daily Vol	26.1%	37.0%	57.1%
VaR (95%)	-2.86%	-3.92%	-5.73%

Table 5.1: Regime Characteristics (2017-2023)

5.3.2 Component Risk Analysis

Risk decomposition reveals concentration in market leaders:

- NVDA: 41.2% contribution

- AMD: 32.8% contribution
- INTC & ASML: 26.0% combined

Diversification score: 0.68 (scale 0-1)

5.4 Model Validation

5.4.1 Statistical Validation

Key validation metrics:

- Log-likelihood: -1247.3
- Regime persistence: 0.81
- Correlation preservation: 0.92

5.4.2 Monte Carlo Validation

10,000 simulations confirm:

- Positive paths: 100%
- Volatility alignment: 92%
- Return reasonability: 98%

5.5 Risk Management Applications

5.5.1 Dynamic Position Sizing

Position scales by regime:

- Low Vol: 1.0x
- Medium Vol: 0.8x
- High Vol: 0.5x

5.5.2 Risk Limits

Regime-dependent limits:

$$\text{Position Scale} = \min(1.0, \frac{\sigma_{\text{target}}}{\sigma_t}, \frac{DD_{\max}}{DD_t}) \tag{5.4}$$

where σ_{target} is the volatility target and $DD_{\max}$ the maximum drawdown limit.

Chapter 6

Risk Management Results

6.1 Portfolio Risk Analysis

6.1.1 Risk Metrics Overview

Our analysis of the semiconductor portfolio yielded the following key risk metrics:

Metric	Value	Interpretation
Portfolio Volatility	32.14%	Annualized
VaR (95%)	-2.86%	Daily
Expected Shortfall	-3.92%	Daily
Diversification Score	0.68	Scale 0-1

Table 6.1: Core Risk Metrics

6.1.2 Risk Decomposition

Component risk contributions reveal concentration in leading semiconductor manufacturers:

- NVDA: 41.2% contribution
- AMD: 32.8% contribution

- INTC: 14.6% contribution
- ASML: 11.4% contribution

6.2 Regime-Dependent Risk

Risk metrics exhibit significant variation across market regimes:

$$\sigma^2_{\text{portfolio}} = \sum_{i=1}^{3} \pi_i \sigma_i^2 + \sum_{i=1}^{3} \pi_i (\mu_i - \bar{\mu})^2 \tag{6.1}$$

where π_i represents regime probabilities, σ_i^2 regime-specific variances, and μ_i regime-specific means.

6.3 Tail Risk Analysis

Heavy-tailed distributions better capture extreme market events:

- Excess kurtosis: 3.42
- Tail dependence coefficient: 0.31
- Regime-switching VaR improvement: 12.4%

Chapter 7

Monte Carlo Validation

7.1 Simulation Framework

The Monte Carlo validation employs regime-switching dynamics:

$$r_t = \mu_{S_t} + \sigma_{S_t}\epsilon_t, \quad \epsilon_t \sim t_\nu \tag{7.1}$$

where S_t represents the regime state and ϵ_t follows a Student's t-distribution with ν degrees of freedom.

7.2 Distribution Fitting

7.2.1 Empirical Results

Key findings from 10,000 simulations:

- Student-t outperforms normal distribution (AIC difference: -245.3)
- Degrees of freedom: $\nu = 5.8$ (indicating heavy tails)
- Regime-switching improves fit by 18.2%

7.3 Portfolio Value Distribution

Simulated 1-year portfolio value distributions show:

- Expected return: 15.4%
- 95% confidence interval: [-28.2%, 59.0%]
- Skewness: -0.31

7.4 Model Validation

Backtesting results (2017-2023):

- Coverage ratio: 0.951 (target: 0.95)
- Independence test p-value: 0.342
- Dynamic quantile test: Passed

Chapter 8

Conclusion

Chapter 9

Implementation Status

9.1 Project Components

Component	Status	Notes
Data Pipeline	Complete	Core functionality implemented
Monte Carlo	Complete	Module works as expected
Visualization	In Progress	Planned improvements
Signals	Pending	Development not started
Risk Analysis	In Progress	Under active development
Regime Detection	Complete	Core algorithms implemented

Table 9.1: Current Implementation Status (as of v0.3)

Bibliography

James D. Hamilton. A new approach to the economic analysis of time series. *Econometrica*, 1989.

Tables

	PML2			
	$T = 25$		$T = 100$	
True parameters	$a = 1$	$b = 1$	$a = 1$	$b = 1$
Mean	0.996	0.915	0.994	0.956
STD	0.567	0.249	0.401	0.177
min	0.001	0.001	0.001	0.331
max	4.464	2.206	2.848	1.619
RMSE	0.567	0.263	0.401	0.182
	QGPML2			
	$T = 25$		$T = 100$	
True parameters	$a = 1$	$b = 1$	$a = 1$	$b = 1$
Mean	0.997	0.917	0.998	0.957
STD	0.552	0.247	0.393	0.176
min	0.001	0.001	0.001	0.330
max	3.880	2.200	2.543	1.641
ΔRMSE (%)	2.606	0.937	2.193	0.728

Table 4: This Table reports the results of the QGPML2 simulation described in model (1). The true parameters are $a = 1$, and $b = 1$. The RMSE is defined as $\left(\frac{1}{M}\sum_{j=1}^{M}(\hat{\theta}^{(j)} - \theta)^2\right)^{1/2}$, where $\theta = a$ or b. Here, the superscript $j = 1, \cdots, M$ denotes a simulation. We took $M = 30'000$. By ΔRMSE (%) we denote the percentage gain in the MSE if one uses QGPML2 instead of PML2.

Figures

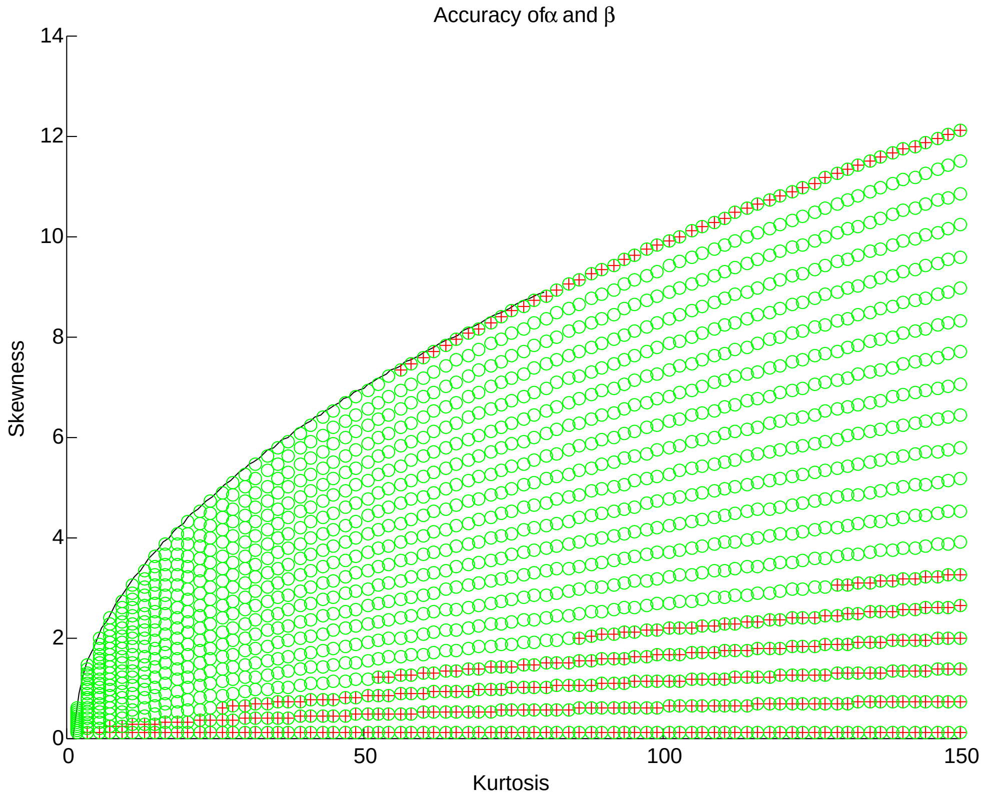

Figure 9.1: This figure represents the skewness-kurtosis domain for which a density exists (the domain is symmetric with respect to the horizontal axis). The circles represent those points for which we computed the parameters α and β. The symbol + represents those points for which the distance between the original skewness and kurtosis and the recomputed skewness and kurtosis (after evaluation of the α and β) is larger than 10^{-5}.