

Dynamic Regime Shifts in Market Portfolios: A Factor Modeling Approach

1. Introduction

Financial markets exhibit time-varying dynamics that challenge traditional asset pricing and portfolio allocation.

Classical factor models such as the Capital Asset Pricing Model (CAPM) [Sharpe, 1964; Lintner, 1965] and the Fama–French multi-factor models [Fama & French, 1993] assume stable relationships between risk factors and asset returns. Yet, empirical evidence shows that these relationships may shift across regimes, influenced by macroeconomic conditions, crises, and structural changes [Ang & Bekaert, 2002].

The study of dynamic regime shifts—periods in which the statistical properties of returns and factor loadings abruptly change—has gained attention in both finance and econometrics. Regime-switching models, such as Hamilton’s Markov Switching Model [Hamilton, 1989], have been widely used to capture such non-linear dynamics. More recent literature integrates factor modeling with regime shifts to analyze portfolio risks under varying economic states [Pastor & Stambaugh, 2003; Guidolin & Timmermann, 2007].

Goal of this study: This report develops and tests a dynamic factor model with regime shifts to analyze market portfolio returns. By incorporating regime-dependence into factor exposures, we aim to (i) identify latent regimes, (ii) assess shifts in factor sensitivities, and (iii) evaluate the implications for portfolio management and risk forecasting.

2. Literature Review

Factor models:

- CAPM: Market as the single risk factor [Sharpe, 1964].
- Multi-factor models: SMB, HML, momentum, quality, profitability [Fama & French, 1993, 2015].

Regime-switching in finance:

- Hamilton (1989): Markov regime-switching in GDP growth.
- Ang & Bekaert (2002): International stock returns and regime-switching volatility.
- Guidolin & Timmermann (2007): Asset allocation under multiple regimes.

Dynamic factor models:

- Stock & Watson (2002): Dynamic factor models for macroeconomic forecasting.
- Bai & Ng (2002): Consistency in estimating large factor models.

Recent work integrates ML methods such as hidden Markov models, recurrent neural nets,

and Bayesian nonparametrics for regime detection [Lamoureux & Lastrapes, 1990; Nguyen & Yin, 2022].

Gap: Few studies directly combine factor modeling of portfolios with explicit, dynamic regime shifts in factor exposures. This work explores that intersection.

3. Hypotheses and Methodology

Hypotheses:

H1: Market portfolio factor loadings vary across latent regimes.

H2: Regime shifts correspond to major economic or volatility events (e.g., crises, recoveries).

H3: Incorporating regime-dependent factor exposures improves portfolio risk-adjusted performance relative to static factor models.

Methodology:

Model setup: Start with Fama–French five-factor model:

$$R_{i,t} - R_{f,t} = \alpha + \beta_{M,t}(R_{M,t} - R_{f,t}) + \beta_{SMB,t}SMB_t + \beta_{HML,t}HML_t + \beta_{RMW,t}RMW_t + \beta_{CMA,t}CMA_t + \epsilon_t$$

Extend with regime-dependent loadings using a Markov Switching structure:

$$\beta_{k,t} = \beta_k(st), \quad st \in \{1, 2, \dots, K\}$$

where st is a latent regime variable governed by a first-order Markov process.

Estimation approach:

- Maximum likelihood estimation with EM algorithm for latent regimes [Hamilton, 1989].
- Alternative: Bayesian estimation with Gibbs sampling for robustness [Kim & Nelson, 1999].

Evaluation:

- Likelihood ratio tests for regime existence.
- Compare out-of-sample predictive performance of dynamic regime-switching factor model vs static Fama–French model.
- Economic evaluation: portfolio backtests (Sharpe ratio, drawdown, turnover).

4. Data Creation

Data source: CRSP for US stock returns; Fama–French factors from Kenneth French's online data library.

Period: 1980–2025 (monthly returns).

Variables: Market excess return, SMB, HML, RMW, CMA, risk-free rate.

Portfolio proxy: CRSP value-weighted market portfolio.

Preprocessing: Winsorization at 1% tails; normalization of factors for stability.

Synthetic regime indicators (optional for validation): Use NBER recession dates or VIX spikes

as proxies to compare with latent regime identification.

5. Results

(to be filled with your empirical analysis)

- Regime identification: e.g., 2–3 regimes corresponding to “bull,” “bear,” and “high-volatility” markets.
- Factor sensitivity: SMB and HML loadings higher in recessionary regimes; market beta elevated in crisis regimes.
- Portfolio implications: Regime-switching model yields higher risk-adjusted returns than static models; reduces downside risk.
- Robustness checks: Out-of-sample predictions, subperiod analyses, Bayesian vs ML estimation consistency.

6. Conclusion

Key findings: Market factor exposures are not stable; they shift systematically across regimes.

Contributions: Demonstrates the usefulness of combining factor modeling with regime-switching methods for portfolio management.

Implications: Regime-aware factor modeling can improve risk forecasting, portfolio allocation, and stress testing.

Future research: Explore higher-dimensional dynamic factor models, deep learning approaches for regime classification, and cross-market applications (crypto, commodities, international equity).

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