

# Market Regime Detection with Hidden Markov Models (HMMs)

Several academic and practical studies have applied HMMs to detect **market regimes** (e.g. bull vs bear markets or high vs low volatility periods) and to adapt trading strategies based on hidden states. Below is a summary of key papers and implementations – especially those with open-source code – highlighting their data, number of regimes, features, modeling assumptions, and code availability:

- **Wang, Lin & Mikhelson (2020)** – *Regime-Switching Factor Investing with HMMs*: This study trained a Gaussian HMM on ~10 years of S&P 500 daily data to classify **three regimes** (interpreted as bull, bear, and neutral/"sideways" markets) <sup>1</sup> <sup>2</sup> . The HMM used **daily returns and a volatility measure** as features, modeling them with a full covariance matrix to capture return-volatility correlation <sup>3</sup> <sup>4</sup> . The authors integrated the HMM signals into a strategy that rotates among factor portfolios, and found that over 2017–2020 the regime-switching strategy outperformed static factor models in returns and risk metrics <sup>5</sup> . *Open-source implementation*: The authors utilized Python's `hmmlearn` library and have released their HMM trading code (e.g. the **HMM\_Trading** repository) on GitHub <sup>6</sup> .
- **Kim, Jeong & Lee (2019)** – *Global Asset Allocation Using an HMM*: This paper applied HMMs to **multi-asset portfolios** over a 15-year period (2004–2018) across global asset classes <sup>7</sup> . Each asset class was modeled as having two latent **phases** (bull vs bear), enabling dynamic allocation: the HMM-driven strategy **increased equity weight in bull phases and shifted to bonds in bear phases**, adjusting portfolio weights in response to regime changes <sup>7</sup> . Using weekly ETF data for 10 broad asset classes (and finer subdivisions into 22 classes), the authors showed that the HMM-based strategy achieved higher performance (e.g. positive Jensen's alpha and Treynor-Mazuy timing gamma) compared to a momentum strategy <sup>8</sup> <sup>9</sup> . (*Code*: Implemented in R using the `depmixS4` HMM package; code not explicitly provided in the paper.)
- **Majumder, Ji & Neerchal (2023)** – *Linked HMMs for Sector-wise Bull/Bear Regimes*: This recent work fits a **multivariate "linked" HMM** to weekly returns of S&P 500 stocks (2011–2016) by sector <sup>10</sup> . Each of the 12 GICS sectors has its own two-state HMM (bull or bear sector trend), and a Gaussian copula links these state processes, allowing **correlated regime switches** across sectors <sup>11</sup> . This hierarchical HMM (an advanced regime model) captures sector-specific heterogeneity in bull/bear dynamics. The authors constructed optimal stock portfolios based on the inferred regimes and found that out-of-sample (2016–2017) the HMM-driven portfolios achieved annual gains comparable to the S&P 500 benchmark, while balancing reward-risk tradeoffs <sup>12</sup> . (*Code*: Methodology described in ArXiv/Sankhya paper; no public code repository mentioned.)
- **Yuan & Mitra (2016)** – *Market Regime Identification (FTSE 100 & Euro Stoxx 50)*: This study used an HMM to detect **unobserved market sentiment** states (bullish vs bearish) in European index data <sup>13</sup> . Using daily returns of FTSE-100 and EuroStoxx-50, the HMM captured regime-dependent **stylized facts** – e.g. one state exhibited higher volatility (fat-tailed returns) and the other lower

volatility – improving on a single-regime Geometric Brownian Motion fit <sup>13</sup> . The **two-state HMM** provided a “market signal” that could forecast future conditions better than a static model <sup>14</sup> . (Code: Not provided; likely implemented with a standard HMM toolkit by the authors at OptiRisk Systems.)

- **Donninger (2017)** – *HMM for Bull/Bear Switching and Tail-Risk*: Donninger’s working papers (SSRN) developed an HMM to time **bull vs bear market regimes** for tactical allocation. An initial study used a 2-state HMM on S&P 500 and **VIX futures** to trigger tail-risk hedges (the “Wool-Milk-Sow” strategy), and a follow-up applied the model to various equity indices and to switch between equity and Treasury bond ETFs <sup>15</sup> . The HMM-based regime filter signaled when to shift into safe assets (or leveraged ETFs) during bearish regimes, demonstrating improved downside protection and **extending the promising results** of the original approach <sup>15</sup> . (Code: Not openly provided in the papers; the methodology is described conceptually, focusing on the HMM’s regime probabilities to drive trading rules.)
- **Fu & Wu (2017)** – *HMM vs. Machine Learning for Market Trend Prediction*: This conference paper (Xiamen University) proposed an HMM-based strategy for **index trend prediction** and compared it to moving-average and k-means clustering methods <sup>16</sup> . The authors generated many technical **features** (e.g. price, volume, indicators) from Chinese CSI 300 index and S&P 500 index data, then used a feature selection process where each candidate feature’s utility was evaluated via HMM likelihood <sup>17</sup> <sup>18</sup> . A multi-feature HMM was trained (number of hidden states not explicitly stated, but effectively distinguishing “strong” vs “weak” market conditions), and used to predict the next day’s market state for a trading strategy. The HMM strategy achieved **more stable and profitable returns** and earlier bear-market warnings than a double moving-average crossover or unsupervised k-means regime clustering <sup>18</sup> . (Code: The study used Python and the TuShare financial data API; no public code link, but the paper’s flowchart and results illustrate the implementation.)
- **Novak (2020)** – *HMM + SVM for Regime Detection (GitHub project)*: In a practical study, Novak uses an HMM to classify the **iShares MSCI EAFE index** (an international equity ETF) into bull vs bear regimes, and then applies an unsupervised SVM to refine these clusters <sup>19</sup> . The HMM (applied to ~20 years of daily prices) proved effective at quickly identifying regime shifts, and the additional one-class SVM helped separate subtle regime variations <sup>20</sup> . The combined model’s outputs are intended to inform a trading strategy for market-on-open orders by predicting short-term market direction <sup>21</sup> . *The full code and report are open-sourced* in a GitHub repository, allowing replication of the HMM/SVM approach <sup>19</sup> .

Each of the above works demonstrates that Hidden Markov Models can effectively uncover **hidden market states** – such as bull vs bear trends or low vs high volatility regimes – and that exploiting these states can improve investment decisions. Many authors also share their implementations or data: e.g. Wang *et al.* (2020) provide a public Python notebook for their 3-state HMM on S&P 500 <sup>6</sup> , and Novak’s GitHub project offers a reproducible HMM/SVM pipeline <sup>19</sup> . These resources underscore the practical applicability of HMM-based regime detection in finance, enabling analysts to detect regime shifts and adapt trading or asset allocation strategies accordingly.

## Sources:

1. Wang *et al.* (2020), "Regime-Switching Factor Investing with Hidden Markov Models," **J. Risk Financial Manag.**, 13(12):311 <sup>1</sup> <sup>5</sup> .
2. Kim *et al.* (2019), "Global Asset Allocation Strategy Using a Hidden Markov Model," **J. Risk Financial Manag.**, 12(4):168 <sup>7</sup> <sup>22</sup> .
3. Majumder *et al.* (2023), "Optimal Stock Portfolio Selection with a Multivariate HMM," **Sankhya B**, 85(S1): 177-198 <sup>10</sup> <sup>12</sup> .
4. Yuan & Mitra (2016), "Market Regime Identification Using HMMs," SSRN Working Paper <sup>13</sup> .
5. Donninger (2017), "Trading Bull- and Bear-Markets with a Hidden Markov Model," SSRN Working Paper <sup>15</sup> .
6. Fu & Wu (2017), "Quantitative Trading Strategy of Market States Prediction Based on HMM," in **Proc. MSMEE 2017** <sup>16</sup> <sup>18</sup> .
7. Novak (2020), "Regime Detection using Machine Learning (HMM & SVM)," GitHub repository and report <sup>19</sup> .

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- <sup>1</sup> <sup>2</sup> <sup>3</sup> **Regime-Switching Factor Investing with Hidden Markov Models**  
<sup>4</sup> <https://www.mdpi.com/1911-8074/13/12/311/pdf?version=1607321519>
  - <sup>5</sup> **Regime-Switching Factor Investing with Hidden Markov Models**  
<https://www.mdpi.com/1911-8074/13/12/311>
  - <sup>6</sup> **Marblez (Matthew Wang) · GitHub**  
<https://github.com/Marblez>
  - <sup>7</sup> <sup>8</sup> <sup>9</sup> **Global Asset Allocation Strategy Using a Hidden Markov Model**  
<sup>22</sup> <https://www.mdpi.com/1911-8074/12/4/168>
  - <sup>10</sup> <sup>11</sup> <sup>12</sup> **[2406.02297] Optimal Stock Portfolio Selection with a Multivariate Hidden Markov Model**  
<https://arxiv.org/abs/2406.02297>
  - <sup>13</sup> **Market Regime Identification Using Hidden Markov Models by Yuan Yuan, Gautam Mitra :: SSRN**  
<sup>14</sup> [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3406068](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3406068)
  - <sup>15</sup> **Trading Bull- and Bear-Markets with a Hidden Markov Model. by Chrilly Donninger :: SSRN**  
[https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2957395](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2957395)
  - <sup>16</sup> <sup>17</sup> <sup>18</sup> **LME206.docx**  
<https://www.atlantis-press.com/article/25877874.pdf>
  - <sup>19</sup> **GitHub - theo-dim/regime\_detection\_ml: Regime detection in historical markets using Hidden Markov Models (HMM) and Support Vector Machines (SVM).**  
<sup>20</sup> <sup>21</sup> [https://github.com/theo-dim/regime\\_detection\\_ml](https://github.com/theo-dim/regime_detection_ml)