Regime-Based Trading Strategy

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1 Project Summary

The objective of this project is to design and test a systematic trading strategy that explicitly accounts for market regime changes. Rather than applying the same trading rules at all times, we aim to first detect the prevailing market environment and then adapt both the signal selection and the traded asset universe accordingly. The central hypothesis is that low-volatility periods are more favorable to persistence effects such as momentum and sentiment continuation, while high-volatility periods are more likely to generate overshooting, liquidity stress, and short-term reversals.

1.1 Regime Detection

To identify market regimes, we use a Hidden Markov Model estimated on market-wide variables. The baseline specification relies on volatility-related information, including realized market volatility and the VIX, while a richer specification may also incorporate aggregate trading volume and other indicators of market stress. The model outputs probabilities associated with each hidden regime, which allows the strategy to account for uncertainty in regime classification rather than relying only on a hard binary switch.

1.2 Regime-Dependent Asset Universe

A key dimension of the project is that the regime does not only determine which signal is used, but also which types of assets are traded. This choice is motivated by empirical evidence showing that volatility and sentiment jointly affect the relative performance of different groups of stocks. In particular, the paper by Ding, Mazouz, and Wang [1] shows that when VIX is low, sentiment-prone stocks tend to outperform in the short run, whereas when VIX is substantially high, sentiment-insensitive stocks perform better.

In our framework, low-volatility regimes will therefore be associated with a more aggressive and sentiment-sensitive universe. In that state, the strategy will prioritize stocks or portfolios that are more exposed to sentiment and trend continuation, such as smaller-cap or growth-oriented names, provided that they remain sufficiently liquid for realistic implementation.

By contrast, high-volatility regimes will be treated as periods of stress in which the strategy rotates toward a more defensive and liquid universe. In that state, the portfolio will give more weight to large-cap or otherwise sentiment-insensitive stocks, as these assets are more robust to panic-driven dislocations and are easier to trade under adverse market conditions. This regime-dependent shift in the traded universe is directly aligned with the empirical findings of the VIX-based cross-sectional strategy literature, which suggests that the relative advantage of sentiment-prone stocks disappears when fear rises and that investors should instead reallocate toward safer and less sentiment-sensitive names. [1]

1.3 Trading Signals Across Regimes

Conditional on the detected regime, the strategy also changes the active signals. In low-volatility environments, the portfolio is driven by two complementary sources of information. The first is a momentum signal based on recent price dynamics, designed to capture persistence in asset returns during calm and trending markets. The second is a sentiment signal extracted from textual data using a large language model. This signal is intended to measure whether the news flow and market narrative around a stock support the continuation of recent trends. In high-volatility environments, the strategy instead shifts toward mean-reversion. The intuition is that during stressed periods, prices are more likely to overshoot because of liquidity shocks, panic selling, or temporary dislocations, creating opportunities for reversals.

1.4 Position Sizing and Tail-Risk Control

Risk management plays a central role in the framework. Position sizes are first scaled by the inverse of volatility so that risk exposure remains more stable across time and across assets. This volatility targeting is complemented by an additional tail-risk overlay based on Expected Shortfall. As a result, the final portfolio construction aims not only to exploit regime-dependent predictability, but also to control drawdowns during stressed market conditions.

1.5 Dataset and Implementation

The empirical analysis will rely on daily financial and textual data. For market regime detection, we plan to use broad market indicators such as index returns, realized volatility, the VIX, and possibly aggregate trading volume. For the trading universe, we will focus on sufficiently liquid equities or equity-based instruments, with particular attention to the distinction between sentiment-prone and sentiment-insensitive assets, for example through size-based groupings such as small-cap versus large-cap stocks or ETFs. These data will then be combined in a backtesting framework to evaluate the performance, robustness, and practical feasibility of the proposed strategy.

References

[1] Wenjie Ding, Khelifa Mazouz, and Qingwei Wang. Volatility timing, sentiment, and the short-term profitability of vix-based cross-sectional trading strategies. *Journal of Empirical Finance*, 63:42–56, 2021.