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Research on State Identification of the U.S. Stock Market and Dynamic Quantitative Trading Strategies

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Abstract: The U.S. stock market is influenced by factors such as the macroeconomic environment, market liquidity, and investor trading behavior, exhibiting different operating states. A single quantitative trading strategy struggles to adapt to the complex and ever-changing market environment. To improve the adaptability and stability of quantitative trading strategies, this paper focuses on the identification of the operating states of the U.S. stock market and the development of dynamic quantitative trading strategies. It analyzes the criteria and methods for market state classification and identification, establishes a multi-dimensional market indicator system and a state identification model, and designs dynamic quantitative trading strategies from aspects including signal generation, trade direction adjustment, position allocation, risk control, and trade execution, providing reference for enhancing the scientific nature of quantitative trading decisions and market adaptability.

1. Introduction

The U.S. stock market is an important component of the global financial system; its price fluctuations reflect business expectations and are influenced by monetary policy adjustments, international capital flows, and changes in market sentiment. Benjamin Graham once pointed out: "In the short term, the market is a voting machine; in the long term, it is a weighing machine." This viewpoint reveals the complex relationship between stock price fluctuations and market value assessment. Against the backdrop of continuous development of high-frequency trading and algorithmic trading, traditional trading methods relying on fixed parameters and single signals face new challenges [1]. How to accurately capture market operation characteristics and transform state changes into effective trading decisions has become an important research topic in quantitative trading. Therefore, it is necessary to explore the dynamic relationship between market states and trading strategies to enhance strategies' adaptability to different market environments.

2. Definition of Related Concepts

(1) Operating Characteristics of the U.S. Stock Market

The U.S. stock market is mainly based on the New York Stock Exchange (NYSE) and the

Nasdaq Stock Market (NASDAQ), comprising large mature enterprises, tech growth companies, and small- and mid-cap firms. Market participants include institutional investors, individual investors, market makers, and quantitative trading firms. In terms of operating mechanisms, the U.S. stock market adopts a combination of centralized auction and market maker systems. The market is quite active with a relatively sound information disclosure system. Meanwhile, factors such as Federal Reserve monetary policy, inflation levels, employment data, and corporate earnings expectations influence stock prices through capital costs and investor risk preferences, resulting in features such as trend shifts, volatility clustering, and phase changes in risk appetite [2]. These characteristics provide practical bases for market state identification.

(2) Connotation and Classification Criteria of Market State

Market state refers to the relatively stable operating characteristics manifested jointly by price trends, volatility levels, trading activity, and capital flows in a stock market during a specific period. Based on the trading rules of the U.S. stock market, classification can be made from two dimensions: trend direction and volatility magnitude. Price trends classify into rising, falling, and sideways states; volatility levels classify into low, medium, and high volatility states. In practice, these two-dimensional classifications can be cross-combined, for example, rising-low volatility, rising-high volatility, falling-high volatility, and sideways-low volatility. Compared with classification based solely on index rise or fall, multi-dimensional classification reflects differences in market direction and risk levels, providing more detailed bases for subsequent strategy selection.

(3) Main Methods for Market State Identification

Market state identification mainly extracts market features from historical trading data and uses statistical analysis or machine learning methods to determine the current market phase. Traditional methods typically use technical indicators such as moving averages, relative strength index (RSI), and average true range (ATR), setting judgment thresholds based on price trend and volatility changes. These methods are intuitive and easy to understand but are prone to parameter setting and market noise influences. Statistical models like Markov regime-switching models describe the probability transition process of market states, while hidden Markov models (HMM) infer unobservable latent states based on observed variables like returns and volatility [3]. Moreover, machine learning methods such as K-means clustering and random forests can also classify market features. Different methods vary in identification accuracy, computational complexity, and interpretability, requiring selection based on research data and trading goals.

(4) Basic Principles of Dynamic Quantitative Trading

Dynamic quantitative trading refers to the investment method that uses algorithmic models to process market data and automatically or semi-automatically adjust trading decisions according to changes in market states, trading signals, and risk levels. The key lies in establishing a mapping between market information and trading behaviors, transforming state identification results into specific operational rules. For example, when the S&P 500 Index is in a rising and low volatility state, the strategy may appropriately increase long positions; when the market turns down and volatility rises, it may reduce stock exposure, increase cash proportion, or set protective stop losses. In practice, dynamic quantitative trading usually involves stages of data input, signal calculation, strategy adjustment, order execution, and performance feedback. By periodically updating model parameters and trading rules, the strategy can adjust risk exposure and capital allocation based on market changes [4].

3. Construction of U.S. Stock Market State Identification Model

(1) Building a Multi-dimensional Market Indicator System

The U.S. stock market state is influenced by many factors including price trend, volatility level,

trading activity, and market sentiment. A single price indicator cannot comprehensively reflect market conditions. Therefore, the S&P 500 Index and Nasdaq Composite Index can be selected as basic observation objects, from which market indicators are constructed in four dimensions: for price trend, index returns and moving average deviation; for volatility level, historical volatility and ATR; for trading activity, trading volume and turnover rate; for market sentiment, VIX volatility index and the ratio of advancing to declining stocks [5]. By integrating indicators from different dimensions, an observational system covering market direction, risk level, trading heat, and investor sentiment is formed, providing a data foundation for subsequent state identification.

(2) Selecting Variables for Market State Identification

After establishing the indicator system, variable selection is necessary based on information content and statistical characteristics to avoid redundancy caused by highly correlated indicators. Specifically, original data undergo missing value treatment, outlier detection, and normalization to unify measurement units. Correlation analysis tests associations among variables, and highly correlated indicators are removed. Principal component analysis (PCA) is used to extract representative comprehensive features, reducing model input dimensionality. For example, both index returns and moving average deviations reflect price trends; if highly correlated, the variable contributing more to identification is retained. Ultimately, a variable set considering trend, volatility, turnover, and sentiment features is formed to improve model computational efficiency and identification stability.

(3) Establishing Market State Identification Model

Based on variable selection, a hidden Markov model (HMM) can be adopted to construct the market state identification model. This model treats market operating state as an unobservable latent variable, using observed variables such as returns, historical volatility, volume changes, and VIX index. The state transition probability matrix describes transitions among market states, and observed data are used to estimate the probability distribution of each state. The model can initially define three states: rising, falling, and oscillating. Economic meanings are assigned based on features such as mean returns, volatility, and duration of each state [6]. For each trading day, the model calculates posterior probabilities of latent states with the latest observations, choosing the state with the highest probability as the current market judgment. To avoid look-ahead bias, model training and state judgment must apply rolling window or expanding window techniques.

(4) Testing Market State Identification Effectiveness

After model construction, testing should be conducted regarding identification accuracy, state stability, and practical application value. For identification accuracy, model results are compared with rule-based classifications set on index returns and volatility, and metrics such as accuracy, precision, recall, and F1 score are calculated. State stability focuses on the duration, frequency of transitions, and consistency across sample intervals to assess whether the model frequently misjudges or lags in switching. For practical value, identification results are used in historical backtesting to compare returns, maximum drawdown, and Sharpe ratios across different market states, verifying whether classification provides effective reference for strategy adjustments [7]. Sensitivity testing by adjusting training windows and model parameters evaluates model adaptability in different market environments.

4. Dynamic Quantitative Trading Strategies Based on Market State Identification

(1) Identifying Market States and Generating Trading Signals

Trading signal generation is based on market state identification results, combining price trends, trading volume, and volatility indicators to determine specific buy or sell conditions. Taking S&P 500 constituent stocks as an example, the model-identified rising, falling, and oscillating states

serve as fundamental conditions for signal generation, supplemented by moving averages (MA) and RSI for auxiliary judgment. When the market is in a rising state and the short-term MA crosses above the long-term MA with volume increasing synchronously, a buy signal is generated; when in a falling state with index below the long-term MA and RSI indicating weakness, a sell or reduce position signal is triggered; for oscillating states, Bollinger Bands upper and lower bands and RSI overbought/oversold zones are used for range trading [8]. To avoid misjudgment caused by a single indicator, multiple indicators confirm together, and signal strength adjusts based on model output probabilities. Only when a state's identification probability reaches a preset threshold is the corresponding trade executed.

(2) Adapting to Market Features and Adjusting Trading Directions

Under different market states, asset price directions and risk-return characteristics vary, so trading strategies must promptly adjust long-short directions and avoid fixed directions for all environments. In the U.S. stock market, differentiated trading rules can be set based on the state identification results of the S&P 500 and Nasdaq Composite indices. When the model identifies a sustained rising state, strategies focus on trend-following long positions, prioritizing stocks with strong profitability and stable prices; when the market shifts to a falling state, long positions are reduced and short selling is moderately adopted on eligible stocks, or inverse ETFs used for hedging; during oscillating states, reduce trend-following strategies, switch to range trading or hold off. If the market state identification probabilities change significantly—such as rising state probability dropping from 75% to 40% while falling state probability rises—the system gradually decreases the weight of long signals to prevent losses caused by slow adjustment in a market reversal.

(3) Optimizing Position Allocation and Dynamically Allocating Capital

Position allocation is dynamically adjusted according to market state, asset volatility, and strategy risk budget to avoid concentration in a single stock or direction. For example, with a $1 million quantitative investment portfolio, differentiated position ranges can be set per market state: 60%–80% stock allocation under rising low-volatility state; 30%–50% in oscillating state; and 10%–30% during falling high-volatility state, with remaining funds held in cash or short-term government bonds [9]. Allocation also accounts for individual stock volatility and asset correlation. For volatile Nasdaq tech stocks, position weights are reduced to avoid excessive impact on portfolio returns. At the portfolio level, inverse volatility weighting is used to assign capital according to each asset’s historical volatility and single-stock holding limits are set. When market states change, target weights are recalculated per a preset rebalancing cycle, and positions adjusted by phased buys or sells, balancing capital efficiency and portfolio stability.

(4) Setting Risk Thresholds and Implementing Dynamic Stop Losses

Risk control involves setting differentiated thresholds according to market volatility to avoid the inadequacy of fixed stop loss ratios for different environments. ATR serves as the basis for dynamic stop loss; based on individual stock purchase price, stop loss distance is set as two times ATR. For example, a stock bought at $100 with current ATR of $2 has an initial stop loss at $96; if price rises to $110, the trailing stop is recalculated based on the highest price, locking in profits while limiting drawdown. During high volatility periods, price fluctuations tolerated per stock can be expanded but position sizes reduced to prevent enlarged single trade risks; when the market is falling and VIX rises sharply, portfolio risk budgets tighten with maximum drawdown thresholds—such as 8% triggering overall position reduction or stopping new trades [10]. Additionally, single-trade loss and consecutive loss limits are set to prevent continued losses if the model temporarily fails.

(5) Improving Execution Mechanism and Reducing Trading Costs

The success of a trading strategy depends not only on signal identification but also on order execution quality. The U.S. stock market is active, but liquidity, bid-ask spreads, and order book

depth vary across stocks, so appropriate execution methods are chosen considering trade size and market state. For liquid large-cap S&P 500 stocks with narrow spreads, limit orders control execution prices; for urgent position adjustments, market orders may be used after evaluating market impact. Large orders can be split and executed using time-weighted average price (TWAP) or volume-weighted average price (VWAP) algorithms to reduce price impact [11]. The system continuously monitors commissions, spreads, slippage, and order fill rates, factoring actual execution costs into performance measurement. When volatility spikes, liquidity declines, or spreads widen abnormally, non-urgent orders may be delayed until trading conditions improve, enhancing strategy execution stability and capital efficiency.

5. Conclusion

The U.S. stock market exhibits strong complexity and dynamism, requiring quantitative trading strategies to consider market changes and maintain flexibility in investment decisions. Market state identification provides critical basis for strategy adjustments, combining to enhance the specificity of trading decisions and the strategies' applicability across varying market environments. Meanwhile, model parameters, data quality, and market shocks can still affect performance, thus continuous market monitoring, model calibration, risk constraint improvement, as well as backtesting and live trading validation of strategies are essential to drive quantitative trading towards greater sophistication and robustness.

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