



# Stock Selection and Portfolio Construction in Emerging Markets Using Quantitative Models: A Focus on the Chinese Market

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# Emerging Markets

**Emerging markets** refer to economies or countries that are experiencing rapid growth and industrialization but have not yet reached the status of developed markets.

- High volatility, high risk-adjusted returns potential
- Examples: BRICS (Brazil, Russia, India, China, South Africa), Mexico, Indonesia, Turkey, Vietnam



# Project Objectives

- Discovering a systematic, quantitative approach to investing in EMs
- Focusing on the Chinese market (CSI 300 Index)
- Integrating machine learning in the stock selection process



# Literature Review

Guerard, Gillam, and Beheshti (2022): Stock Selection Modeling and Portfolio Selection in Emerging Markets

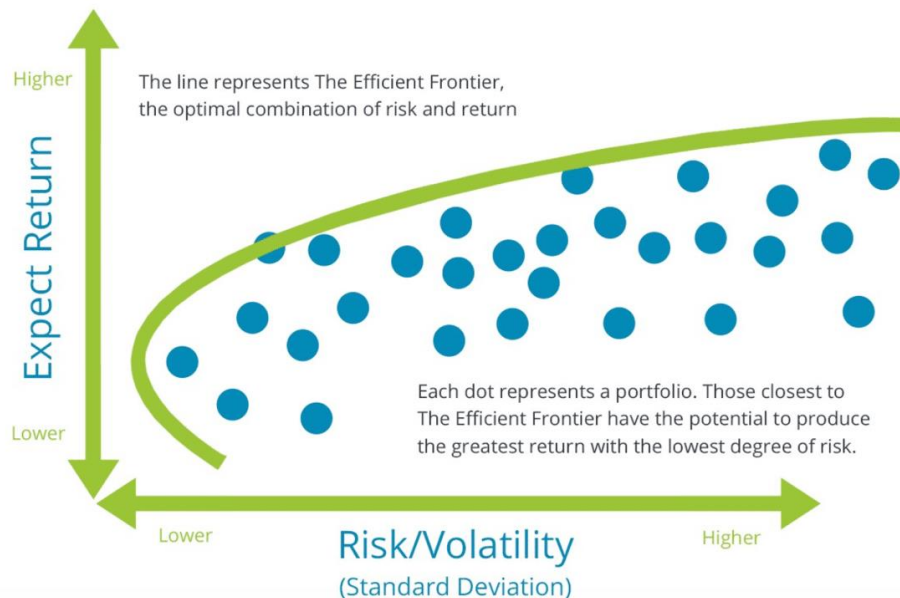
$$\begin{aligned} TR_{t+1} = & a_0 + a_1EP_t + a_2BP_t + a_3CP_t + a_4SP_t + a_5REP_t + a_6RBP_t \\ & + a_7RCP_t + a_8RSP_t + a_9CAE_t + a_{10}PM71_t + e_{t+1} \end{aligned} \quad (1)$$

where

EP = [earnings per share] / [price per share] = earnings-to-price ratio;  
BP = [book value per share] / [price per share] = book-to-price ratio;  
CP = [cash flow per share] / [price per share] = cash flow-to-price ratio;  
SP = [net sales per share] / [price per share] = sales-to-price ratio;  
REP = [current EP ratio] / [average EP ratio over the past five years];  
RBP = [current BP ratio] / [average BP ratio over the past five years];  
RCP = [current CP ratio] / [average CP ratio over the past five years];  
RSP = [current SP ratio] / [average SP ratio over the past five years];  
CAE = consensus earnings-per-share I/B/E/S forecast, revisions, and agreement;  
PM71 = price momentum; and  
e = randomly distributed error term.

## Markowitz: Modern Portfolio Theory (MPT)

- Investors can construct an "optimal" portfolio that maximizes expected return for a given level of risk, or alternatively, minimizes risk for a given level of expected return by carefully selecting and combining assets.



# Relevant Advancements

- Advances in EM stock selection (e.g., Harvey 1995, Haugen & Baker 1996).
- Recent applications of nonlinear models for stock selection, such as XGBoost (Zhang & Li 2020)

# Research Framework

- This project aims to integrate both fundamental and technical analysis for the Chinese market portfolio construction.
- Stocks are selected quarterly based on predicted quarterly returns according to fundamental data, and each quarter's portfolio either (1) assigns equal weights to all selected stocks for the whole quarter or (2) is dynamically optimized on a weekly basis via technical analysis
- Comparisons to the CSI 300 index are made in the end to determine each method's performance





# Data Preprocessing & Feature Engineering

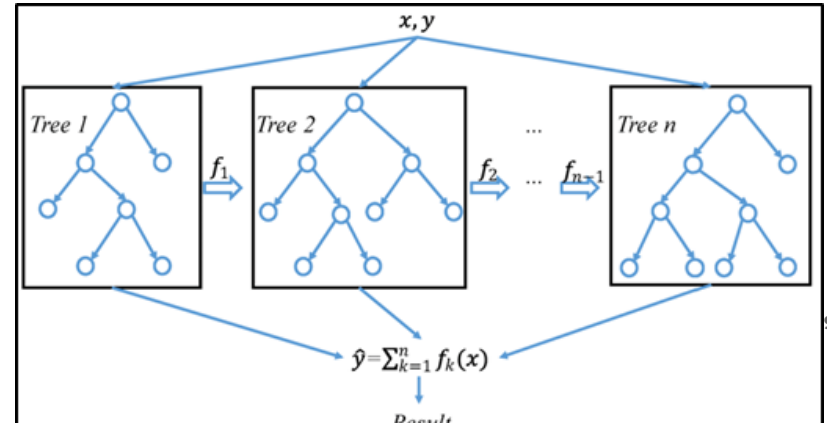
- Fundamental data source: Bloomberg Terminal
- Technical data: generated from daily stock closing prices by TA-Lib
- Fundamental features: book value per share, earnings per share, revenue per share, etc.
- Technical features: TRIX, RSI, PPO, MOM, etc
- Data preprocessing steps: handling missing values, winsorizing outliers, standardization

The Bloomberg logo, consisting of the word "Bloomberg" in a bold, orange, sans-serif font, is positioned on a solid black rectangular background.



# XGBoost

- Gradient boosting: each new model (decision tree in this case) attempts to correct the errors made by previous models by minimizing an objective function, improving overall accuracy
- Regularization: XGBoost includes L1 (Lasso) and L2 (Ridge) regularization terms in its objective function, which helps prevent overfitting and makes it more robust
- Non-linear relationship is captured



# Stock Return Prediction with XGBoost

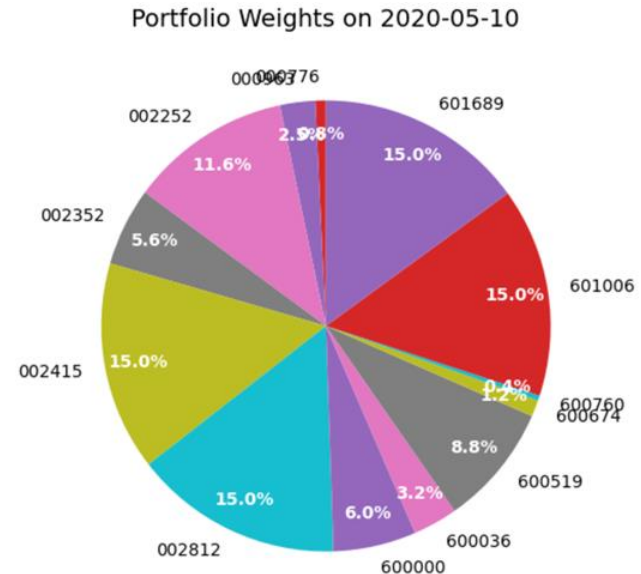
- Features: either fundamental features (quarterly) or technical features (weekly)
- Training period: 2001-2020
- Testing period: 2020-2024
- Regression: XGBRegressor
- Loss: MSE, MAPE, etc

# Portfolio Construction Strategies

- Quarterly Rebalanced Equal-Weighted Portfolio
  - Selects stocks with predicted quarterly returns in the top 25% percentile
  - Every stock has the same weight in the portfolio for the whole quarter
  - Ensures transparency and simplicity
- Weekly Rebalanced Non-Equal-Weighted Portfolio
  - Still includes the same stocks in the above portfolio
  - Uses technical features and XGBoost to predict next week's returns for each stock
  - Applies Markowitz mean-variance analysis in Riskfolio-Lib to find the efficient portfolio with the minimum risk for next week

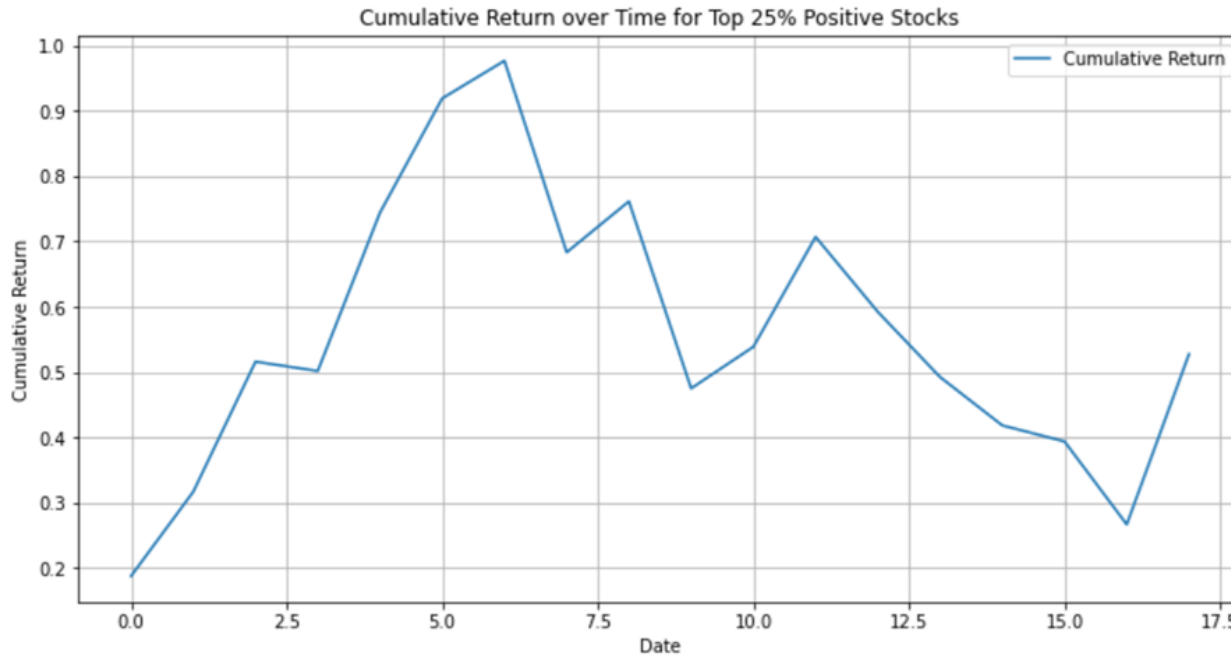
# Riskfolio-Lib

- An open-source Python library designed to simplify the process of portfolio optimization and risk management
- 15% cap on individual stock weights
- Full capital allocation (sum of weights=1)
- No shorting



# Portfolio Performance

Equal-weighted portfolio cumulative return:



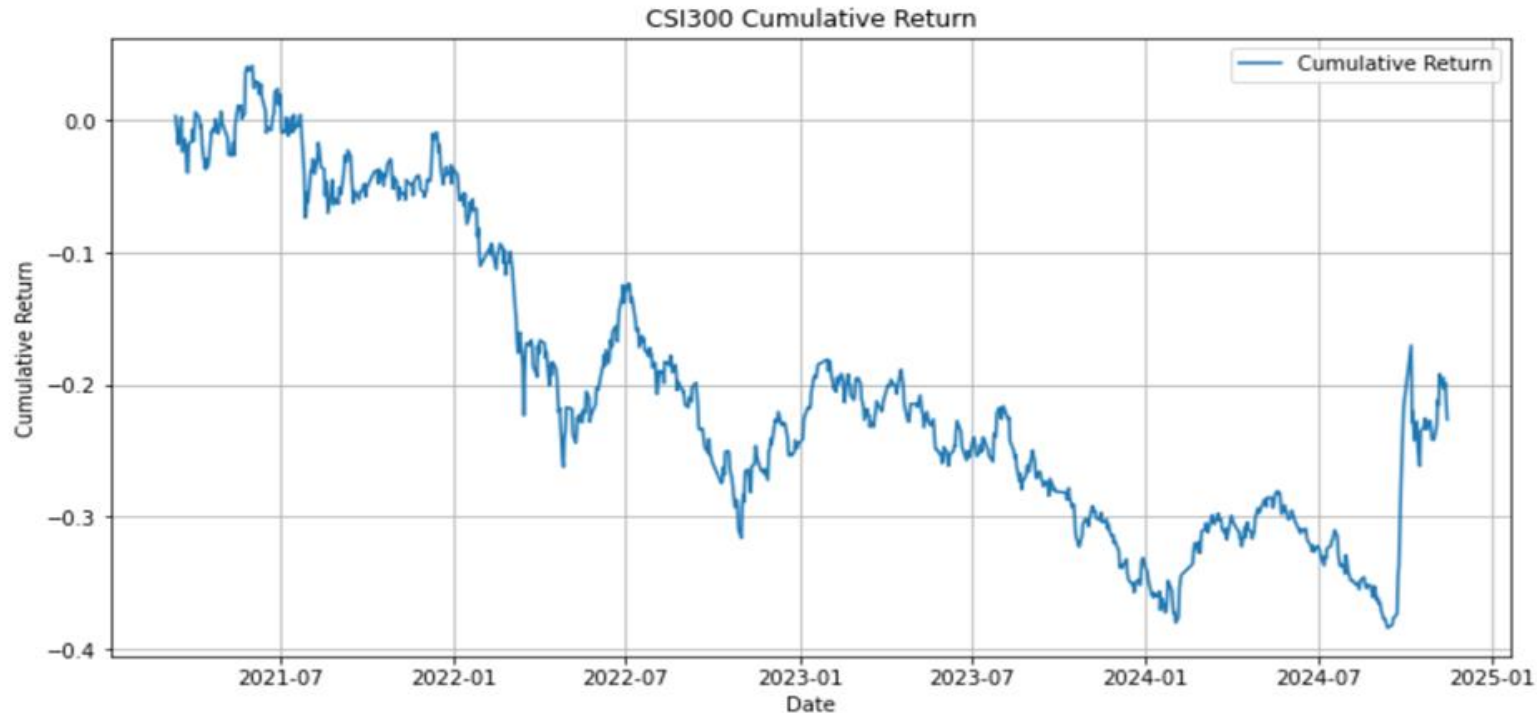
# Portfolio Performance

Weekly-optimized portfolio cumulative return:



# Benchmark

CSI 300 cumulative return:





# Portfolio Performance Stats

Table 1. Comparison of CSI 300 and portfolios

Metrics	CSI300	Portfolio	Quarterly Portfolio
Cumulative Return	-29.45%	52.75%	47.63%
Annualized Return	-8.97%	9.87%	9.21%
Volatility	18.04%	21.99%	21.74%
Sharpe Ratio	-0.50	0.45	0.42
Max Drawdown	-46.66%	-35.94%	-44.18%

# Insights from the Results

- Both strategies outperform CSI 300 benchmark
- Equal-weighted strategy is simpler, fundamental-driven and has competitive performance
- Minimum-risk strategy is dynamic; it yields marginal improvements (lower volatility) but is more complex and costly to implement



# Key Findings and Practical Implications

- In emerging markets like China, fundamental analysis still holds significant value
- Dynamic rebalancing with technical indicators offers limited additional benefit in this context
- Practical implications for portfolio managers focusing on EMs



# Conclusion and Future Research

- Importance of fundamentals in the Chinese equity market
- Complex technical-based optimization may not always lead to superior results
- Potential areas for future research: exploring other EMs, fine tuning parameters through gridsearch, applying deep learning models, further analyzing the role of technical indicators.



The End