Time-Series trading strategy based on Factor stock selection

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Introduction

- Most factor based models used in trading strategies are cross-sectional
- It ignored the possible time-series effect
- We are interesting integrating time-series component on a factor-based trading strategy

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Analysis of time series effects exists

Stationarity Tests

- Augmented Dickey-Fuller (ADF) Test
  - Null hypothesis (H_0): The series has a unit root (non-stationary)
  - If p-value < 0.05, we reject (H_0), suggesting stationarity.
- KPSS Test
  - Null hypothesis H_0: The series is stationary
  - If p-value > 0.05, we fail to reject H_0, suggesting stationarity.

A series is considered stationary only if:

- ADF test rejects H_0 ($p < 0.05$), and
- KPSS test fails to reject H_0 ($p > 0.05$)

About 96.8% of the return series are confirmed to be stationary.

Analysis of time series effects exists

- Autocorrelation via Box Test

$$H_0 : \text{The series is white noise (no autocorrelation up to lag k).}$$

A significant p-value (typically $p < 0.05$) suggests that the series exhibits Autocorrelation.

- ARCH Effect via LM Test

$$H_0 : \text{No ARCH effect (the squared residuals are not autocorrelated, variance is constant over time).}$$

p-value	Conclusion
p-value < 0.05	Reject H_0: ARCH effects detected (volatility clustering exists).
p-value ≤ 0.05	Fail to reject H_0: No significant ARCH effects, variance can be considered constant.

Analysis of time series effects exists

- Test Results

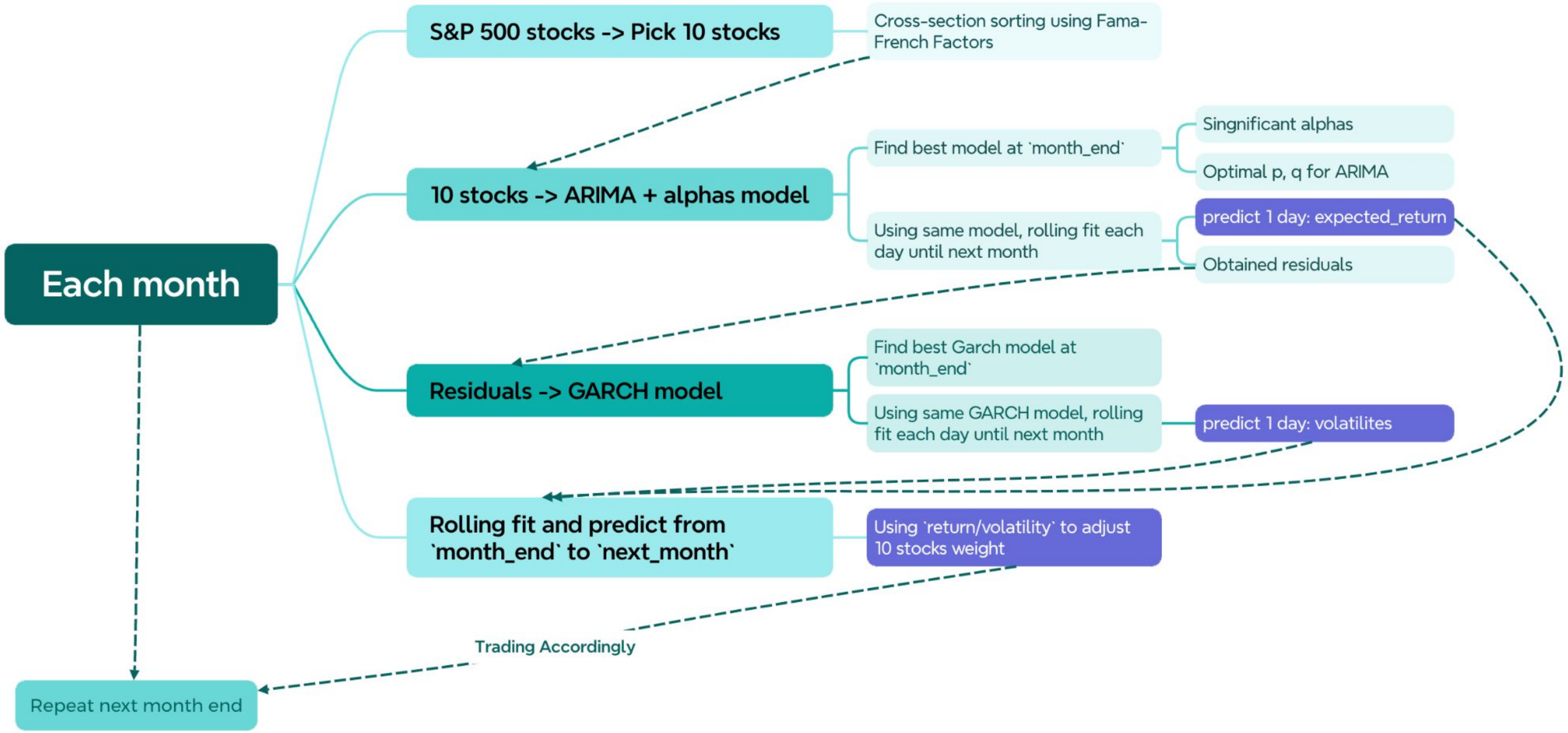
symbol	box_stat	box_pvalue	LM_stats	LM_pvalue	Exist_Arch	Exist_Autocorr
CSCO	67.4781	0.0005	321.0422	0.0000	True	True
UAL	103.5778	0.0000	674.0067	0.0000	True	True
TROW	97.5386	0.0000	107.2964	0.0000	True	True
ISRG	20.5516	0.4239	0.8469	1.0000	False	False
NVR	52.5150	0.0001	1092.4693	0.0000	True	True

Methodology for constructing the model

Goals:

- Factor model to pick stocks
  - Monthly
  - Using fundamental factors
- Time-series model for individual stocks
  - Daily prediction
  - Using short-term anomaly (101 Formulaic Alphas) + ARIMA (ARIMAX) -> predict daily return
  - GARCH model on residuals of ARIMAX -> predict daily volatility
- Using predicted `return/volatility` to trade

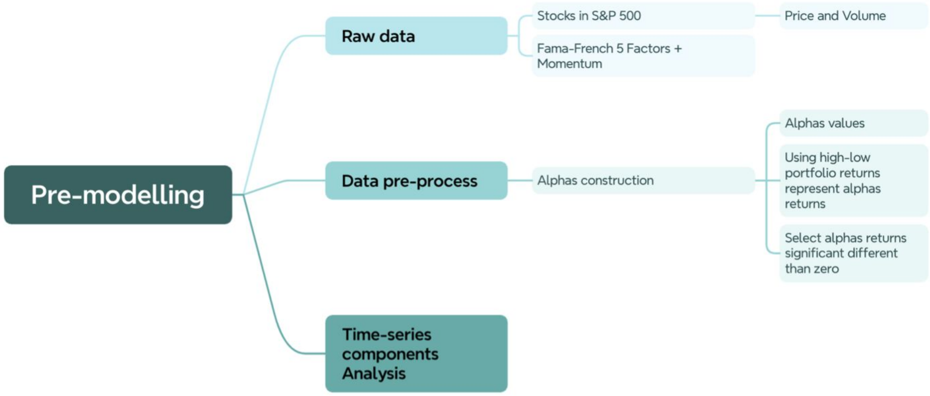
Methodology for constructing the model



Data

To achieve this process, we need:

- Stock price and volume
  - all stocks in S&P 500
- Fundamental factors
  - Fama-French 5 factors + Momentum
- Alphas (Anomaly)
  - Constructed using price and volume data
  - Alphas value
    - further used in ARIMAX
  - Alphas return (high - low)
    - Pick significant return alphas



Model Construction

Each month end:

- Using 3-month lookback period to identify “best” ARIMAX model
- Using ARIMAX residuals to identify “best” GARCH model

We defined “best” as:

- Only included significant alphas (p-value <= 0.05)
- Lowest AIC for p, q ranging 1 to 4 (limited compute resources)

Once the model is established at time t, it does not remain static.

- Throughout the following month, we fit the model on a daily basis.
- Until next stock selection period (Next month end)

Prediction sample

Stock picking time: 2024-10-31, prediction period: 2024-11-01 to 2024-11-29

Expected Daily Returns

Date	NVDA	AVGO	IP	BLDR	QCOM	URI	POOL	IVZ	KLAC	PHM
2024-11-01	-0.0018	0.0037	0.0293	0.0171	0.0223	0.0006	-0.0088	-0.0042	0.0139	0.0012
2024-11-04	-0.0299	0.0022	-0.2409	-0.0132	0.0054	-0.0005	0.0004	-0.0100	0.0006	0.0003
...	...	...	...	...	...	...	...	...	...	...
2024-11-27	-0.0122	0.0000	-0.0065	0.0108	-0.0025	0.0012	-0.0062	0.0073	0.0001	-0.0012
2024-11-29	0.0066	-0.0026	-0.0068	0.0097	-0.0046	0.0145	-0.0067	0.0136	-0.0059	-0.0001

Expected Daily Volatilities

Date	NVDA	AVGO	IP	BLDR	QCOM	URI	POOL	IVZ	KLAC	PHM
2024-11-01	0.0268	0.0309	0.0685	0.0196	0.0235	0.0126	0.0147	0.0155	0.0369	0.0172
2024-11-04	0.0295	0.0281	0.1361	0.0194	0.0205	0.0148	0.0142	0.0162	0.0204	0.0169
...	...	...	...	...	...	...	...	...	...	...
2024-11-27	0.0281	0.0191	0.0132	0.0217	0.0204	0.0191	0.0217	0.0171	0.0318	0.0232
2024-11-29	0.0284	0.0306	0.0143	0.0215	0.0201	0.0191	0.0185	0.0165	0.0203	0.0231

Strategy Design

- Monthly Stock Selection and Prediction
- Mean–Variance Ratio Calculation

$$\mathrm{MVR}_{i,t} = \frac{\hat{\mu}_{i,t}}{\hat{\sigma}_{i,t}}$$

- Average MVR and Ranking
  - Calculate the average daily MVR for each stocks

$$\overline{\mathrm{MVR}}_i = \frac{1}{N}\sum_{t=1}^{N}\mathrm{MVR}_{i,t}$$

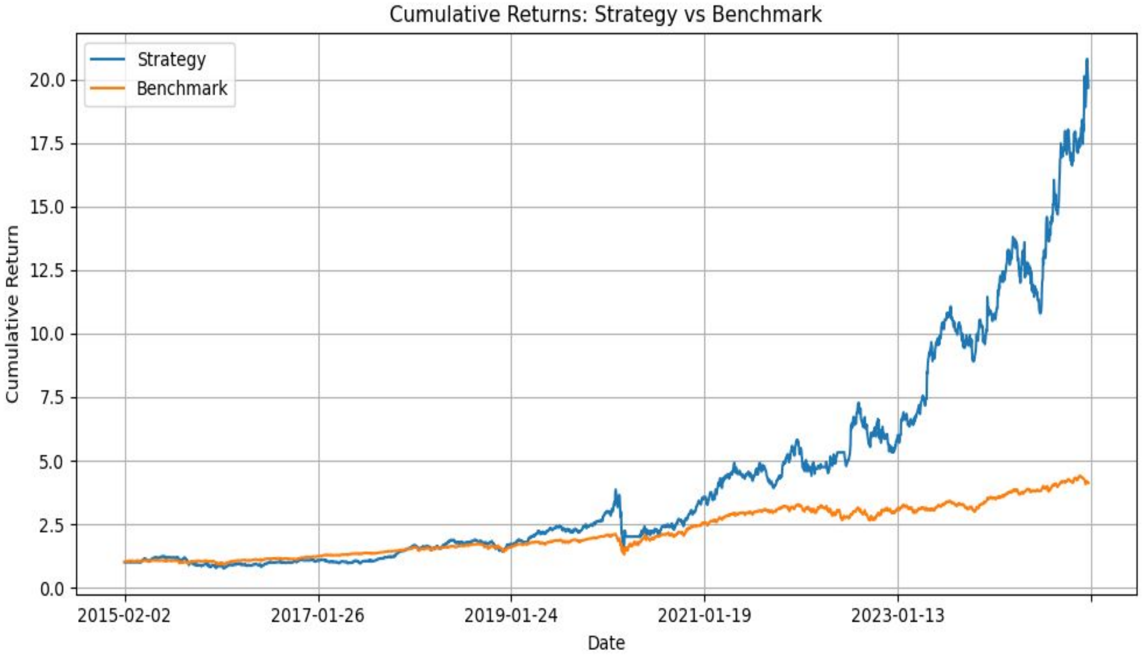
  - Sort the 10 stocks in ascending order of MVR_Average, assign ranks, then set weights by

$$w_{i,\tau} = \frac{r_{i,\tau}}{\sum_{j=1}^{10} r_{j,\tau}} = \frac{r_{i,\tau}}{55}$$

Back-testing Assumptions

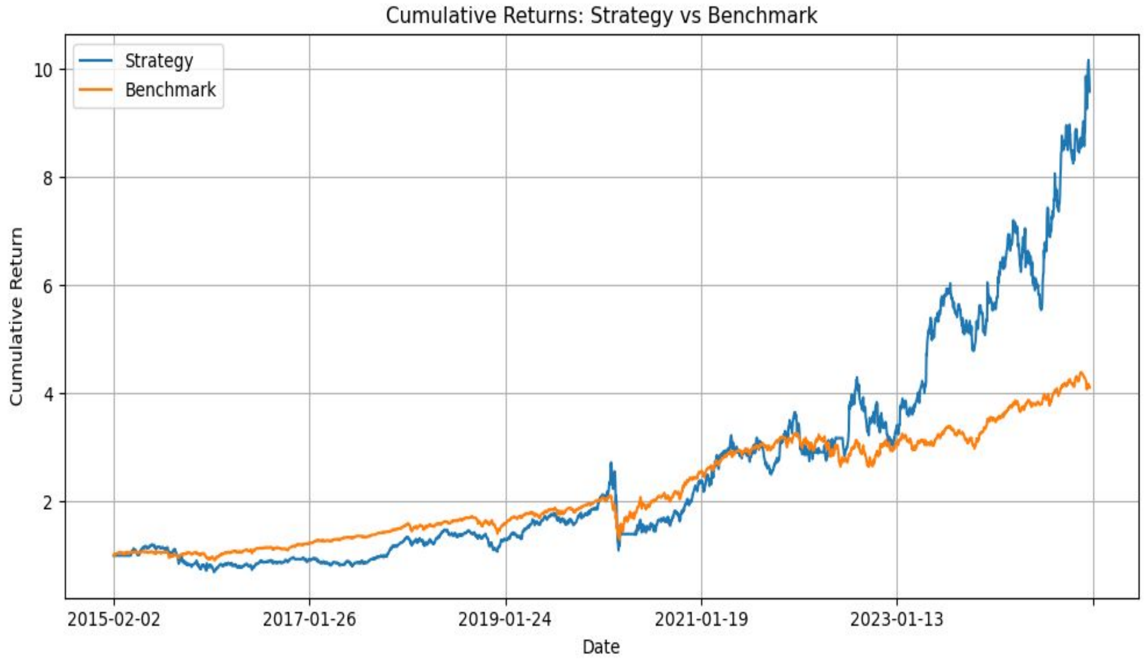
- The transaction cost is 20 basis point.
- Trades executed at daily closing prices.
- Stocks are picked on the first trading day of each month and rebalanced daily.
- Benchmark is buy-and-hold with no dividends reinvested.
- Unlimited liquidity and zero market impact.

Backtesting Performance Summary (No Transaction Cost)



Metric	Strategy	Benchmark
Annualized Return	35.15%	15.39%
Annualized Volatility	35.25%	18.22%
Sharpe Ratio	0.997	0.844
Maximum Drawdown	–59.40%	–38.15%

Backtesting Performance Summary (with Transaction Cost)



Metric	Strategy	Benchmark
Annualized Return	25.67%	15.36%
Annualized Volatility	35.23%	18.22%
Sharpe Ratio	0.73	0.84
Maximum Drawdown	–59.64%	–38.15%

Conclusion and Future Improvement

Major findings include:

- Time-series components did outperform the equal-weighted benchmark
- However, it incurred higher volatility and maximum drawdown, indicating a need for improved risk management.

We believe that the overall research structure is solid, we could further enhance the model by:

- Incorporating additional factors or alternative models to improve predictive power.
- Exploring different portfolio construction techniques to optimize risk-return profiles.
- Implementing advanced risk management strategies to mitigate drawdowns.
- Conducting further research on the impact of transaction costs and market conditions on strategy performance.
- Investigating the potential for machine learning techniques to enhance alpha generation and risk management.