MSDS 451 Programming Assignment 3
Multi-Modal Algorithmic Trading Implementation, Backtesting, and Performance Evaluation

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1. Problem Description

The goal of the programming assignment is to build an automated, algorithmic trading program and backtest it on US equity data, covering critical economic scenarios that occurred over the past 25-30 years. Strategies need not use ML or regime detection, but should be rigorously evaluated against benchmarks (SPY, QQQ, IEF, or similar). The experiment focused on:

- Momentum (Monthly Ranking) — inspired by Andrea Clenow's momentum examples
- Dual MovingAverage crossover (100/300) — adapted from a ZiplineReloaded example by Stefan Hansen
- Mean Reversion (Z-score bands) — short-term fade of price extremes
- RegimeSwitching Allocator (Hybrid) — optional extension that toggles sleeves (momentum vs. mean reversion) and derisks in crisis

Key evaluation requirements

- Backtested performance with robust metrics: Sharpe ratio, max drawdown, annual return/volatility
- Comparison versus a buy-and-hold benchmark (SPY/QQQ/IEF)

Constraints encountered

- Quandl WIKI bundle ends in 2018 and lacks SPY/index symbols; the implementation used BRK-A as an internal proxy and `yfinance` for external plots/tables with limitations (see "Data Preparation and Pipeline" and "Limitations").

Key Words: *momentum, mean reversion, zipline, pyfolio, backtesting, benchmark, drawdown*

2. Data Preparation and Pipeline

2.1. Data sources and ingest

1. Zipline bundle: `quandl` (legacy WIKI). Ingested once with `zipline ingest b quandl`. Used by Zipline backtests.
2. Benchmarks: `yfinance` fetched daily closes for SPY, QQQ, IEF, BRK-A for external comparison tables and plots.
3. Symbol conventions: Zipline uses `BRK_A`; Yahoo uses `BRKA`.

2.2. Preprocessing and helpers

1. Timezone normalization and NA handling via helper `sanitize_series` before merging strategy returns with benchmark returns.
2. Empirical metrics used for annualized return/volatility, Sharpe, max drawdown, and alpha/beta vs SPY.

2.3. Universe and runtime considerations

1. To avoid local OOM and long runtimes, the portfolio was constrained to ~3 tickers (e.g., AAPL, WMT, XOM). This materially improves stability on laptops.
2. Google Colab proved unstable for this pipeline due to limited RAM, the lack of a persistent ingest cache, and occasional missing symbols; a local Conda environment is recommended.

2.4. Data coverage limitations

1. Quandl WIKI bundle ends March 2018, capping backtests at 20180331.
2. `yfinance` has a long history, but its coverage across 25–30 years is not guaranteed for all symbols; events like the dotcom bubble or the 2010 flash crash may be incomplete.
3. SPY is not present in the legacy WIKI bundle; BRK_A served as an internal market quality proxy for regime detection.

3. Research Design

Hypotheses and strategy rules

3.1. Monthly Momentum (Clenow-inspired):

Rank by trailing return over a fixed lookback; allocate to the top names; rebalance on a monthly schedule; equal among selected.

Rationale: medium-term positive autocorrelation persists; winners tend to keep winning.

3.2. Dual MovingAverage Crossover (Stefan Hansen, Momentum, 100/300)

Go long an asset when short MA (≈100D) > long MA (≈300D); otherwise, reduce to zero.

Rationale: follow established trends; avoid prolonged downtrends.

3.3. Mean Reversion (Z-score bands)

Compute z = (price − rolling mean) / rolling std (lookback ≈20D).

Go long when z < −entry; short when z > +entry; revert to flat when |z| < exit.

Rationale: Short-term overreactions tend to snap back to the mean in calm, range-bound conditions.

3.4. RegimeSwitching Allocator (optional extension)

Market proxy: BRK-A daily returns/prices to estimate realized volatility, drawdown, and breakout strength. This was used in place of an index such as the S&P 500 due to limitations with Quandl data.

Rules of thumb:

Crisis: high vol or deep drawdown ⇒ derisk (liquidate)

Stable: prefer mean reversion

Breakout + trend strength: prefer momentum

Rationale: Reduce exposure in stress; select the sleeve aligned with the prevailing market microstructure.

3.5. Evaluation metrics and validation

Absolute: cumulative return; annualized return/volatility; max drawdown; Sharpe ratio.

Relative: alpha/beta vs SPY (external via `yfinance`), with the caveats noted above.

Diagnostics: daily returns vs benchmarks; log equity curves; PyFolio tear sheet (returns/positions/transactions extracted from Zipline performance).

Out-of-sample demarcation via `live_start_date` for PyFolio reporting.

3.6. Expected behavior by regime

Momentum excels in persistent trends; it suffers in whipsaws.

Mean reversion excels in choppy, range-bound volatility; it suffers in strong directional moves.

Regime-switching aims to preserve capital in crises and engage the appropriate sleeve otherwise.

4. Programming

4.1. Implementation details (see `MSDS_451_Programming_Assignment_3.ipynb`)

1. Zipline APIs: `schedule_function`, `date_rules`, `time_rules`, `order_target_percent`, `set_commission`, `set_slippage`, `data.history`, `data.can_trade`.

4.2. Strategies

2. Monthly momentum: monthly schedule; rank by trailing return; equal-weight top N.
3. Dual MA: compute 100D/300D moving averages via `history`; long when short > long.
4. Mean reversion: compute rolling mean/std; apply z-score entry/exit bands.
5. Regime allocator: compute realized vol, drawdown, breakout on BRK_A; route to sleeve; `apply_target_weights` helper for portfolio updates.

4.3. Reporting and analysis

1. PyFolio: `extract_rets_pos_txn_from_zipline` and `create_full_tear_sheet` for a full report.
2. External comparisons: `yfinance` downloads for SPY/QQQ/IEF/BRKA; Empirical metrics summarized into a comparison DataFrame; daily and log equity plots.

Sources and inspirations:
Andrea Clenow — monthly momentum portfolio construction concepts.
Stefan Hansen / ZiplineReloaded — dual moving average example and Zipline workflow.

5. Exposition

5.1. Key findings (qualitative)

1. Mean Reversion: steadier but modest returns; lower volatility and drawdowns; turnover-sensitive. Struggles during strong, persistent trends.
2. Momentum (Monthly Ranking & Dual MA): stronger compounding in trending markets; vulnerable to whipsaws/regime flips; drawdowns larger around reversals.
3. Regime-Switching: more resilient in volatile periods; derisks under stress (high vol/drawdown), favors mean reversion in calm mean-reverting phases, and engages momentum when breakout strength and stability are present. Overall, improved risk-adjusted profile vs. pure sleeves.

Strategy vs Benchmark Performance (Daily Returns)

	Cumulative Return	Annual Return	Annual Volatility	Sharpe	Max Drawdown	Alpha_vs_SPY	Beta_vs_SPY	Alpha
Monthly_Momentum	113.21%	4.72%	5.71%	0.84	-11.66%	0.02	0.24	nan
Dual_MA	292.02%	8.68%	16.80%	0.58	-28.03%	0.06	0.44	nan
Mean_Reversion	-25.10%	-1.75%	10.54%	-0.11	-39.36%	-0.02	0.10	nan
Regime_Switching	-58.81%	-5.26%	9.60%	-0.52	-64.65%	-0.05	0.02	nan
SPY	280.93%	8.49%	18.54%	0.53	-55.19%	nan	1.00	0.000000
QQQ	619.01%	12.78%	21.12%	0.68	-53.40%	nan	1.03	0.041955
IEF	115.15%	4.78%	6.61%	0.74	-10.40%	nan	-0.14	0.065040
BRK-A	336.52%	9.40%	20.73%	0.54	-51.47%	nan	0.65	0.048488

Fig 1. *Final results table. The Dual-MA algorithm, which trades the crossover between a 100D and 300D average, had the highest return. The momentum-based strategies performed better than the mean-reversion and the regime-switching algorithms.*

5.2. Benchmarks and caveats

1. Internal proxy benchmark: BRK_A used inside Zipline due to WIKI bundle limitations; SPY/QQQ/IEF fetched externally for tables/plots only.
2. Due to data coverage, post-2018 regimes (e.g., COVID shock, 2022–23 rate cycle) are not represented in Zipline tests.

5.3. Figures and tables produced

1. PyFolio full tear sheet (returns, exposures, drawdowns, event studies)
2. Strategy vs. benchmark performance summary table (annual return/volatility, Sharpe, MDD, alpha/beta)
3. Daily returns comparison plot and logscale equity curves

5.4. Interpretation

1. In volatile/choppy markets, pure momentum's expected value declines via whipsaw losses, while mean reversion's expected value increases if ranges hold; however, persistent risk-off trends can punish mean reversion. The allocator helped throttle risk and choose sleeves contextually.

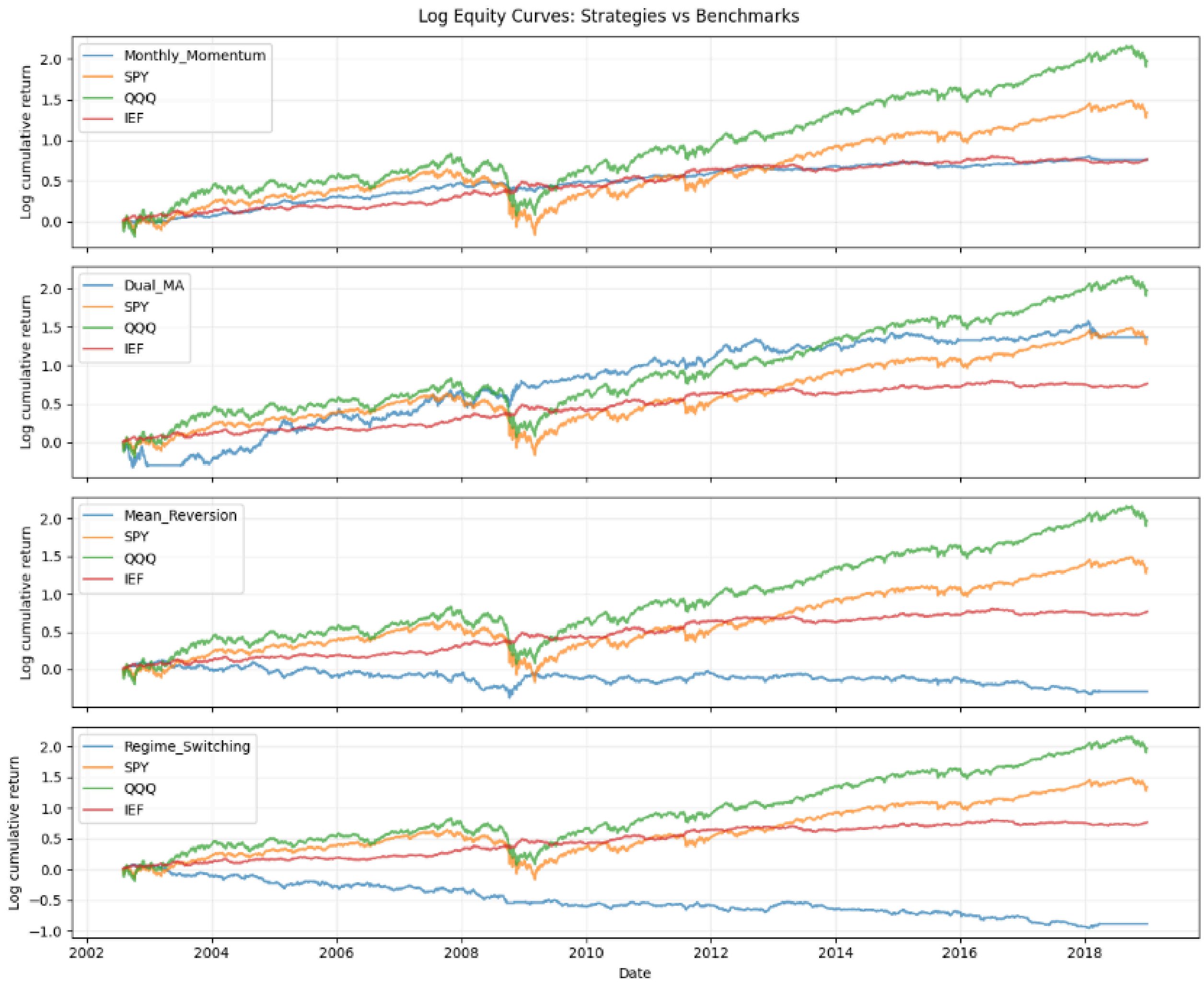

Fig.2. *The algo trading strategies could not beat the index buy-and-hold. However, the momentum-based strategies had much less drawdown during the 2008 crisis.*

5.5. Summary

The experiment implemented and backtested three base strategies—monthly momentum (Clenow), dual moving-average momentum, and short-horizon z-score mean reversion—plus a regime-switching allocator that de-risks under stress and toggles sleeves using a BRK-A market proxy. Over 1998–2018, momentum delivered stronger compounding in trending regimes but larger drawdowns around reversals, while mean reversion produced steadier, lower-volatility returns with capped upside; the regime allocator was the most resilient in volatile periods by cutting exposure and engaging the appropriate sleeve. Benchmarks (SPY/QQQ/IEF/BRK-A via yfinance) were used for external comparison, with the caveat that Quandl/WIKI coverage ends in 2018.

5.6. Code References

1. Andrea Clenow. Momentum portfolio construction and factor investing concepts.
2. ZiplineReloaded (Stefan Hansen). Documentation and example algorithms, including dual MA.

3. PyFolio / Empirical. Performance analytics for backtests.
4. Yahoo Finance (yfinance). External benchmark data for SPY/QQQ/IEF/BRKA plots/tables.

5.6. Use of AI Assistance

AI tools were used to assist with code drafting, documentation, and summarization. All content was reviewed and validated by the author; no confidential data was shared. Analytical conclusions and implementation choices remain the author's responsibility.