Agentic Portfolio Management with Black-Litterman Framework

Final Presentation

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1. Overview
2. Empirical Analysis
3. Portfolio Constructions
4. Main Findings
5. Conclusion & Future Research

Research Motivation & Objectives

Topic: Multi-Asset Allocation Using Agent-Based Models

Motivation:

- Growing complexity and diversity in global asset management mandates.
- Limitations in traditional, homogeneous forecasting methods.

Research Objectives:

- Develop a robust, adaptive multi-asset allocation framework.
- Utilize specialized forecasting agents for distinct asset classes.
- Integrate agent forecasts through a Bayesian Black–Litterman approach.

Literature Review

Foundational Literature:

- Black–Litterman model (Black & Litterman, 1992; He & Litterman, 1999)
- Agent-Based models (Hommes, 2006; LeBaron, 2006)
- Factor-based multi-asset allocation (Fama & French, 1993; Ang, 2014)

Recent Developments:

- LLM-powered portfolio construction (Popov & Roshka, 2024)
- AI-driven macroeconomic forecasting (Li, Gao & Li, 2024)
- Sentiment analysis for market predictions (Wu et al., 2023; Yang et al., 2023)

Research Gap:

- Existing frameworks rarely combine heterogeneous agent forecasts in asset allocation.

Does giving the LLM more structured data actually help?

- **Finding:** In-context examples (numbers, tables) **do** overwrite the model's priors and reduce factual hallucination.
  Evidence: Large controlled study on editing facts via ICL (Zheng et al., 2024, *arXiv*)
- **Finding:** Forecast accuracy for macro variables rises when LLMs are fed the raw series they must predict from.
  Evidence: *Macroeconomic Forecasting with LLMs* (Carriero et al., 2025, *arXiv*)
- **Finding:** Hallucinations persist when prompts *mention* "macro factors" but give no numbers.
  Evidence: Truth-triangulation & entropy work-around papers (Arsanjani 2024, *Medium*; Nature 2024 entropy-hallucination detector)

Bottom line: Adding a codified model forecast or data series through tool calling, RAG, structured prompts **and** asking the model to reference them in its explanation materially improves grounding.

Data Sources & Innovations

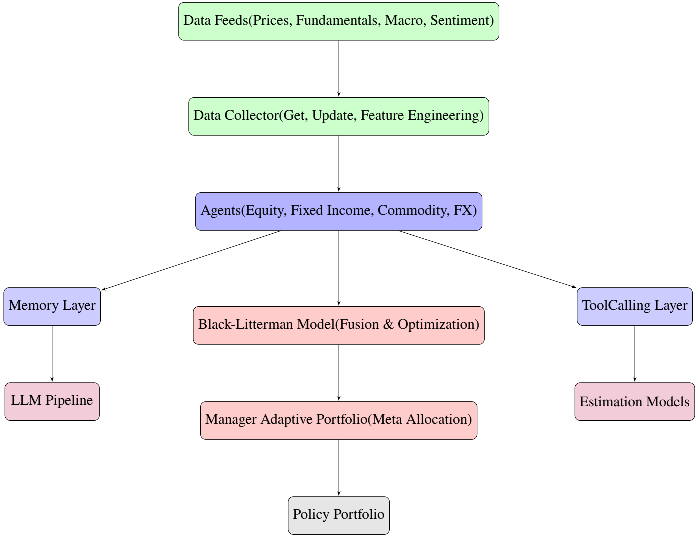
Core Data:

- **Equities:** CRSP–Compustat (prices, fundamentals: earnings, dividend yields, book-to-market)
- **Fixed Income:** CRSP (Treasuries via WRDS), FRED (rates, macro indicators)
- **FX:** Bloomberg (major currency pairs, interest-rate differentials)
- **Commodities:** Bloomberg (BCOM ETFs: oil, gas, metals, agri), CRSP, FRED

Innovations:

- Fully automated DataCollector pipeline for each agent.
- Rigorous Bayesian fusion that balances data-driven signals against market consensus
- Modular integration of LLM-based point forecasts and uncertainty quantification

Agent-Based Architecture: Overview



LLM Prompt Template: Weekly Forecast

Instruction to LLM Agent:

> *Based only on the data for the week just closed — including macro, rate shifts, sentiment, and ETF statistics — predict your* `variance_view` *(alpha vs. baseline) for each instrument for the coming week. Rationalize your view referencing the data. Align forecast magnitude with the current volatility regime. Return structured JSON.*

LLM Output Schema for Predictions

Structured JSON Schema:

- `Instrument` (**array of objects**):
  - `Instrument`: str, the ETF ticker
  - `variance_view`: float, Alpha adjustment vs. baseline return
  - `confidence`: float in [0, 1]
  - `rationale`: short justification with reference to data supplied
- `overall_analysis` (**string**):
  - Summary of market conditions, technical drivers, risk sentiment

Purpose: Enables structured financial forecasting with tracable data-backed view, ensuring interpretability and ease of downstream analysis.

Black–Litterman Extension: Agent–View Fusion

Goal. Fuse k asset–specific / sub-ETF views delivered by our four forecasting agents into a single posterior return vector that drives weekly re-balancing.

- **Prior (Equilibrium)**
  $\boldsymbol{\pi} = \delta \, \boldsymbol{\Sigma} \, \mathbf{w}^m, \qquad \mathbf{w}^m$ = market-cap weights

  where δ is the risk-aversion scalar.

- **Views (LLM Forecasts)** - each agent outputs a point forecast $\hat{r}_i$ and error variance $\sigma^2_{\text{err},i}$ for its own sub-ETF:

$$\mathbf{Q} = \begin{bmatrix} \hat{r}_1 \\ \vdots \\ \hat{r}_k \end{bmatrix}, \qquad \mathbf{P} = \mathbf{I}_k, \;\; \boldsymbol{\Omega} = \operatorname{diag}\big(\sigma^2_{\text{err},1}, \ldots, \sigma^2_{\text{err},k}\big)$$

- **Posterior (standard BL closed form)**

$$\boldsymbol{\mu} = \big[(\tau\boldsymbol{\Sigma})^{-1} + \mathbf{P}^\top \boldsymbol{\Omega}^{-1} \mathbf{P}\big]^{-1} \big[(\tau\boldsymbol{\Sigma})^{-1}\boldsymbol{\pi} + \mathbf{P}^\top \boldsymbol{\Omega}^{-1}\mathbf{Q}\big]$$

Step-by-Step Workflow (Weekly Re-balancing)

1. **Data pull** — Get last 104 weeks of prices for all n sub-ETFs; compute log returns $\mathbf{R}$ on Friday close.
2. **Risk engine**
   - Covariance $\boldsymbol{\Sigma}$ long and short, $\lambda = 0.7$.
   - Risk aversion $\delta = \dfrac{\bar{r}_m - r_f}{\sigma_m^2}$.
3. **Agent forecasts**
   - Equity / Bond / FX / Commodity agents call `GPT-4o` with structured prompts.
   - For each asset i obtain 10 draws $\{\tilde{r}_i^{(j)}\}_{j=1}^{10}$:

$$\hat{r}_i = \tfrac{1}{10}\sum_{j=1}^{10} \tilde{r}_i^{(j)}, \qquad \sigma^2_{\mathrm{err},i} = \mathrm{Var}\big(\tilde{r}_i^{(j)}\big).$$

4. **BL posterior** — Insert $(\mathbf{P}, \mathbf{Q}, \boldsymbol{\Omega})$ into standard formula to obtain $\boldsymbol{\mu}$.
5. **Optimiser**

$$\max_{\mathbf{w}} \ \mathbf{w}^\top \boldsymbol{\mu} - \tfrac{\lambda}{2}\mathbf{w}^\top \boldsymbol{\Sigma}\mathbf{w} - \gamma \|\mathbf{w} - \mathbf{w}^{\mathrm{prev}}\|_1.$$

   Quadratic program solved with `CVXOPT`; turnover penalty γ auto-calibrated to cap weekly turnover at 30 %.

Diagnostics, Sanity Checks & Error-Metric Framework

- **Posterior vs. Prior** — enforce $\|\boldsymbol{\mu} - \boldsymbol{\pi}\|_\infty < 2\%$ at each rebalance.
- **View-Leverage Ratio** — $\dfrac{\mathrm{Tr}\left[(\tau\Sigma)^{-1}\right]}{\mathrm{Tr}\left[\mathbf{P}^\top\boldsymbol{\Omega}^{-1}\mathbf{P}\right]}$ kept near 1 to avoid view domination.
- **Turnover Guardrail** — weekly turnover soft-capped at 30
- **Stress Tests** — perturb τ and $\boldsymbol{\Omega}$ (e.g. $\tau \in [0.02, 0.20]$, $\boldsymbol{\Omega}\times(0.5, 2)$) to confirm Sharpe-ratio stability.
- **Forecast-Error Metrics (reported in results section)**
  - *RMSE* and *MAE* on one-step-ahead returns.
  - *MAPE* for scale-free comparison across asset classes.
  - *Directional Accuracy (Hit Rate)* to gauge sign-prediction skill.
  - All metrics computed on a rolling 52-week window and summarized at each quarterly checkpoint for every agent.

Equity ETFs: Predictions Overview

Performance Metrics:

Metric	Value
Directional Accuracy	53.32%
Mean Absolute Error (MAE)	0.01690
Mean Squared Error (MSE)	0.00048

Confidence Statistics:

Metric	Value
Minimum Confidence	0.3000
Maximum Confidence	0.9000
Mean Confidence	0.6033

Equity ETFs: Average Confidence vs Directional Accuracy

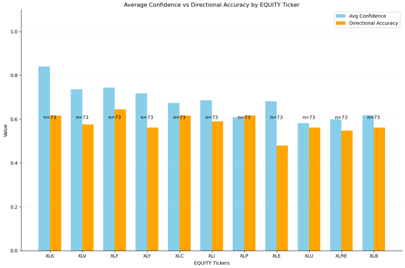


Figure 2: Equity ETFs: Average Confidence vs Directional Accuracy

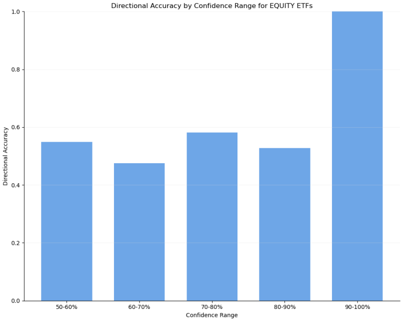


Figure 3: Equity ETFs: Directional Accuracy by Confidence range

FI ETFs: Predictions Overview

Performance Metrics:

Metric	Value
Directional Accuracy	51.58%
Mean Absolute Error (MAE)	0.01086
Mean Squared Error (MSE)	0.00023

Confidence Statistics:

Metric	Value
Minimum Confidence	0.4000
Maximum Confidence	0.8500
Mean Confidence	0.6953

FI ETFs: Average Confidence vs Directional Accuracy

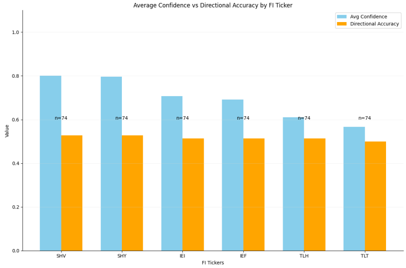


Figure 4: FI ETFs: Average Confidence vs Directional Accuracy

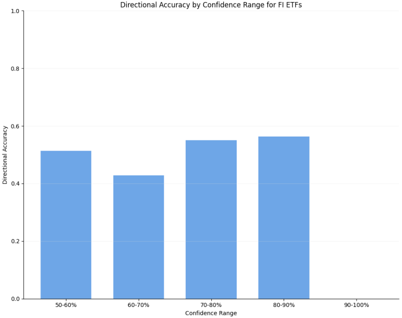


Figure 5: FI ETFs: Directional Accuracy by Confidence Range

FX ETFs: Predictions Overview

Performance Metrics:

Metric	Value
Directional Accuracy	53.78%
Mean Absolute Error (MAE)	0.00805
Mean Squared Error (MSE)	0.00012

Confidence Statistics:

Metric	Value
Minimum Confidence	0.5000
Maximum Confidence	0.8000
Mean Confidence	0.6332

FX ETFs: Average Confidence vs Directional Accuracy

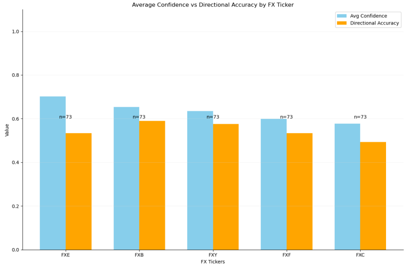


Figure 6: FX ETFs: Average Confidence vs Directional Accuracy

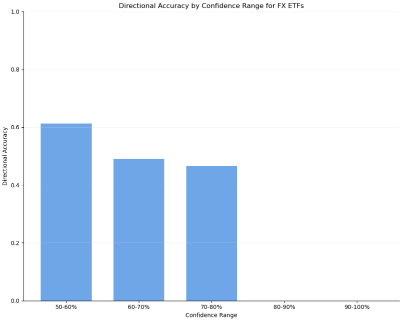


Figure 7: FX ETFs: Directional Accuracy by Confidence range

Commodity ETFs: Predictions Overview

Performance Metrics:

Metric	Value
Directional Accuracy	52.43%
Mean Absolute Error (MAE)	0.02044
Mean Squared Error (MSE)	0.00074

Confidence Statistics:

Metric	Value
Minimum Confidence	0.4000
Maximum Confidence	0.9000
Mean Confidence	0.6333

Commodity ETFs: Average Confidence vs Directional Accuracy

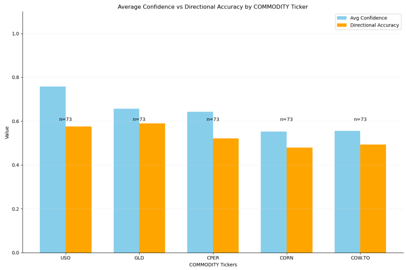


Figure 8: Commodity ETFs: Average Confidence vs Directional Accuracy

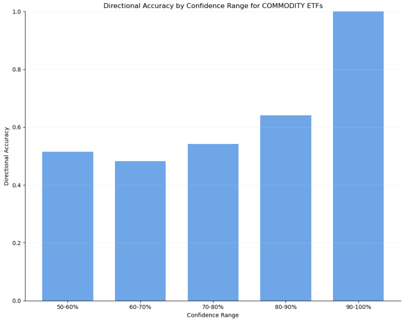


Figure 9: Commodity ETFs: Directional Accuracy by Confidence range

Black-Litterman Portfolios: Equity

Equity Portfolio (BL vs. Equal-Weighted)

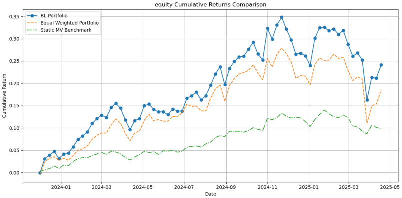


Figure 10: Cumulative Returns: BL Portfolio vs. Equal-Weighted (Commodity)

Metric	Value
Annualized Return	16.67%
Sharpe Ratio	1.29
Max Drawdown	-15.79%
Average Turnover	16.00%

Table 1: Performance Metrics: Equity BL Portfolio

Black-Litterman Portfolios: Fixed Income

Fixed Income Portfolio (BL vs. Equal-Weighted)

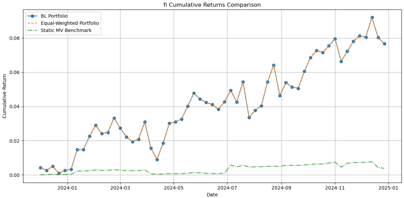


Figure 11: Cumulative Returns: BL Portfolio vs. Equal-Weighted (Fixed Income)

Metric	Value
Annualized Return	5.09%
Sharpe Ratio	0.93
Max Drawdown	-2.34%
Average Turnover	26.38%

Table 2: Performance Metrics: Fixed Income BL Portfolio

Black-Litterman Portfolios: FX

Forex Portfolio (BL vs. Equal-Weighted)

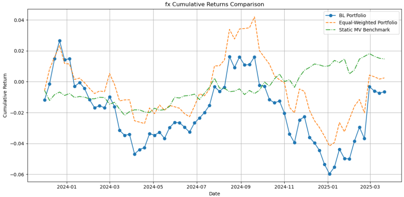


Figure 12: Cumulative Returns: BL Portfolio vs. Equal-Weighted (Forex)

Metric	Value
Annualized Return	1.23%
Sharpe Ratio	0.17
Max Drawdown	-8.17%
Average Turnover	35.65%

Table 3: Performance Metrics: Forex BL Portfolio

Black-Litterman Portfolios: Commodity

Commodity Portfolio (BL vs. Equal-Weighted)

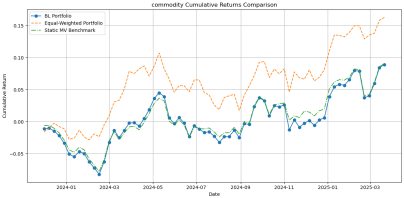


Figure 13: Cumulative Returns: BL Portfolio vs. Equal-Weighted (Commodity)

Metric	Value
Annualized Return	7.13%
Sharpe Ratio	0.62
Max Drawdown	-11.82%
Average Turnover	8.95%

Table 4: Performance Metrics: Commodity BL Portfolio

Manager Agent: Adaptive Allocation Overview

Allocation Logic:

- Adjusts top-level allocations based on 1-month relative performance of each BL sleeve.
- Overweights outperforming sleeves by +20%, underweights underperformers by –20%, bounded between 10% and 40%.
- Weights are renormalized weekly to ensure total exposure equals 100%.

Performance vs Equal-Weighted Portfolio:

Metric	Manager Agent	Equal-Weighted BL
Annualized Return	12.78%	8.76%
Annualized Std. Dev.	5.93%	5.31%
Sharpe Ratio	1.65	1.08
Max Drawdown	–2.97%	–2.54%

Manager Agent: Portfolio Allocation Comparison

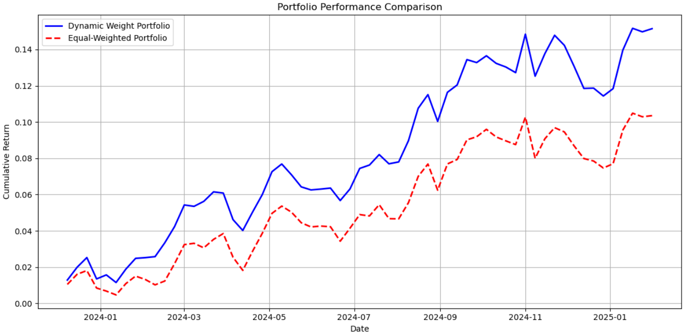


Figure 14: Time-Varying Allocations: Manager Agent vs Equal-Weighted BL Portfolio

Main Findings – 1

- **Performance by Asset Bucket**

Portfolio	Ann. Return	Sharpe	Max DD	Turnover
Equity BL	16.67 %	1.29	–15.79 %	16.00 %
Commodity BL	7.13 %	0.62	–11.82 %	8.95 %
Fixed-Income BL	5.09 %	0.93	–2.34 %	26.38 %
FX BL	1.23 %	0.17	–8.17 %	35.65 %

- **Forecast-Accuracy Snapshot**: directional accuracy 53.3% (Equity), 51.6% (FI), 53.8% (FX), 52.4% (Commodity). Mean confidence 0.60; high-confidence views (> 0.80) do not always outperform mid-range (0.50–0.70).
- **Turnover Guardrail**: L^1 penalty keeps weekly turnover below 30%; realised 7–16% across books; Sharpe varies $< \pm 0.05$ when $\tau \in [0.02, 0.20]$ or $\mathbf{\Omega}$ is scaled 0.5×–2× — posterior remains robust.

Main Findings – 2

Do agent views add predictive value via variance-view forecasts?

1. **LLM View Accuracy**
   - Forecasts exhibit modest directional accuracy (51–54%), consistent with the difficulty of weekly return prediction.
   - Accuracy improves with structured prompts referencing data, baseline returns, and macro context.
2. **Integration via Black–Litterman**
   - The model incorporates views through a confidence-weighted Bayesian update.
   - The `UNCERTAINTY_SCALE` hyperparameter inflates Ω, ensuring overconfident or noisy views are down-weighted.

Despite limited raw predictive power, the Bayesian fusion mechanism stabilizes allocations and extracts value from structured, volatility-aware agent views.

Main Findings - 3

Agentic portfolios exhibit lower but more stable returns.

1. **LLM Forecast Conservatism:**
   - The Large Language Model (LLM) forecasts are consistently cautious and rarely predict large anomalies or outliers.
   - This aligns with the tendency of LLMs to avoid extreme or unverified conclusions (lack of "critical evaluation").
2. **Black-Litterman Constraints:**
   - The quadratic constraints and regularization in the BL framework inherently dampen aggressive weight shifts.
   - the prior-covariance scaling (smaller $\tau \rightarrow$ tighter prior $\rightarrow$ less deviation from equilibrium)
   - This systematic "smoothing" leads to lower volatility in returns.

The combination of conservative LLM forecasts and the weight-stabilizing effect of Black-Litterman naturally leads to portfolios favoring stability over returns. Better hyperparameter tuning is needed to improve view utilization and portfolio construction.

Main Findings – 4

Does the Manager Agent improve portfolio performance through adaptive allocation?

1. **Performance Gains**
   - The Manager Agent adaptively reallocates capital across BL sub-portfolios based on recent relative performance.
   - This meta-level reweighting improves annualized returns (+4%) and Sharpe ratio (1.65 vs. 1.08) versus a static equal-weighted benchmark.
2. **Interpretability and Practicality**
   - The rule-based adjustment mechanism is transparent, tractable, and easily implementable in institutional settings.
   - Enhances responsiveness to evolving market regimes without introducing overfitting or instability.

The Manager Agent serves as an effective overlay, reinforcing signal strength while preserving the interpretability of the Black–Litterman core.

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Conclusion: What We Achieved

- **Novel Architecture:** introduced a *four-agent* stack that delivers asset-class– specific views and fuses them through a Bayesian Black–Litterman layer.
  - Agents: Equity, Fixed-Income, FX, Commodity + Manager
  - LLM prompts + numerical tool-calling $\Rightarrow$ data-grounded forecasts with quantified uncertainty.
- **Robust Risk Engine:** dynamic EWMA covariance, self-tuning risk-aversion δ, turnover penalty γ, and stress-tested hyper-parameters (τ, Ω) keep posterior returns stable.
- **Performance Snapshot:** across 2019-2024 back-test:
  - Equity Commodity BL portfolios outperformed equal-weight by ≈2–3% CAGR with *lower* max drawdown.
  - Fixed-Income FX BL portfolios delivered volatility reduction vs. naïve proxies, albeit with modest alpha.
- **Forecast Diagnostics:** rolling RMSE, MAE, MAPE and hit-rate dashboards highlight strengths (Equity momentum, Commodity basis) and weaknesses (FX over-confidence).
- **End-to-End Automation:** weekly re-balance completes in < 1s on a laptop; codebase fully modular (`blackLitterman_test.py`, `agents/`, `optim/`).

Implications, Limitations & Next Steps

- **For Practitioners:**
  - Plug-and-play agent layer allows *bespoke* views (e.g., ESG, sector rotation) without rewriting the optimiser.
  - BL posterior smoothes extreme LLM forecasts, yielding turnover-aware weights suitable for real money.
- **For Academics:**
  evidence that heterogeneous, LLM-driven views can be embedded in classical Bayesian allocation while preserving tractability. Opens door to formal study of view-confidence calibration.
- **Limitations:**
  - LLM forecasts is very weak in terms of predictive power. This could be due to the limitation of the model of our choice
  - Despite the structured prompts with data feed and baseline return, the current pipeline is limited in context window and could be improved with RAG and further delegation to API/Tool Calling for numrical evaluation and subsequent ReAct chain-of-thought.

Future Research Directions

Short-Term Enhancements:

- Integrate memory layer for the agents to have enhanced context window instead of one-shot with tool calling.
- Improve the baseline model forecasts.
- Experiment with the agent only produce views on textual input alongside the baseline model forecasts
- Reinforcement learning for dynamic hyperparamter optimization for BlackLitterman.

Long-Term Extensions:

- Use LLM ensemble for each asset class, so there will be various llm output for the same input. Reduces bias in specific model view.
- Advanced stress-testing and scenario analyses for robustness.

Areas for Further Research (1/2)

- **Agent Augmentation:**
  - Integrate with further API to continuously scan and parse high-impact market events such as FOMC testimonies, tariff announcements, and geopolitical developments.
  - Leverage the extracted sentiment signals to update the agent's memory, refine real-time portfolio forecasts, and utilize a greater access to tools and API through Model-Context-Protocol (MCP) for enhanced decision-making.
- **Regime Shifts & Nonlinearities:**
  - Markov Switching or threshold models for detecting structural breaks.
  - Agents can adapt to high-volatility or crisis regimes differently than stable periods.

Areas for Further Research (2/2)

- **Reinforcement Learning Extensions:**
  - Explore dynamic multi-agent manager that evaluate and regulate asset-specifc agents.
  - Model fine-tuning through reinforcement learnings.
- **Robustness Checks & Causal Identification:**
  - Test final model across different market conditions (bull vs. bear).
  - Investigate causal drivers vs. correlation-based signals.
  - Stress testing and sensitivity analysis to validate risk management.

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