Thesis Week 2 Assignment

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Main Idea

The overarching goal of this thesis is to develop an **Agent-Based Black-Litterman (ABBL)** framework for *multi-asset allocation*. Traditionally, the Black-Litterman model from our **banchmark paper (Black & Litterman, 1992)** blends market equilibrium information (often proxied by market-cap weights) with investor "views" on expected returns to produce a posterior distribution of returns. Our proposed **agent-based extension** enriches this approach by introducing specialized forecasting agents for multiple asset classes—namely equities, fixed income, foreign exchange (FX), and commodities.

Each agent deploys a distinct modeling technique relevant to its asset class. For example, the equity agent may rely on both sector-based fundamentals and technical factor models; the fixed-income agent may focus on yield curve dynamics and inflation indicators; the FX agent leverages interest rate differentials and monetary policy signals; and the commodity agent incorporates supply-demand metrics and futures term structures. By aggregating these heterogeneous agent "views" in the spirit of the Black-Litterman model, the framework aims to **produce a unified multi-asset allocation** that adapts to changing market conditions while maintaining robust risk management.

In essence, the **original contribution** of this research is to *integrate multi-asset agent-based predictions with the Black-Litterman methodology in a coherent mathematical framework*. Unlike traditional approaches that might only include ad-hoc or single-asset forecasting, the ABBL model will systematically handle multiple layers of uncertainty, attach confidence levels to each agent's forecast, and compute a posterior return vector and covariance matrix for the overall portfolio. This extension **contributes to the literature** by showing how agent-based heterogeneity in views can be formally incorporated into a well-known mean-variance optimization scheme, potentially enhancing out-of-sample performance and risk control.

Literature Review

Black-Litterman Foundations The Black-Litterman approach (Black & Litterman, 1992; He & Litterman, 1999) has long served as a mainstay for portfolio optimization, providing a Bayesian framework that blends equilibrium returns with subjective views. Empirically, several studies (e.g., Satchell & Scowcroft, 2000) have examined how imposing systematic "views" on returns can improve diversification and out-of-sample performance compared to naive mean-variance approaches. However, classical Black-Litterman implementations typically assume that the investor's subjective views are generated by a single process or a homogeneous model, thus overlooking the possibility of merging diverse forecasting techniques under one coherent Bayesian structure.

Agent-Based Models in Finance Agent-based models have a rich history in the finance literature (Hommes, 2006; LeBaron, 2006). They are widely used to explain heterogeneous beliefs among market participants and the resulting market dynamics that deviate from purely rational expectations. In particular, agent-based models can capture the interplay among different investor types—fundamentalists, chartists, noise traders, etc.—and thus are well-suited for illustrating how market inefficiencies or regime shifts arise. While many studies in agent-based finance focus on simulating price dynamics or testing policy interventions, fewer works directly *integrate* the outputs of agent-based simulations into a *portfolio optimization* framework akin to Black-Litterman.

Multi-Asset Allocation and Factor Models Traditional multi-asset allocation methodologies often rely on factor-based approaches (Fama & French, 1993; Ang, 2014). These methods decompose returns into risk factor exposures (e.g., size, value, momentum for equities; term structure or credit spreads for fixed income). Although these factor-based methods can provide intuitive structure for multi-asset investment, they typically *do not* combine multiple specialized predictive models for each asset class within a single Bayesian updating mechanism. Moreover, classical factor models do not easily allow dynamic weighting of conflicting or *heterogeneous* beliefs across different asset classes.

Macro Activities Simulation Li, Gao, and Li (2024) introduce EconAgent, a large language model (LLM)-powered agent-based framework for simulating macroeconomic activities. Unlike traditional agent-based models (ABMs) that rely on fixed decision rules or reinforcement learning (Farmer & Foley, 2009; Zheng et al., 2022), EconAgent integrates LLMs to enhance agent heterogeneity, long-term memory, and adaptive decision-making. The framework constructs a dynamic simulation environment encompassing labor, consumption, financial markets, and government taxation, where agents make work and spending decisions based on perception, memory, and action modules. The model outperforms rule-based and learning-based baselines in reproducing realistic macroeconomic trends, such as inflation, unemployment, and GDP fluctuations, while also demonstrating Phillips Curve and Okun's Law correlations. Through external shock tests, including a simulated COVID-19 economic downturn, EconAgent exhibits human-like behavioral adaptation, reinforcing its potential for macroeconomic policy analysis. The study highlights LLMs' capacity to model complex economic behaviors, though challenges remain in incorporating firm dynamics and forecasting policy impacts.

LLM-Based Portfolio Construction Popov and Roshka (2024) develop FolioLLM, a domain-specific large language model (LLM) for ETF portfolio construction, advancing prior financial LLM applications (Yang et al., 2023; Wu et al., 2023). Unlike general models, FolioLLM integrates Retrieval-Augmented Generation (RAG), Low-Rank Adaptation (LoRA), and Kolmogorov-Arnold Networks (KAN) to enhance structured financial data processing and portfolio optimization. Trained on 12,224 ETFs and incorporating Markowitz's mean-variance optimization, it outperforms GPT-3.5 in generating higher-return, lower-volatility portfolios based on Sharpe ratios and Harmonic Portfolio Symmetry (HPS). While demonstrating AI's potential in wealth management, the authors address challenges in data quality, ethical risks, and regulatory needs, emphasizing responsible deployment of AI-driven investment tools.

Contribution and Extension Our research aims to *bridge* the gap between agent-based forecasting techniques and Bayesian portfolio construction. Specifically, we will:

- **Adapt the Black-Litterman framework** to incorporate multiple forecasting agents, each specialized in a particular asset class with unique data sources and predictive models.
- **Embed heterogeneity explicitly** by assigning different confidence levels to the agents' forecasts, reflecting their historical accuracy and market conditions.
- **Demonstrate comparative advantages** over both (i) standard Black-Litterman models relying on a single forecast source and (ii) simpler factor-based models that do not dynamically aggregate multi-asset views.

Hence, the main **novelty** lies in designing a flexible architecture that *systematically* reconciles heterogeneity from specialized agents with the equilibrium prior. In doing so, we contribute to the broader discussion on how to incorporate real-world complexity—such as different information signals, market frictions, and sentiment data—into robust portfolio management. By drawing on agent-based insights, we also situate our work at the intersection of the agent-based finance literature and practical asset allocation research.

Data Source

To implement and validate the Agent-Based Black-Litterman framework, we will employ **multi-asset data** from:

1. **WRDS (Wharton Research Data Services):** Historical equity returns, fundamental data such as balance sheet and income statement items, credit spreads, and macroeconomic indicators can be accessed here. We will primarily draw on datasets such as FRED (for macro indicators and fixed income), CRSP & Compustat (for equity returns), and Compustat (for company fundamentals) and CRB (for commodity).
2. **Bloomberg:** This platform is critical for real-time and historical data on fixed income (e.g., treasury yields, corporate bond yields, yield curve data), foreign exchange rates, commodity prices, and relevant technical indicators. Bloomberg also provides consensus macroeconomic forecasts and inflation outlook measures.
3. **Auxiliary Sources (Potential):**
    - *Central Bank Communications:* Textual or sentiment data from central bank announcements (e.g., Federal Reserve, ECB) used for constructing FX agents' monetary policy views.

- *News and Sentiment Indicators:* Third-party sentiment data vendors (e.g., RavenPack, Refinitiv) or self-trained models for capturing real-time news sentiment, which can be mapped to equity or macro signals.

Data cleaning and preprocessing steps will involve aligning frequency (e.g., daily or monthly), removing outliers, and adjusting for corporate actions in equity returns. We plan to create a **rolling window** structure for calibration, where each agent's predictive model is updated over time. For instance, the equity agent's fundamental signals may be refreshed quarterly, while the FX agent's macro signals could be updated monthly.

After each update, the specialized forecasts from all agents are fed into the Black-Litterman module, which aggregates these views with the market equilibrium prior. The entire process is then *backtested* over an out-of-sample period to evaluate portfolio performance and risk metrics. By combining robust data from WRDS, Bloomberg, and specialized providers, the thesis will ensure that the agent-based approach captures a realistic cross-section of market information, thus reinforcing the reliability and practical relevance of our ABBL framework.

Future Plans

Moving forward, we envision several avenues for expanding and refining the Agent-Based Black-Litterman (ABBL) framework:

- **Integration of LLM Agents for Economic Forecasting:** Inspired by *EconAgent* (Li et al., 2024), future work could incorporate large language models to simulate macroeconomic shocks and policy effects, thereby enriching the signals used by the ABBL agents.

- **Advanced Sentiment and News Data:** Following the successes of LLM-driven portfolio construction (Popov & Roshka, 2024) and AI-driven sentiment models (Wu et al., 2023), we can integrate real-time or event-driven sentiment analysis, refining how "views" are generated and updated in response to unfolding market events.

- **Regime Shifts and Nonlinear Dynamics:** Future iterations could explore dynamic regime-switching models or machine learning techniques to detect market shifts, applying specialized agent-based "views" tailored to different economic or volatility regimes.

- **Customization for ESG and Thematic Investing:** Another promising direction involves extending the model to account for environmental, social, and governance (ESG) factors or thematic strategies. By building specialized ESG or theme-based agents, we could incorporate sustainability or sector-based constraints into the ABBL framework.

By pursuing these directions, the ABBL model can evolve into a more holistic ecosystem for multi-asset investing—one that not only accounts for diverse data sources and agent heterogeneity but also adapts to structural changes in markets and emerging investment themes. These expansions align with a growing body of literature that employs ever more sophisticated agent-based and AI-driven methods for portfolio optimization and economic simulation (e.g., LeBaron, 2006; Li et al., 2024).

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