Title: Hybrid Financial Market Simulation: Bridging Stochastic and Agent-Based Models

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1. Purpose and Overview

Financial markets exhibit both stochastic randomness and structured trader behavior, making their price dynamics complex to model. Traditional models like Geometric Brownian Motion (GBM) capture random price fluctuations, while Agent-Based Modeling (ABM) simulates trader behavior and decision-making processes.

This project develops a hybrid model that integrates GBM and ABM to simulate financial markets more realistically by:
Modeling random external shocks using GBM.
Simulating heterogeneous agents (fundamentalists, chartists, contrarians, etc.) using ABM.
Introducing Markov Chains to allow agents to adapt their strategies dynamically.
Evaluating how price dynamics emerge due to the interaction of stochastic processes and agent-driven trading.

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2. Entities, State Variables, and Scales

2.1 Agents in the Model

The financial market consists of multiple trader types, each following a distinct trading strategy:

Agent Type	Trading Strategy
Fundamentalists	Buy as per is fundamental value, sell when price
Chartists (Trend-Followers)	Buy if the trend is positive, sell if negative
Contrarians (Reversal Traders)	Sell when price rises, buy when price drops
Noise Traders	Random buying and selling decisions
Institutional Traders	Trade in larger volumes based on fundamentals

2.2 Environment & State Variables

- **Stock Price (S_t):** The asset's price at time ttt.
- **Market Volatility (σ)**: Measures fluctuations in price.
- **Drift (μ)**: Expected return of the stock.
- **Agent Wealth**: Tracks capital held by each trader.
- **Agent Risk Preferences**: Determines how aggressively traders buy or sell.

2.3 Time Scale

- The simulation runs for 252 days (one trading year).
- Agents trade daily based on their strategies.

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3. Process Overview & Scheduling

3.1 Initialization

1. **200 agents** are created with assigned trading types based on probabilities.
2. **Stock price starts at $100**.
3. **GBM parameters (μ = 5%, σ =20%)** are initialized.

3.2 Trading Process (Daily Updates)

Each trading day:

1. **Agents decide whether to buy, sell, or hold**.
2. **Buy and sell orders are aggregated**.
3. **Stock price is updated using a Hybrid Equation**:

$$S_{t+1} = S_t * (1 + \mu dt + \sigma dW_t + \beta(agent\ impact))$$

4. **Agent types may change based on Markov Chain probabilities**.
5. **Repeat for 252 days**.

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4. Design Concepts

4.1 Theoretical Basis

- **GBM (Stochastic Process):** Captures random fluctuations.
- **ABM (Heterogeneous Agents):** Models strategic trading behavior.
- **Markov Chains:** Allows agents to adapt trading strategies over time.

4.2 Key Hypotheses

- **H1:** The hybrid model better reflects real-world price fluctuations than GBM alone.
- **H2:** The presence of chartists amplifies market bubbles and crashes.
- **H3:** Institutional traders reduce volatility by stabilizing prices.

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5. Implementation Details

- **Programming Language:** Python
- **Key Libraries Used:** NumPy, Matplotlib
- **Model Outputs:**
  - Stock price time series
  - Volatility clustering analysis
  - Agent behavior transition tracking

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6. Results & Model Validation

- The Hybrid Model shows more realistic price movements compared to pure GBM.
- Chartists & noise traders increase volatility, while fundamentalists & institutions stabilize it.
- Markov Chain transitions allow agents to adapt, making the model more dynamic.

Comparison: GBM vs. Hybrid Model

Feature	GBM Only	Hybrid Model (GBM + ABM)
Random Price Movements	Yes	Yes
Trader Behavior Impact	No	Yes
Volatility Clustering	No	Yes
Market Bubbles & Crashes	No	Yes
More Realistic Market Simulation?	No	Yes

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7. Conclusion & Future Work

7.1 Conclusion

- **Financial markets are not purely random—they are shaped by traders decisions.**
- **Hybrid models (GBM + ABM) capture both randomness and trader influence more accurately.**
- **Markov Chains allow traders to evolve over time, making the model dynamic.**
- **This approach provides a better foundation for risk management, algorithmic trading, and financial regulation studies.**

7.2 Future Improvements

Introduce AI-based traders using **reinforcement learning**.
Incorporate macroeconomic shocks (e.g., interest rate hikes, inflation).
Test different agent compositions (e.g., increase institutional traders to reduce volatility).
Apply this model to cryptocurrencies & forex markets.

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8. References:

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