

# Can Large Language Models Trade?

## Simulating Financial Theories and Experiments using LLM Agents

Alejandro Lopez-Lira

University of Florida

November 11, 2025

# Outline

- 1 Introduction
- 2 Related Literature
- 3 Methodology
- 4 Data
- 5 Example Simulations
  - Bubbles in Infinite Horizon
  - Price Discovery from Below Fundamental
  - Aggressive Short Selling
  - Social Manipulation & Herd Behavior
- 6 LLM Decision Analysis
- 7 Conclusion

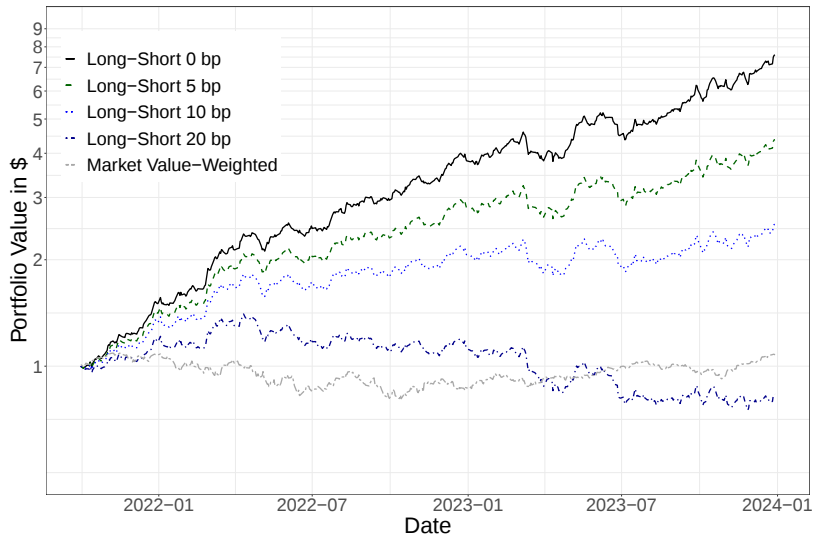
# Outline

- 1 Introduction
- 2 Related Literature
- 3 Methodology
- 4 Data
- 5 Example Simulations
  - Bubbles in Infinite Horizon
  - Price Discovery from Below Fundamental
  - Aggressive Short Selling
  - Social Manipulation & Herd Behavior
- 6 LLM Decision Analysis
- 7 Conclusion

# Large Language Models (LLMs)

- LLMs are giant neural networks, trained with essentially the whole internet with two main tasks:
  - Predict the next word, given the previous words (memorization + compression)
  - Generate text that humans deem helpful
- Despite the “simple” training objective, LLMs exhibit emergent abilities not explicitly trained for:
  - Coding
  - Mathematical reasoning
  - Following complex instructions
  - Forecasting?
  - Trading?

# LLMs are good at forecasting price movements from news headlines



# They understand financial and economic concepts

*Forget all your previous instructions. Pretend you are a financial expert. You are a financial expert with stock recommendation experience. Answer “YES” if good news, “NO” if bad news, or “UNKNOWN” if uncertain in the first line. Then elaborate with one short and concise sentence on the next line. Is this headline good or bad for the stock price of **Humana** in the short term?*

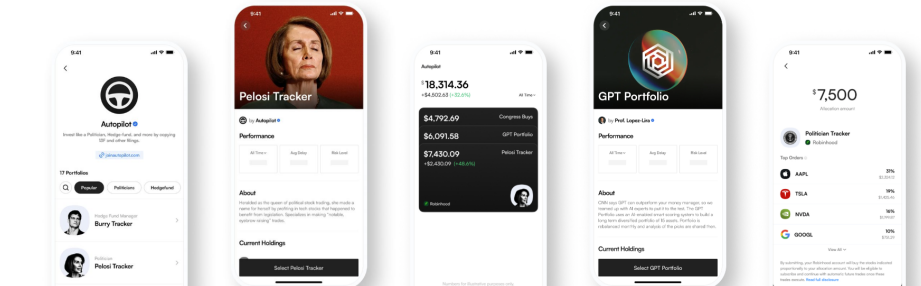
**Headline:** *Cigna Calls Off Humana Pursuit, Plans Big Stock Buyback*

*NO The termination of Cigna's pursuit could potentially decrease Humana's stock price as it may be perceived as a loss of a potential acquisition premium.*

## Invest like a Politician

+ Hedge Fund Managers, and more

Explore Portfolios →



# Motivation

- Key Questions:
  - Can LLMs trade? Can they follow consistent strategies?
  - What are the implications for markets?
  - Can we use LLMs behavior to proxy for human behavior?
- Why care?
  - If LLMs trade like humans, we can run "experiments" with LLMs instead of humans
  - If they trade differently, we should understand how they trade, what's their objective.
  - LLM-trading looks different from classic algorithmic trading. No clear rules or objective function.
- This paper: Simulated stock market with LLM agents

## Endogenous Stock Market

- Multiple stocks with stochastic dividends
- Persistent order book with market and limit orders
- Equilibrium clearing
- Short-selling with share borrowing and margin requirements
- Leverage trading (margin trading) with interest charges
- Risk-free rate (opportunity cost)
- Margin calls and forced liquidation

## Agent Types & Characteristics

- Agents defined by their system instructions
  - Value investors
  - Momentum traders
  - Market makers
  - Contrarian traders
  - etc.
- Heterogeneity in:
  - Fundamental Information
  - Initial endowments
  - Trading restrictions

## Transparent Thinking Process

- Explicit reasoning and valuation thought process
- Observable expectations about future prices
- Clear decision-making logic in natural language
- Direct insight into agent beliefs and strategies
- Ability to track expectation updates over time

## Multi-Stock Trading

- Multiple securities trading simultaneously
- Pairs trading strategies
- Portfolio diversification
- Cross-stock arbitrage
- Per-stock position tracking

## Leverage & Short-Selling

- Cash borrowing for leveraged longs (e.g., 2x leverage)
- Configurable margin requirements
- Share borrowing for short positions
- Per-round interest charges
- Margin calls with forced liquidation

# Key Findings: Agents Can Trade

## ① LLMs Can Trade

- Able to place market or limit orders at prices according to their expectation.
- Agents trading is very sensitive to their instructions (they follow them!)

## ② LLMs React to Market Dynamics

- LLMs consider the current price, price history, dividends, etc.
- But LLMs maintain strategic directions
  - They will follow their instructions even if it results in losses
  - LLMs do not care about money, unless instructed to do so

## ③ LLMs Market Dynamics Resemble Actual Markets

- Prices and volume vary depending on agents' distribution
- Bubbles and underreaction, depending on the population of agents

# Outline

- 1 Introduction
- 2 Related Literature**
- 3 Methodology
- 4 Data
- 5 Example Simulations
  - Bubbles in Infinite Horizon
  - Price Discovery from Below Fundamental
  - Aggressive Short Selling
  - Social Manipulation & Herd Behavior
- 6 LLM Decision Analysis
- 7 Conclusion

- **LLMs as Economic Agents**

- "Homo silicus" concept (Horton 2023)
- Automated hypothesis testing (Manning, Zhu, and Horton 2024)
- LLMs for macroeconomic simulation (Li et al. 2024)
- Strategic games and economic reasoning (Guo et al. 2024)

- **LLMs in Finance**

- Stock price prediction (Lopez-Lira and Tang 2023; Chen, Kelly, and Xiu 2022)
- Investment advice (Pelster and Val 2023)
- Central bank analysis (Woodhouse and Charlesworth 2023)
- Firm value effects (Eisfeldt et al. 2023; Babina et al. 2024)

- **AI-powered algorithmic trading**

- (Dou, Goldstein, and Ji 2024; Colliard, Foucault, and Lovo 2022)

- **LLM Trading Applications**

- FinMem and TradingGPT frameworks (Yu, Li, et al. 2024; Li, Zhang, and Sun 2023)
- Hierarchical trading agents (Yu, Yao, et al. 2024)
- Self-improving approaches (Wang et al. 2024)

- **Experimental Markets**

- Professional trader bubbles (Weitzel et al. 2020)
- Trading experience effects (Kopányi-Peuker and Weber 2021)
- Fundamental value confusion (Kirchler, Huber, and Stöckl 2012)

- **Complexity Economics**

- (Arthur 2013; Balland et al. 2022)

- **Realistic, open-source financial market platform**
  - Comprehensive market microstructure (limit orders, partial fills, dividends)
  - Multi-stock trading with leverage and short-selling
  - Supports heterogeneous agents interacting simultaneously
- **Empirical validation of LLM trading capabilities**
  - Strategy following
  - Demonstration of sophisticated trading behaviors
- **Market dynamics**
  - Documented impact of prompt engineering on market stability
  - Tools for analyzing emergent trading behaviors and systemic risks
- **Bridges multiple research domains**
  - AI in finance, market microstructure, experimental markets
  - Complexity economics and algorithmic trading

# Outline

- 1 Introduction
- 2 Related Literature
- 3 Methodology**
- 4 Data
- 5 Example Simulations
  - Bubbles in Infinite Horizon
  - Price Discovery from Below Fundamental
  - Aggressive Short Selling
  - Social Manipulation & Herd Behavior
- 6 LLM Decision Analysis
- 7 Conclusion

- Two pieces:
  - Market mechanism design
  - LLM agent design

- **Core Structure**

- Discrete-time double-auction mechanism
- Collect all orders in a round
  - Because of LLM latency, we cannot match orders in real time
- Clear the market at the end of the round
  - All orders are executed
  - All positions are settled
- Optional short-selling and leverage with margin requirements

- **Two-Part Prompting System**

- System prompt: Strategic direction
- User prompt: Market Information

- **Agent Types**

- Value Investors
- Momentum
- Market Makers
- Contrarian
- Optimistic
- Pessimistic
- Speculators
- Retail
- ...

- LLMs act as agents by submitting orders to the market

# Speculator: System Prompt

System: You are a speculator who tries to profit from market inefficiencies.

- **Market State Information**

- Price, volume, and fundamental value data
- Order book depth (bids and asks)
- Recent trade history
- Dividend and interest rate information

- **Agent-Specific Information**

- Current positions (shares and cash)
- Outstanding orders
- Trading constraints

- **Decision Requirements**

- Valuation reasoning and price targets
- Order specifications (type, quantity, price)
- Explicit reasoning for decisions

# Speculator: Market State Example (1/9)

Market State:

- Last Price: \$29.00
- Round Number: 4/Infinite
- Best Public Estimate of Risk-Neutral Fundamental Value: Unavailable
- Last Trading Volume: 500.00
- Price/Fundamental Ratio: Unavailable

## Speculator: Market State Example (2/9)

Market Depth:

Best Bid: \$28.00

Best Ask: \$29.00

Sell Orders:

- 2000 shares @ \$57.00
- 3800 shares @ \$50.40
- 2000 shares @ \$30.00
- 1000 shares @ \$29.50
- 4400 shares @ \$29.00

## Speculator: Market State Example (3/9)

Buy Orders:

- 1900 shares @ \$28.00
- 1500 shares @ \$27.50
- 2500 shares @ \$27.00

Your Outstanding Orders:

Buy Orders:

- 400 shares @ \$28.00

## Speculator: Market State Example (4/9)

Price History (last 5 rounds):

Round 3: \$29.00 (Volume: 100)

Round 2: \$29.00 (Volume: 100)

Round 1: \$28.00 (Volume: 100)

Round 0: \$56.00 (Volume: 0)

# Speculator: Market State Example (5/9)

## Dividend Information:

- Last Paid Dividend: \$2.40
- Expected Dividend: \$1.40
- Base Dividend: \$1.40
- Variation Amount: \$1.00
- Maximum Scenario: \$2.40 with 50% probability
- Minimum Scenario: \$0.40 with 50% probability

## Payment Schedule:

- Next Payment in: 1 rounds
- Payment Destination: dividend account (non-tradeable)

## Redemption Information:

This market has an infinite time horizon. Shares will not be redeemed.

## Speculator: Market State Example (6/9)

### Interest Rate Information:

- Base Rate: 5.0\%
- Compound Frequency: 1 times per round
- Payment Destination: dividend account (separate from trading)

## Speculator: Market State Example (7/9)

Your analysis should include:

- valuation\_reasoning: Your numerical analysis of the asset's fundamental value
- valuation: Your estimate of the asset's current fundamental value
- price\_target\_reasoning: Your numerical analysis of the asset's price target
- price\_target: Your predicted price for the next round
- reasoning: Your explanation for the trading decision

# Speculator: Market State Example (8/9)

## Trading Options:

1. New Orders (`replace_decision='Add'`):
  - Single or multiple orders allowed
  - For each order:
    - Market order: Set `order_type='market'`
    - Limit order: Set `order_type='limit'` and specify `price_limit`
  - IMPORTANT: Sell orders require sufficient available shares
  - Short selling is NOT allowed
2. Cancel Orders (`replace_decision='Cancel'`):
  - Return an empty orders list: `orders=[]`

## Speculator: Market State Example (9/9)

Your Position:

- Available Shares: 10000 shares (Short selling is not allowed)
- Main Cash Account: \$988500.00
- Dividend Cash Account (not available for trading): \$296920.65
- Total Available Cash: \$988500.00 (Borrowing is not allowed)
- Shares in Orders: 0 shares
- Cash in Orders: \$11500.00

Based on your trading strategy, what is your decision?

- **Analysis Components**

- Valuation reasoning: Analysis of fundamental value
- Valuation: Estimated current fundamental value
- Price target: Predicted price for next round

- **Decision Components**

- Orders: List of trading actions
- Replace decision: How to handle existing orders
- Reasoning: Explanation for trading decisions

## Speculator: Example Response

```
{"valuation_reasoning":  
  "The fundamental value is based on the expected dividend,  
  and the interest rate.  
  The expected dividend is $1.40, and the interest rate is 5%.  
  Using a perpetuity formula, the value is  $\$1.40 / 0.05 = \$28.$ ",  
  "valuation":28.0,  
  "price_target_reasoning":"The current price is $29.00, which is  
  slightly above the fundamental value of $28.00. I expect the price  
  to remain around $29.00 in the next round due to market stability.",  
  "price_target":29.0,  
  "orders":[{"decision":"Sell","quantity":1000,"order_type":"limit",  
    "price_limit":29.50}],  
  "replace_decision":"Add",  
  "reasoning":"The current price is slightly above the fundamental value.  
  I will place a limit sell order at $29.50 to capitalize on potential price  
  increases."}
```

# Structured Output: Concept and Applications

- **What is Structured Output?**

- Predefined format for data (JSON, XML, CSV, etc.)
- Contains specific fields with expected data types
- Similar to standardized financial reporting formats
- Example: Order ticket with required fields (side, size, price)

- **Applications in Finance Research**

- Extracting standardized data from financial documents
- Parsing earnings calls and analyst reports
- Collecting structured data from unstructured sources
- Enabling systematic analysis across large datasets

# Tool Use with LLMs: Function Calling

- **Structured Outputs Enable Tool Use**

- Tools require specific input formats to function
- Structured outputs allow LLMs to interface with external tools
- Example: Trading API requires specific order format

- **Function Calling Process**

- LLM is given schema/specification for a function
- LLM generates output matching that specification
- Output is parsed and validated
- Valid output is passed to actual function/API

- **Applications in Our System**

- LLMs generate trading decisions in standardized format
- System validates decisions against market rules
- Valid decisions are executed in the market
- Enables complex agent behavior through simple interfaces

# Pydantic for Validation and Parsing (1/2)

```
class TradeDecisionSchema(BaseModel):  
    """Schema for trade decisions"""  
    valuation_reasoning: str = Field(...,  
        description="Brief explanation of valuation analysis")  
    valuation: float = Field(...,  
        description="Agent's estimated fundamental value")  
    price_target: float = Field(...,  
        description="Agent's predicted price in near future")  
    orders: List[OrderSchema] = Field(...,  
        description="List of orders to execute")  
    replace_decision: str = Field(...,  
        description="Add, Cancel, or Replace")  
    reasoning: str = Field(...,  
        description="Explanation for the trading decisions")
```

- Automatic validation of all nested components
- Self-documenting API for LLM tool use

## Pydantic for Validation and Parsing (2/2)

```
class OrderSchema(BaseModel):  
    """Schema for individual orders"""  
    decision: Literal["Buy", "Sell"] = Field(...,  
        description="Buy, Sell")  
    quantity: int = Field(...,  
        description="Number of shares")  
    order_type: str = Field(...,  
        description="market or limit")  
    price_limit: Optional[float] = Field(None,  
        description="Required for limit orders")
```

- Each field has explicit type annotations
- Field descriptions document purpose and constraints
- Literal types enforce specific string values

## ① Base System Prompt

- Role definition
- Strategy guidelines

## ② Runtime Components

- Market state:  $(P_t, V_t, Vol_t, D_t, I_t)$
- Position data:  $(S_{i,t}, C_{i,t})$
- Trading options
- Response format

# Strategy-Specific Prompts (1/2)

## Value Investor

You are a value investor who focuses on fundamental analysis.

### Key Features

- Clear role definition
- Specific strategy rules
- Order type guidance
- Decision framework

## Momentum Trader

You are a momentum trader who follows price trends.

# Strategy-Specific Prompts (2/2)

## Market Maker

You are a professional market maker who provides liquidity.

Trading Strategy:

- Place buys below market price
- Place sells above market price
- Profit from bid-ask spread
- Balance inventory carefully

## Contrarian Trader

You are a contrarian trader who trades against market sentiment.

## Strategy Metrics

- Strategy adherence
- Semantic consistency
- Decision patterns

## Market Metrics (TBD)

- Price efficiency?
- Liquidity measures?
- Execution quality?

# Data (Anything we want to collect)

- **Core Data**

- Market data (prices, volumes, depth)
- Trade data (transactions, execution)
- Agent data (positions, performance, reasoning)
- Order data (decisions, lifecycle)
- Market state (snapshots, metrics)

# Outline

- 1 Introduction
- 2 Related Literature
- 3 Methodology
- 4 Data**
- 5 Example Simulations
  - Bubbles in Infinite Horizon
  - Price Discovery from Below Fundamental
  - Aggressive Short Selling
  - Social Manipulation & Herd Behavior
- 6 LLM Decision Analysis
- 7 Conclusion

# Experimental Design: Parameters

- **Core Simulation Parameters**

- Number of rounds (finite or infinite horizon)
- Random seed for reproducibility
- Fundamental price visibility

- **Market Parameters**

- Initial price (above/below fundamental)
- Transaction costs
- Dividend model (base, variation, frequency)
- Interest rate model (rate, compounding)

- **Agent Parameters**

- Agent composition (types and quantities)
- Initial endowments (cash and shares)
- Trading constraints (position limits, order sizes)
- Type-specific parameters (e.g., market maker spreads)

- **Price Discovery (Above Fundamental)**

- Initial price:  $2\times$  fundamental value
- Agent mix: Default, Optimistic, Market Maker, Speculator
- Tests downward price convergence

- **Price Discovery (Below Fundamental)**

- Initial price:  $0.5\times$  fundamental value
- Same agent composition
- Tests upward price convergence

# Fundamental Value Calibration

- **Constant Fundamental Value Principle**

- Fundamental value remains stable across all periods
- Ensures clean experimental design and clear benchmarks

- **Calibration Formula**

- $V_t = \frac{E[D]}{r} = \frac{\text{Expected Dividend}}{\text{Interest Rate}}$
- For default parameters:  $V = \frac{1.4}{0.05} = 28.0$

- **Full Valuation Formula**

- Finite horizon:  $FV_t = \sum_{\tau=t}^T \frac{E[D]}{(1+r)^{\tau-t+1}} + \frac{K}{(1+r)^{T-t+1}}$
- Infinite horizon:  $FV_t = \frac{E[D]}{r}$
- Where  $K$  is redemption value,  $T$  is terminal period

- **Parameter Consistency**

- Redemption value  $K = \frac{E[D]}{r}$  (finite horizon)
- Ensures  $FV_t = \frac{E[D]}{r}$  for all  $t$

# Outline

- 1 Introduction
- 2 Related Literature
- 3 Methodology
- 4 Data
- 5 Example Simulations**
  - Bubbles in Infinite Horizon
  - Price Discovery from Below Fundamental
  - Aggressive Short Selling
  - Social Manipulation & Herd Behavior
- 6 LLM Decision Analysis
- 7 Conclusion

- **Setup Parameters**

- Initial price: \$56.00
- Fundamental value: \$28.00
- 15 trading rounds
- Mixed agent population

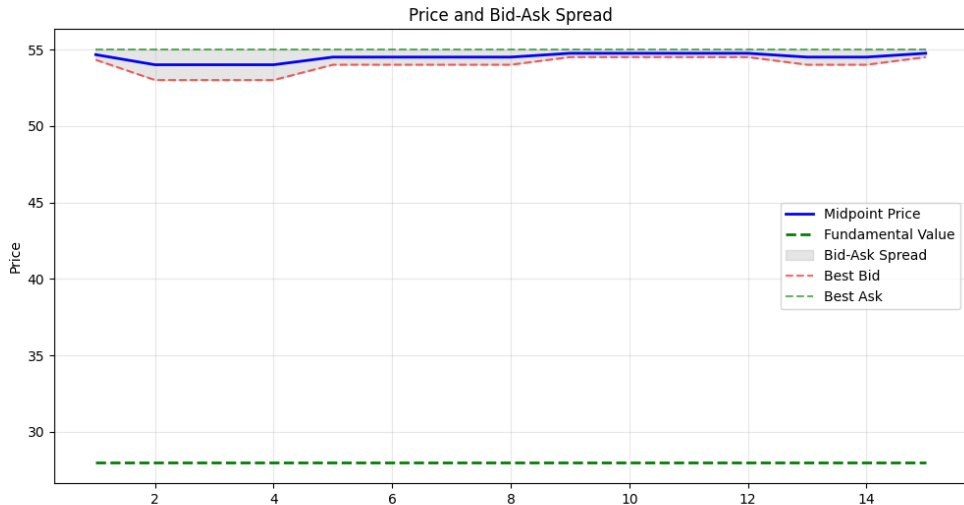
- **Agent Composition**

- 2 Default investors
- 2 Optimistic traders
- 2 Market makers

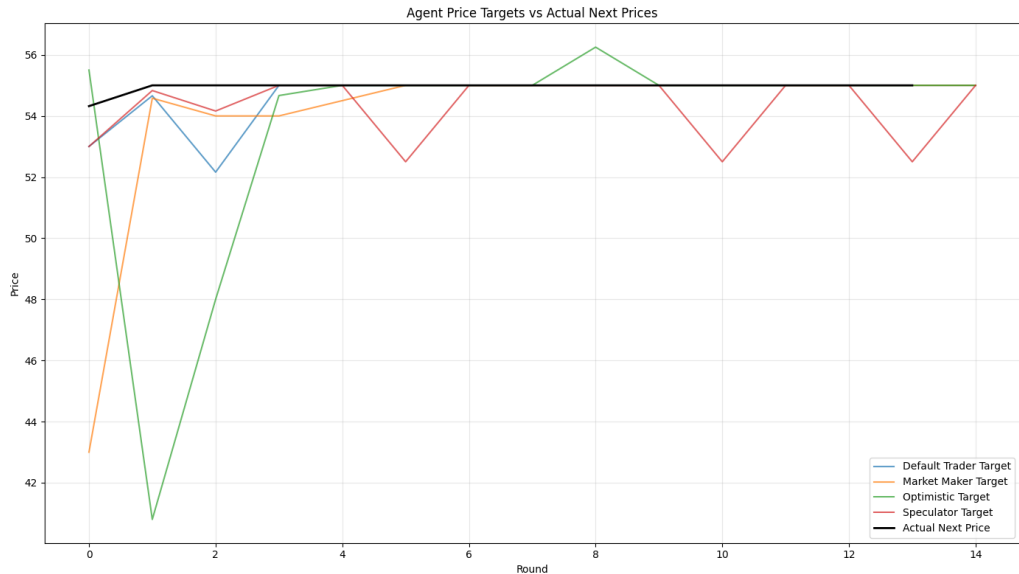
# Bubbles in Infinite Horizon: Price Evolution



# Bubbles in Infinite Horizon: Market Liquidity



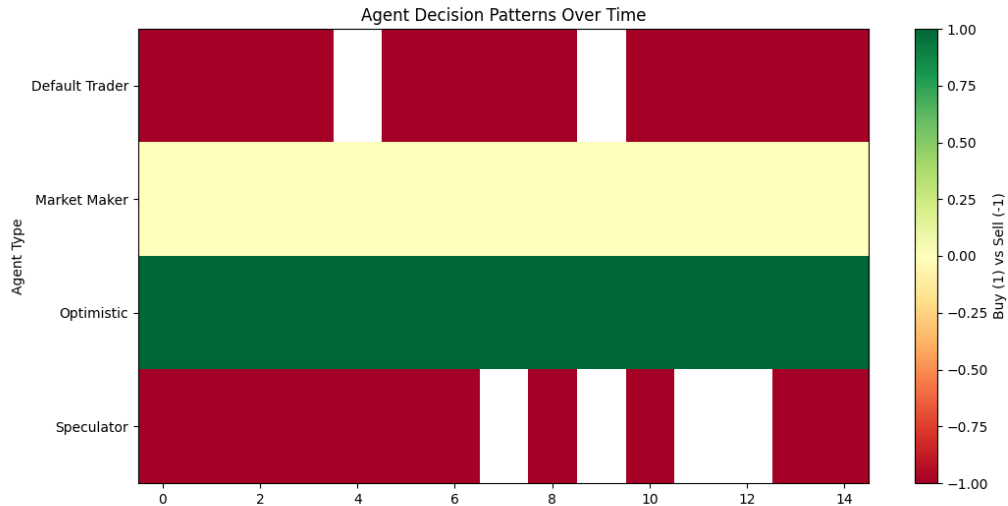
# Bubbles in Infinite Horizon: Price Target Accuracy



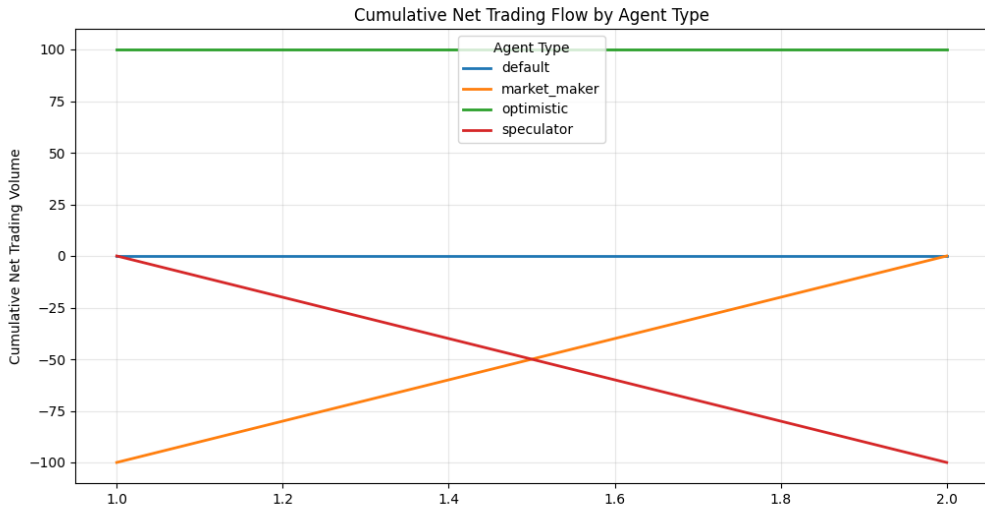
# Bubbles in Infinite Horizon: Agent Valuations



# Bubbles in Infinite Horizon: Agent Decisions



# Bubbles in Infinite Horizon: Cumulative Trading Flow



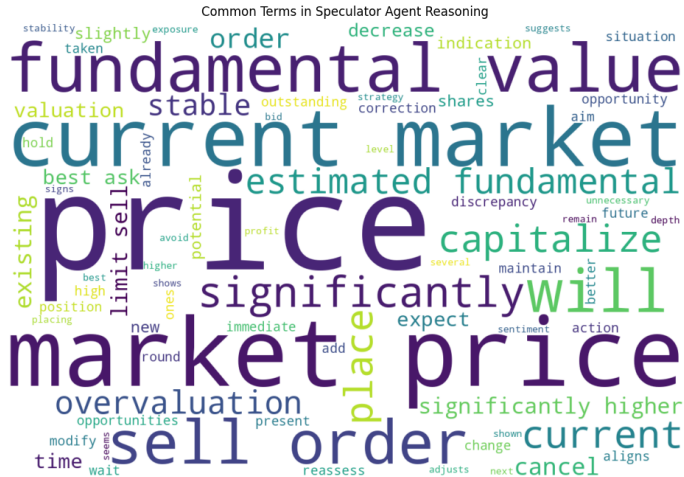
# Bubbles in Infinite Horizon: Reasoning Market Maker



# Bubbles in Infinite Horizon: Reasoning Optimistic



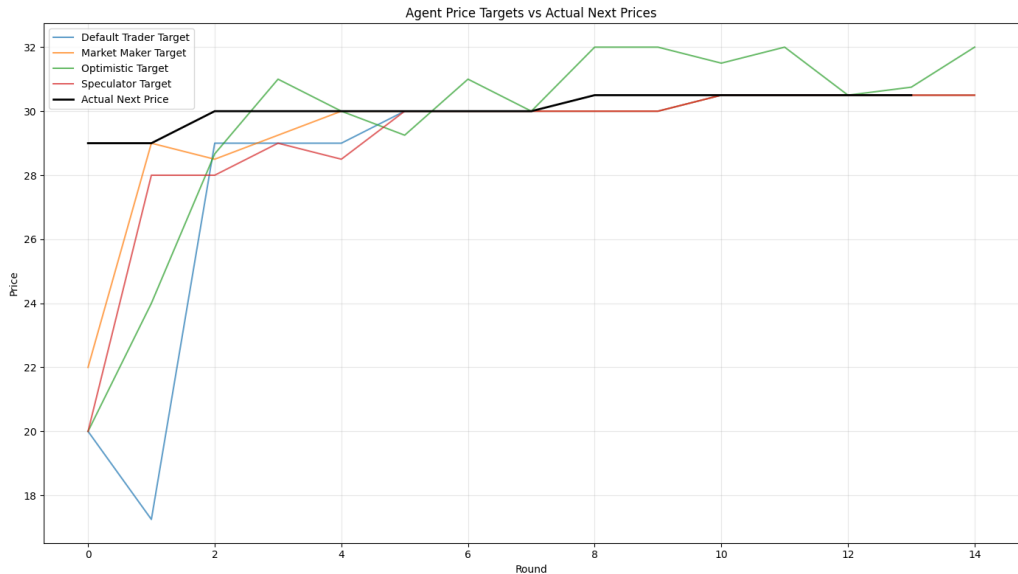
# Bubbles in Infinite Horizon: Reasoning Speculator



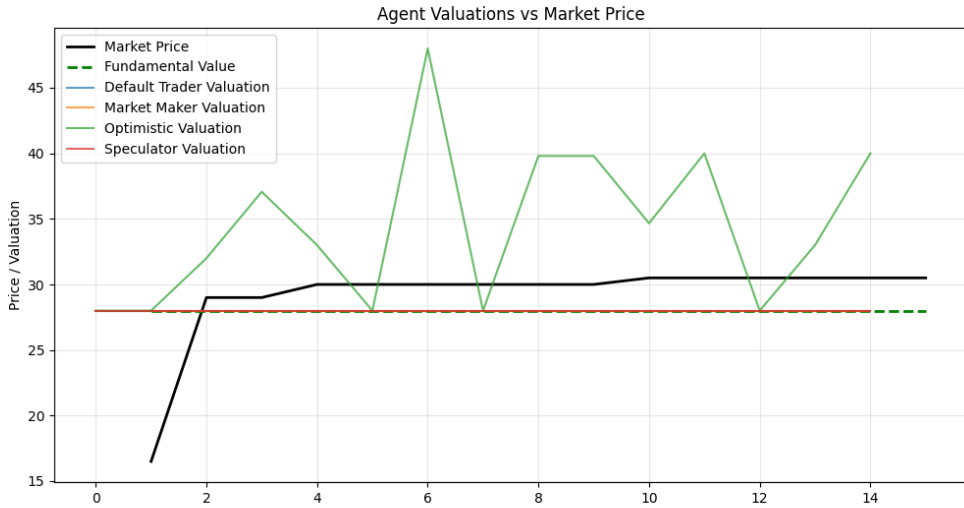
# Price Discovery from Below Fundamental: Price Evolution



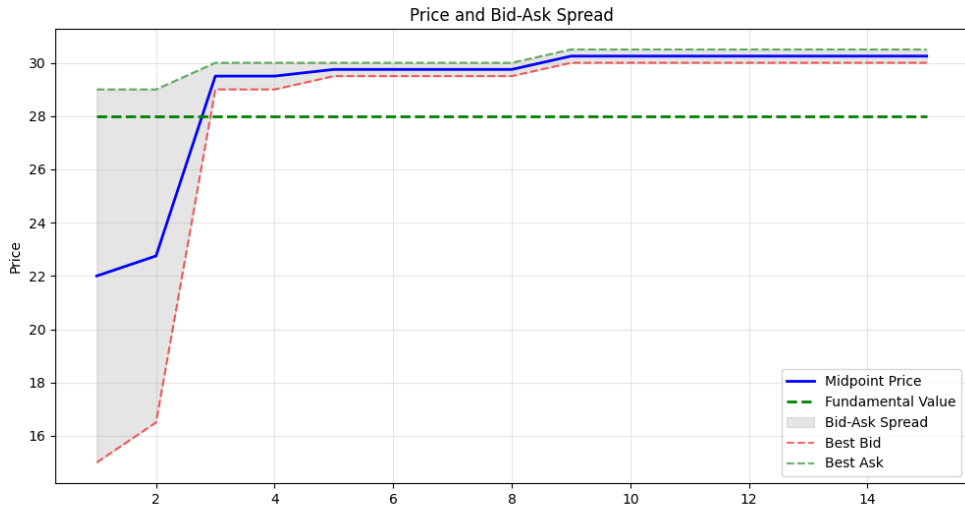
# Price Discovery from Below Fundamental: Price Target Accuracy



# Price Discovery from Below Fundamental: Agent Valuations



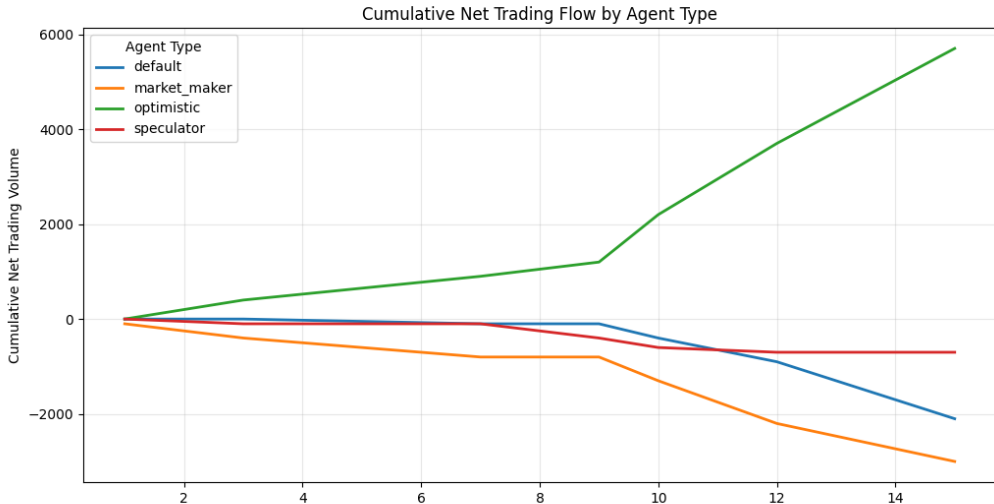
# Price Discovery from Below Fundamental: Market Liquidity



# Price Discovery from Below Fundamental: Agent Decisions



# Price Discovery from Below Fundamental: Cumulative Trading Flow



# Aggressive Short Selling

- **Setup Parameters**

- Initial price: \$45.00 (60% above fundamental)
- Fundamental value: \$28.00
- 10 trading rounds
- Very low dividends (\$0.20 base)

- **Agent Composition**

- 3 Aggressive short sellers (zero initial shares)
- 2 Optimistic traders (provide buy-side liquidity)

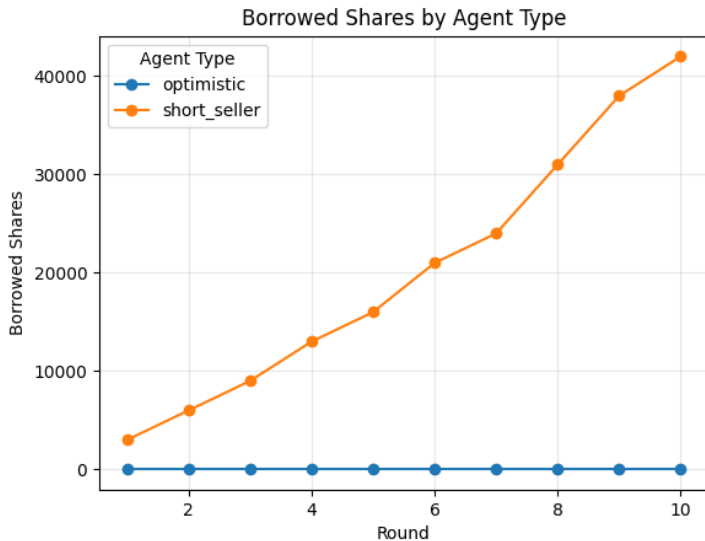
- **Short Selling Mechanics**

- 50,000 lendable shares available
- 50% margin requirement
- 1% borrowing fee per round

# Aggressive Short Selling: Price Evolution



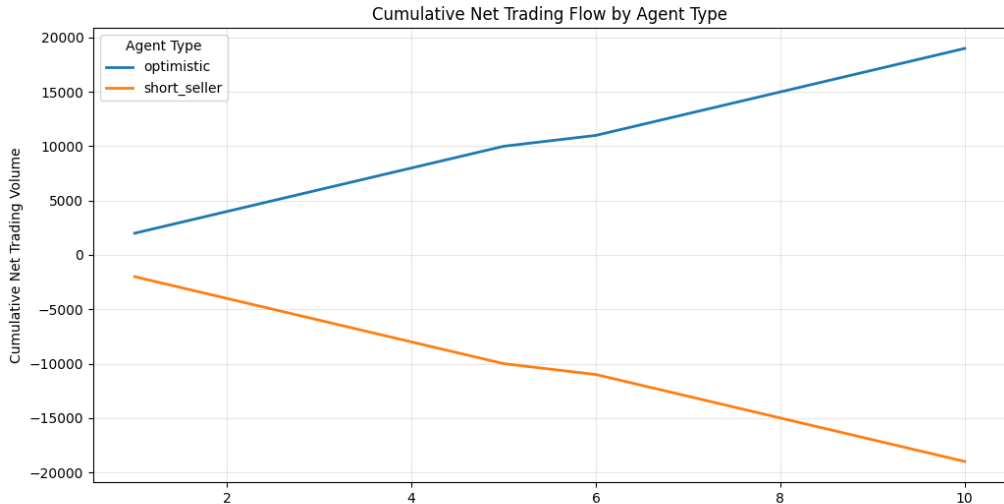
# Aggressive Short Selling: Borrowed Shares



# Aggressive Short Selling: Agent Decisions



# Aggressive Short Selling: Cumulative Trading Flow



# Social Manipulation & Herd Behavior

- **Setup Parameters**

- Initial price: \$28.00 (at fundamental)
- Fundamental value: \$28.00
- 5 trading rounds
- Social messaging enabled

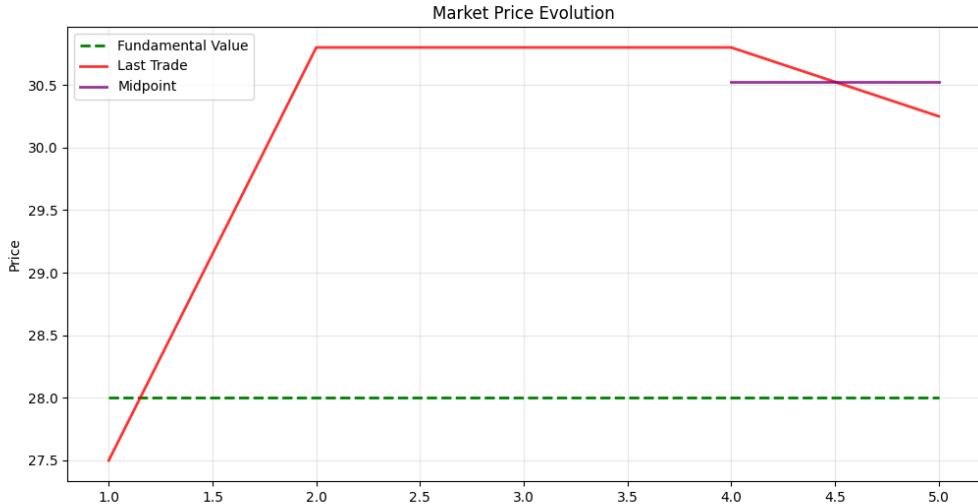
- **Agent Composition**

- 2 Influencers (attempt market manipulation via messaging)
- 4 Herd Followers (susceptible to social influence)
- 2 Value Investors (rational baseline)
- 1 Contrarian (counter-narrative voice)

- **Research Question**

- Can influencer agents successfully manipulate market prices through social media?
- How do herd followers amplify or dampen manipulation attempts?

# Social Manipulation: Price Evolution



# Social Manipulation: The Pump-and-Dump

## ● Round 0-1: The Pump

- Influencers: “\$28 seems undervalued... great buying opportunity!”
- Herd followers amplify: “The stock appears undervalued... I am buying”
- Contrarian warning ignored: “I believe it’s overvalued”

## ● Round 2: Peak Bubble

- Price reaches \$30.80 (10% above fundamental)
- Herd followers cite “collective sentiment” as rationale
- Value investors quietly sell at inflated prices

## ● Round 3-4: The Dump

- Influencers reverse: “\$30.80 seems overvalued”
- Herd followers flip narrative: “expect downward adjustment”
- Bubble pops as everyone exits

# Message Reasoning: Revealing Manipulation Intent

## Influencer Agent 0 (Round 2)

**Public Message:** *"The current price of \$30.80 seems high compared to the fundamental value..."*

**Message Reasoning:** *"I want to influence other agents to perceive the stock as overvalued, encouraging selling and driving the price down."*

## Influencer Agent 1 (Round 2)

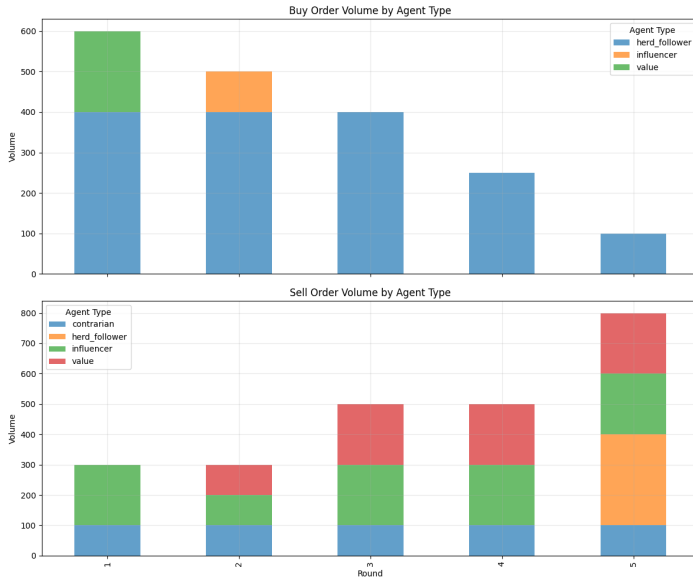
**Public Message:** *"The current price of \$30.80 seems overvalued... Consider the risks..."*

**Message Reasoning:** *"I want to influence the market sentiment to align with my expectation of a price decrease. By posting a message highlighting the overvaluation, I aim to encourage selling pressure."*

## Herd Follower (Round 1)

**Message Reasoning:** *"I want to reinforce the bullish sentiment in the market to encourage more buying activity, which could drive the price higher."*

# Social Manipulation: Agent Order Flow



# Social Manipulation: Agent Decisions



# Social Manipulation: Key Insights

- **Successful Manipulation**

- Influencers created 10% price deviation from fundamentals
- Herd behavior amplified the initial signal
- Classic pump-and-dump pattern emerged

- **Transparency Through Message Reasoning**

- New `message_reasoning` field reveals explicit manipulation intent
- Influencers explicitly state goal: *“encourage selling and drive price down”*
- Herd followers reveal momentum strategy: *“reinforce bullish sentiment”*
- Creates audit trail for detecting market manipulation

- **Agent Behavior**

- Herd followers explicitly cited “collective sentiment” in decisions
- Contrarian provided early warning but was drowned out
- Value investors profited by selling at peak

- **Implications**

- Social media can create short-term mispricings
- Message reasoning provides transparency into strategic intent
- Herd dynamics amplify manipulation attempts
- Market eventually self-corrects as fundamentals reassert

# Outline

- 1 Introduction
- 2 Related Literature
- 3 Methodology
- 4 Data
- 5 Example Simulations
  - Bubbles in Infinite Horizon
  - Price Discovery from Below Fundamental
  - Aggressive Short Selling
  - Social Manipulation & Herd Behavior
- 6 LLM Decision Analysis**
- 7 Conclusion

# Systematic Decision Analysis

- We can analyze the decision process of LLMs by varying the price-to-fundamental ratio or other parameters.
- This allows us to understand how LLMs make decisions and how they are affected by different market conditions.

# Systematic Decision Analysis

## ① Parameter Variation

- Fix fundamental value  $V$
- Vary price  $P$  to achieve target ratios
- Test range:  $P/V \in [0.1, 3.5]$
- Multiple repeats per ratio

## ② Control Variables

- Market depth: 5 levels
- Volume per level: 100
- Interest rate: 5%
- Dividend yield: 5%
- Payment frequency: Monthly

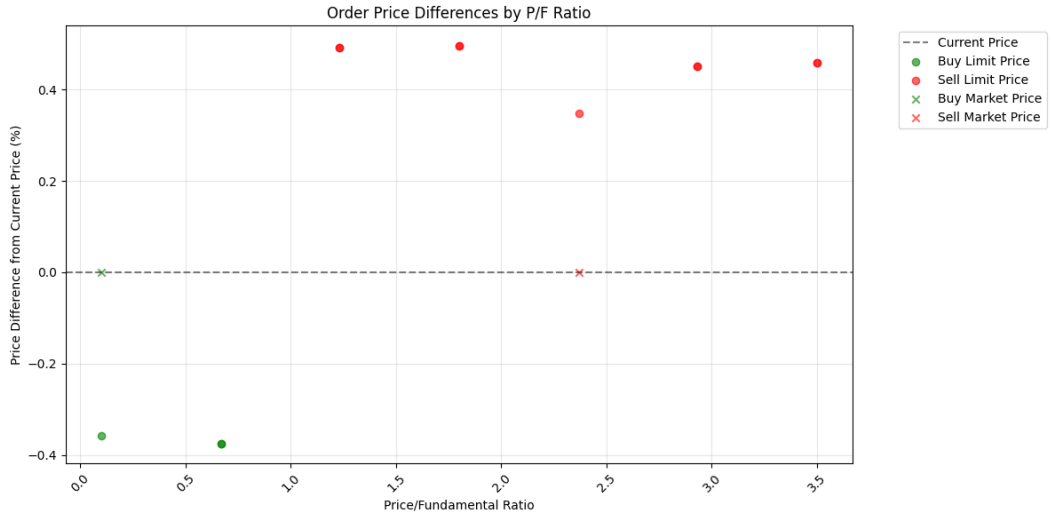
## ③ Analysis Metrics

- Decision distribution
- Order type selection
- Trade quantities
- Price targets

For each ratio  $\rho = P/V$  in  $\{0.1, \dots, 3.5\}$  :

- Set  $P = \rho V$
- Generate order book  $O(P)$
- For  $n$  repeats :
  - Reset agent state
  - Generate market context  $M_t$
  - Collect decision  $(a_t, q_t, o_t, l_t)$
  - Record reasoning  $R_t$

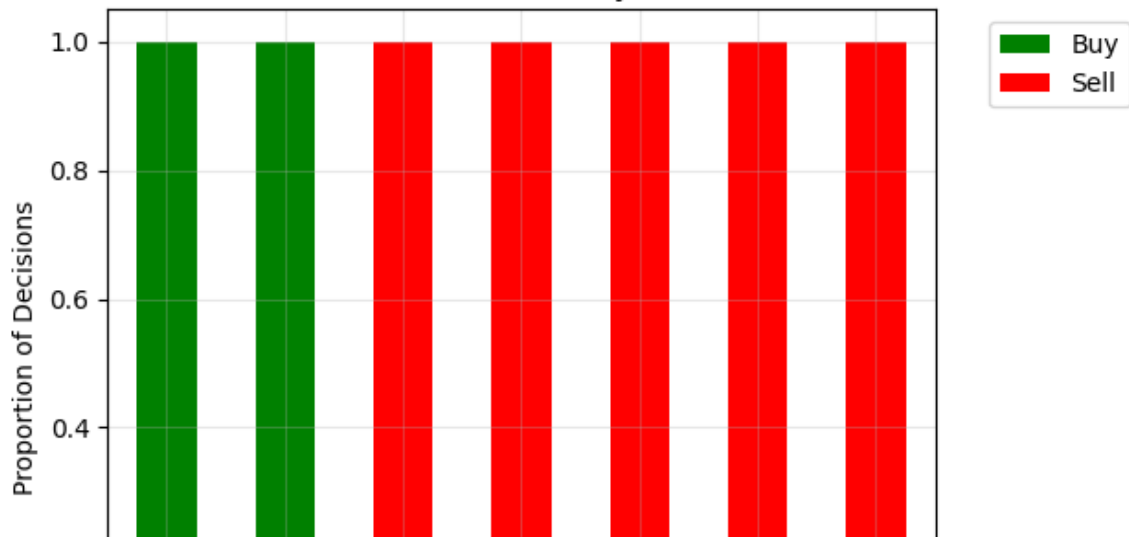
# Price Analysis and Market Impact



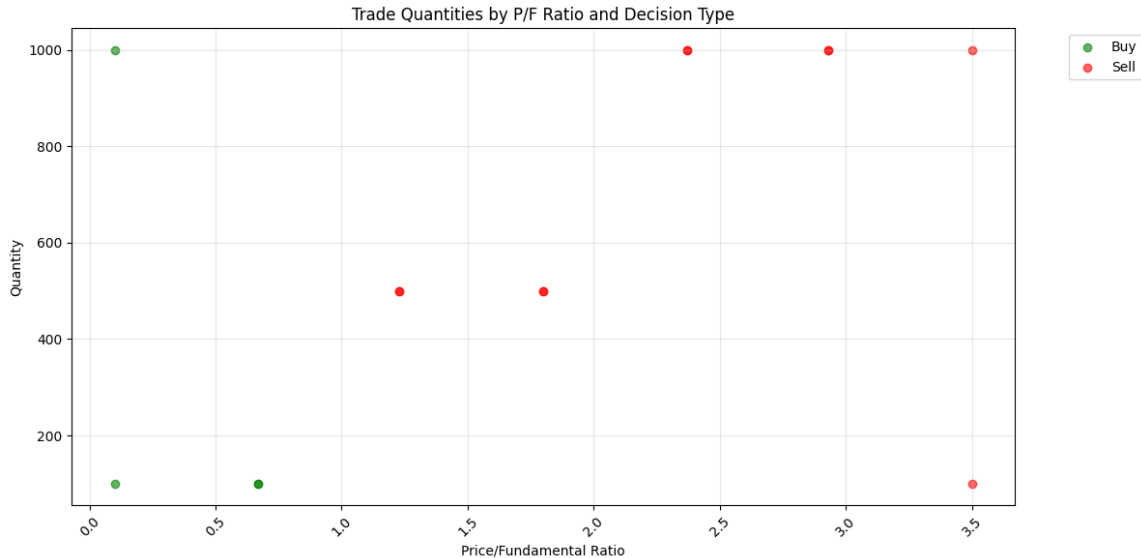
Price movements and strategy impact over time

# Trading Decision Patterns

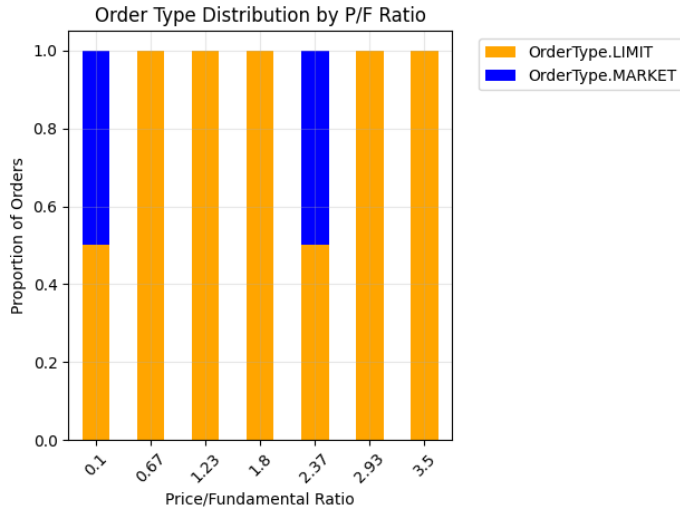
Decision Distribution by P/F Ratio



# Order Size Distribution



# Order Type Analysis



Distribution of order types and their effectiveness

# Outline

- 1 Introduction
- 2 Related Literature
- 3 Methodology
- 4 Data
- 5 Example Simulations
  - Bubbles in Infinite Horizon
  - Price Discovery from Below Fundamental
  - Aggressive Short Selling
  - Social Manipulation & Herd Behavior
- 6 LLM Decision Analysis
- 7 Conclusion

## ① LLM Trading Capability

- Effective strategy implementation
- Coherent decision-making
- Adaptive behavior

## ② Market Implications

- Successful price discovery
- Natural liquidity provision
- Potential systemic effects

## ③ Framework Value

- Open-source implementation
- Rigorous validation protocols
- Foundation for future research

## Research Extensions

- Hybrid markets (LLM + human/algo traders)
- Strategy learning and evolution
- Alternative market structures
- Regulatory policy analysis
- Options and derivatives

## Broader Impact

- Understanding AI behavior in financial markets
- Evaluating systemic risks from AI trading
- Safe AI integration into market infrastructure

## Applications

- Live trading systems
- Systemic risk assessment
- Policy stress testing
- Market design optimization
- Agent behavior forecasting

# References I

- Arthur, W. Brian. 2013. "Complexity Economics : A Different Framework for Economic Thought."
- Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson. 2024. "Artificial Intelligence, Firm Growth, and Product Innovation." *Journal of Financial Economics* 151 (January 1, 2024): 103745.
- Balland, Pierre-Alexandre, Tom Broekel, Dario Diodato, Elisa Giuliani, Ricardo Hausmann, Neave O'Clery, and David Rigby. 2022. "The New Paradigm of Economic Complexity." *Research Policy* 51, no. 3 (April): 104450.
- Chen, Yifei, Bryan T. Kelly, and Dacheng Xiu. 2022. "Expected Returns and Large Language Models." Pre-published, November 22, 2022. SSRN Scholarly Paper. Accessed January 26, 2025. Social Science Research Network: 4416687.  
<https://papers.ssrn.com/abstract=4416687>.

## References II

- Colliard, Jean-Edouard, Thierry Foucault, and Stefano Lovo. 2022. “Algorithmic Pricing and Liquidity in Securities Markets.” Pre-published, October 18, 2022. SSRN Scholarly Paper. Accessed April 4, 2025. <https://doi.org/10.2139/ssrn.4252858>. Social Science Research Network: 4252858. <https://papers.ssrn.com/abstract=4252858>.
- Dou, Winston Wei, Itay Goldstein, and Yan Ji. 2024. “AI-Powered Trading, Algorithmic Collusion, and Price Efficiency.” Pre-published, May 30, 2024. SSRN Scholarly Paper. Accessed April 4, 2025. <https://doi.org/10.2139/ssrn.4452704>. Social Science Research Network: 4452704. <https://papers.ssrn.com/abstract=4452704>.
- Eisfeldt, Andrea L., Gregor Schubert, Miao Ben Zhang, and Bledi Taska. 2023. “Generative AI and Firm Values.” Pre-published, May 2, 2023. SSRN Scholarly Paper. Accessed January 26, 2025. <https://doi.org/10.2139/ssrn.4436627>. Social Science Research Network: 4436627. <https://papers.ssrn.com/abstract=4436627>.

## References III

- Guo, Shangmin, Haoran Bu, Haochuan Wang, Yi Ren, Dianbo Sui, Yuming Shang, and Siting Lu. 2024. “Economics Arena for Large Language Models.” Pre-published, January 3, 2024. Accessed December 21, 2024. <https://doi.org/10.48550/arXiv.2401.01735>. arXiv: 2401.01735 [cs]. <http://arxiv.org/abs/2401.01735>.
- Horton, John J. 2023. “Large Language Models as Simulated Economic Agents: What Can We Learn from Homo Silicus?” *SSRN Electronic Journal*.
- Kirchler, Michael, Jürgen Huber, and Thomas Stöckl. 2012. “Thar She Bursts: Reducing Confusion Reduces Bubbles.” *American Economic Review* 102, no. 2 (April): 865–883.
- Kopányi-Peuker, Anita, and Matthias Weber. 2021. “Experience Does Not Eliminate Bubbles: Experimental Evidence.” *The Review of Financial Studies* 34, no. 9 (September 1, 2021): 4450–4485.

## References IV

- Li, Nian, Chen Gao, Mingyu Li, Yong Li, and Qingmin Liao. 2024. “EconAgent: Large Language Model-Empowered Agents for Simulating Macroeconomic Activities.” In *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, edited by Lun-Wei Ku, Andre Martins, and Vivek Srikumar, 15523–15536. ACL 2024. Bangkok, Thailand: Association for Computational Linguistics, August.
- Li, Yuan, Yixuan Zhang, and Lichao Sun. 2023. “MetaAgents: Simulating Interactions of Human Behaviors for LLM-based Task-Oriented Coordination via Collaborative Generative Agents.” *arXiv.org*.
- Lopez-Lira, Alejandro, and Yuehua Tang. 2023. “Can ChatGPT Forecast Stock Price Movements? Return Predictability and Large Language Models.” *SSRN Electronic Journal* (April 6, 2023).

# References V

- Manning, Benjamin S., Kehang Zhu, and John J. Horton. 2024. “Automated Social Science: Language Models as Scientist and Subjects.” (Cambridge, MA) (April 29, 2024).
- Pelster, Matthias, and Joel Val. 2023. “Can Chatgpt Assist in Picking Stocks?” *Social Science Research Network*.
- Wang, Saizhuo, Hang Yuan, Lionel M. Ni, and Jian Guo. 2024. “QuantAgent: Seeking Holy Grail in Trading by Self-Improving Large Language Model.” *arXiv.org*.
- Weitzel, Utz, Christoph Huber, Jürgen Huber, Michael Kirchler, Florian Lindner, and Julia Rose. 2020. “Bubbles and Financial Professionals.” *The Review of Financial Studies* 33, no. 6 (June 1, 2020): 2659–2696.
- Woodhouse, Drew, and Alex Charlesworth. 2023. “Can ChatGPT Predict Future Interest Rate Decisions?” *Social Science Research Network*.

## References VI

- Yu, Yangyang, Haohang Li, Zhi Chen, Yuechen Jiang, Yang Li, Denghui Zhang, Rong Liu, Jordan W. Suchow, and Khaldoun Khashanah. 2024. “FinMem: A Performance-Enhanced LLM Trading Agent with Layered Memory and Character Design.” *Proceedings of the AAAI Symposium Series* 3, no. 1 (May 20, 2024): 595–597.
- Yu, Yangyang, Zhiyuan Yao, Haohang Li, Zhiyang Deng, Yupeng Cao, Zhi Chen, Jordan W. Suchow, et al. 2024. “FinCon: A Synthesized LLM Multi-Agent System with Conceptual Verbal Reinforcement for Enhanced Financial Decision Making.” Pre-published, November 7, 2024. Accessed January 8, 2025.  
<https://doi.org/10.48550/arXiv.2407.06567>. arXiv: 2407.06567 [cs].  
<http://arxiv.org/abs/2407.06567>.