

Member Introductions



**Muxin
Ge**



**Nolan
Trinh**



**Audrey
Haynes**



**Grant
Simon**



**Bryson
Frazee-Duffin**



**Quinn
O'Malley**

Agenda

I

Strategies & Ideology

Overview, Strategy to Generate Alpha

II

Matrices Breakdown

Architecture of the Model

III

Pivot

Traditional Finance → Quantitative Methods

IV

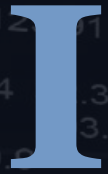
LLM Integration

Research Papers, Data, Model Selection

V

Looking Forward

Focus & Goals with Research



Strategies & Ideology

Overview: Creating a Strategy to Generate Alpha

Strategy Selection

Options-Implied Sentiment

- U.S. Equities, liquid
- 1-3 week hold period
- Built Signals from Call/Put volume imbalance, net delta, and IV skew
- Ranks stocks top to bottom by Sharpe or QMJ Z-Score
- Long the top and short the bottom

Mean Reversion & Pairs

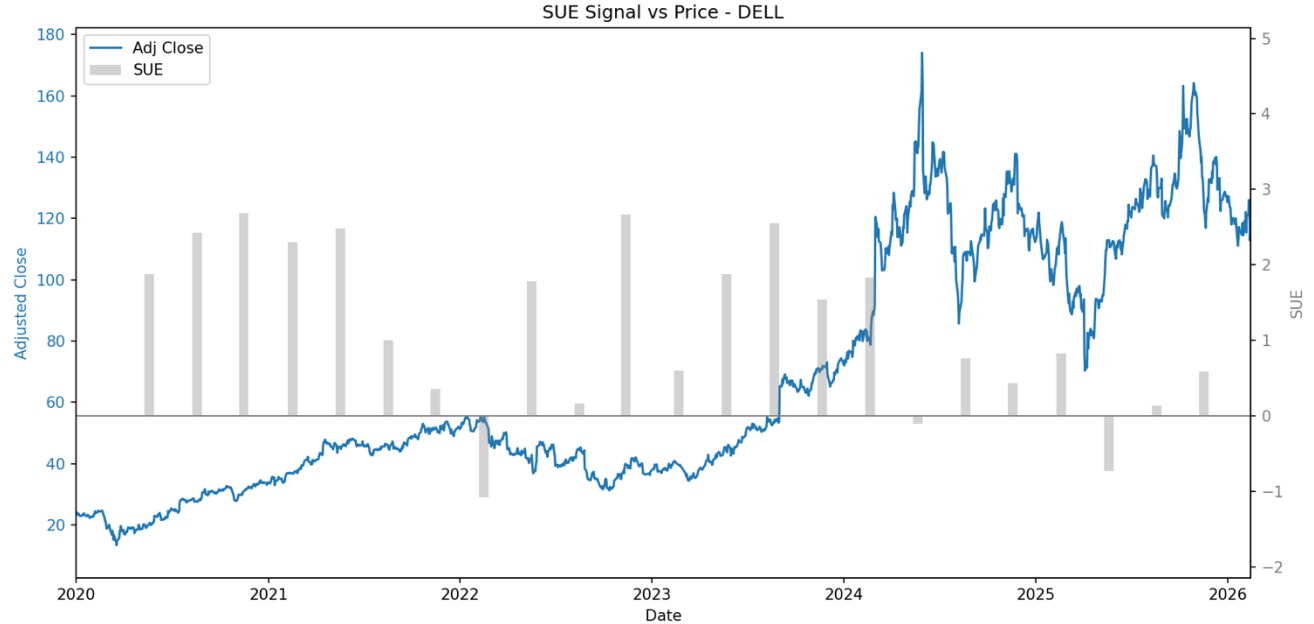
- U.S. Equities, mid-cap and large cap.
- 2-5 week hold period
- 20-day rolling Z-score of stock returns V.S. sector ETF
- Long if Z-score < -2.00
- Short if Z-score > 2.00
- Filter out major news

Commodities Risk Premium With Mean Reversion

- U.S. Energy Companies
- Oil weighted large caps
- Oil is underpriced relative to its embedded geo-political risk premium
- Natural gas trades rich on residual winter demands

Version 1

**Can options
market activity
before earnings
predict post-
announcement
returns?**



Strategy Evolution

Version 1

- Captured market *positioning*
- But missed **WHY** the market was positioned that way

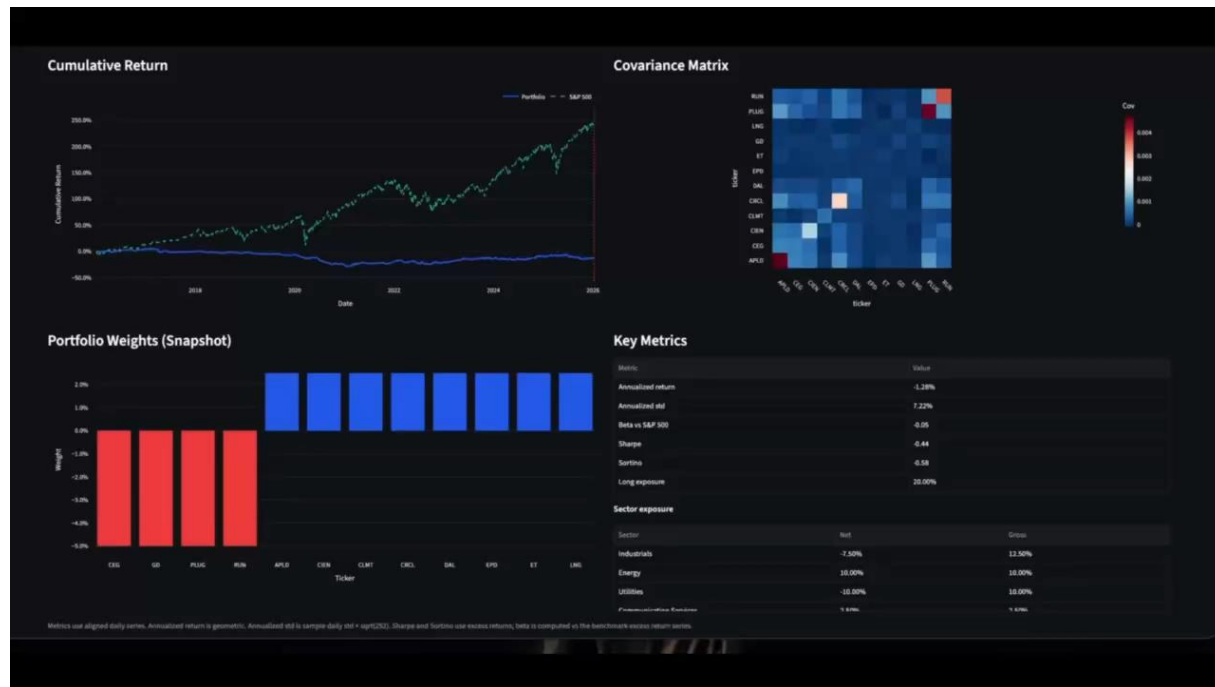


Version 2

- **Human-driven qualitative investment theses**
- **Update model with LLM component**
- **Automate away data scraping and risk calculations**
- **AI agents to deploy and paper trade model with fetched API access to earnings data**

Version 2

Combination of quantitative signals with qualitative context will improve signal quality



II

Matrices Breakdown

Overview: Architecture of the Model

Event to SUE



Event/ Earnings Announcement

Extract prices relative to event/earnings announcement ($t = 0$), analyze behavior before ($t = -1, -2$) & after ($t = 1, 2$) event



Standardized Unexpected Earnings

Necessary to standardize surprise swings because of different levels of **volatility**, answers how big surprise was relative to what's normal

$$SUE_{i,t} = \frac{\text{Actual EPS} - \text{Expected EPS}}{\sigma_i}$$

- i : stock
- t : event (earnings date)
- σ_i : historical volatility of surprises for that stock



(PEAD) Post-Earnings Announcement Drift

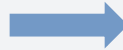
After earnings announcements, stock prices continue moving in the direction of the surprise for weeks or months

SUE to ALPHA



What We Have

Vector across stocks $[SUE_{1,t}, SUE_{2,t}, \dots, SUE_{N,t}]$



Problem

SUE measures the outcome of surprising earnings, but trading requires ranking stocks based on those surprises in real time



Cross-Sectional Z-Scoring

Transforms SUE into a ranking of signals across a given time

$$\alpha_{i,t} = Z_{i,t} = \frac{SUE_{i,t} - \mu_t}{\sigma_t}$$

- μ_t : mean SUE across all stocks at time t
- σ_t : std dev across stocks



Alpha Matrix (Time x Stocks)

At a specific time, how attractive is a stock relative to the others

$$\alpha = \begin{bmatrix} \alpha_{1,1} & \alpha_{1,2} & \dots \\ \alpha_{2,1} & \alpha_{2,2} & \dots \\ \vdots & & \end{bmatrix}$$

ALPHA to Information Coefficient



Validate with IC

Signal predictability: compare α rankings to realized returns
Spearman: measures rank correlation, not raw values

$$IC_t = \text{Spearman}(\alpha_t, r_{t+1})$$



Covariance Matrix

Account for risk: avoid concentration in a single stock or sector
Build covariance matrix: correlations + variances capture co-movement

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1N} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1} & \sigma_{N2} & \cdots & \sigma_{NN} \end{bmatrix}$$



Building Matrix

Large $\lambda \rightarrow$ smoother, slower changing | Small $\lambda \rightarrow$ more reactive

$$\Sigma_t = \lambda \Sigma_{t-1} + (1 - \lambda) r_t r_t^\top$$

$\lambda =$ controls memory of risk model



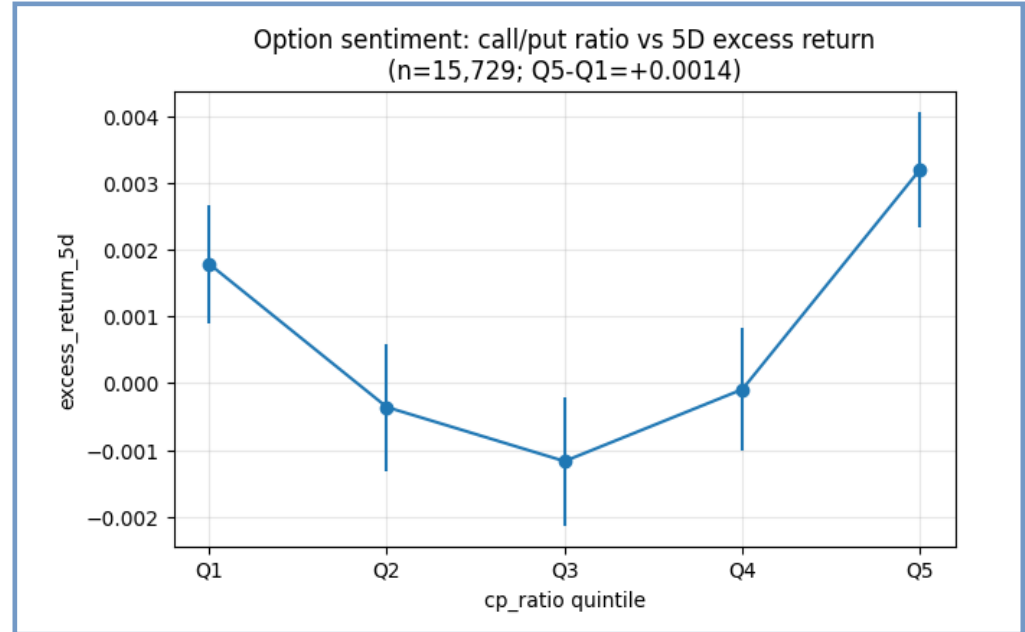
Pivot

Traditional Finance → Quantitative Methods

Problems with Findings

Problems with Findings

- Pre-earnings signals yielded insufficient results
- Options signals could not interpret market signals properly
- Combined quantitative signals with fundamental research



Traditional Finance

Methods

- Conducted comparable company analysis
- Analyzed macroeconomic factors as well as key drivers and risks
- Added tear sheets to LLM with a higher weight

Comps

Stanley Black & Decker, Inc. (SWK)		Market Data (\$)				Financial (\$)				Valuation (x)
Company				Shares Ou Shares Out						EV/
Ticker	Price	Mkt Cap (M)	EV (M)	(M)	Diluted (M)	Sales (M)	EBIT (M)	EBITDA (M)	EBITDA	
SWK-US	72.19	11,387.8	16,964.1	155.3	151.9	15,130.4	1,244.6	1,753.1		9.68x
ATCO.A-SE	20.00	93,654.6	94,943.6	3,357.6	4,873.0	17,164.7	3,613.4	4,562.2		20.81x
ITW-US	272.25	78,797.1	86,916.1	288.2	292.3	16,044.0	4,216.0	4,613.0		18.84x
SFSN-CH	157.21	6,109.0	6,348.1	38.9	38.9	3,667.0	348.2	519.6		12.22x
FII-FR	71.92	3,271.0	3,588.4	46.5	46.4	1,972.7	181.7	286.6		12.52x
HWM-US	258.03	104,019.9	106,867.9	400.9	406.0	8,252.0	2,130.0	2,413.0		44.29x
7988-JP	29.10	2,730.9	2,059.6	100.2	93.4	2,348.6	327.9	413.6		4.98x
Average										17.62x
Median										12.52x

Selected Tickers

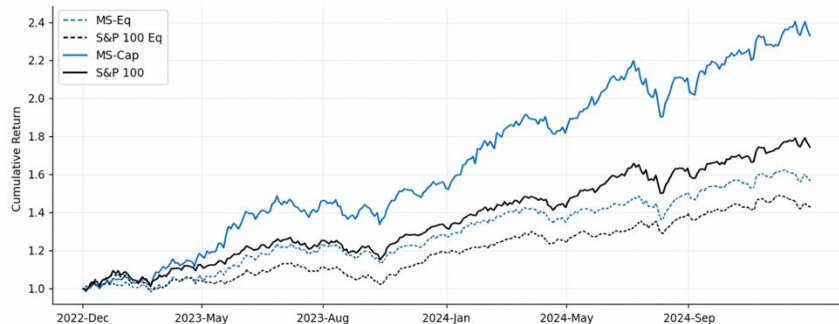
- SWK, DAL, DELL, TOL, CAT, AROC, LNG, RUN

Quantifying Traditional Approaches

Our Solution

- Combine matrices and findings with pre-earnings sentiment and traditional finance in an LLM
- Limit Russell 3000 selection to thesis-driven, hand-picked stocks

MarketSenseAI Results



Portfolio	Beta	Alpha (%)	Total Trades	Win Rate (%)	Buy Signals ^a
S&P 100 Analysis (2023-2024)					
MS-Eq	0.96	8.0	584	77.1	35.1 (7.95)
MS-Cap	1.24	10.6	548	77.0	35.1 (7.95)

IV

LLM Integration

Research, Data Pipeline Integration, and Results

LLM Research

Agent Architecture

MarketSenseAI showed specialized agents outperform LLMs.

Why?

Each dedicated data pipeline narrows domain rather than diluting signal across one giant prompt.

Utilizing Matrices

Structured numerical inputs (risk matrix, alpha matrix) constrain LLM reasoning to finance-native objects.

Why?

The LLM outputs a scalar signal per ticker that plugs directly into the optimizer.

Reduce Context Rot

LLMs degrades when fed too much irrelevant context.

Why?

Splitting into focused agents keeps each context window small and relevant, preserving reasoning quality.

LLM Data Pipeline

General Data

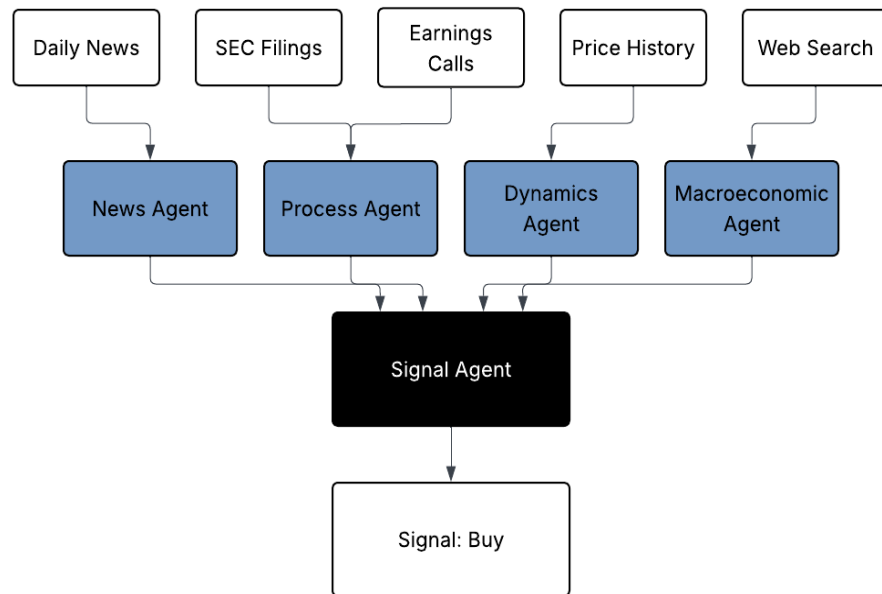
Every stock in Russell 3000 is scanned during every rebalance

Data Sources:

- Daily news (FinnHub)
- SEC filings (EdgarTools, 10-K/Q)
- Price & Greeks history
- Earnings call transcripts
- Macro indicators (FRED)

Investment Thesis Weighting

Our pre-defined investment theses act as scoring rubrics. The LLM evaluates each ticker against the theses, ensuring outputs are actionable within our strategy framework.



LLM Results

What is Significant?

- Converts investment thesis into scoring rubrics.
- Translates qualitative inputs into our matrices.
- Produces a long/short basket.

What are the Pitfalls?

- Based on short four-month paper-trade sample.
- Bias selection for stocks due to recent global conflict.
- Historical data may not fully represent live conditions.

Overall

- Demonstrates an LLM-supported research framework.
- Connects thesis development, matrices, and portfolio construction.
- Should be viewed as a proof of concept.

MODEL RESULTS

Four-month paper trade

4M RETURN

23.65%

SHARPE

3.49

ANN. VOL

18.33%

MAX DD

-4.68%

GROSS

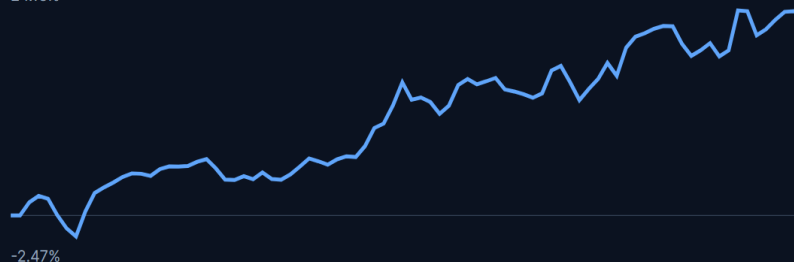
0.87

NET

0.00

24.16%

-2.47%



Latest weight sizing matrix

LNG	<div style="width: 30.79%;"></div>	30.79%
CIEN	<div style="width: 12.10%;"></div>	12.10%
DAL	<div style="width: 0.79%;"></div>	0.79%
GD	<div style="width: -29.21%;"></div>	-29.21%
CEG	<div style="width: -14.46%;"></div>	-14.46%

Long top / short bottom

TICKER	ALPHA	WEIGHT
LNG	1.20	30.79%
CIEN	0.45	12.10%
DAL	0.42	0.79%
GD	-0.33	-29.21%
CEG	-1.75	-14.46%

Looking Forward

Focus & Goals with Research

- Discern the paper trading errors not found in back testing and see if we can enhance gains.
- Expand Options research layer to test model performance by sector.
- Integrate a different LLM model framework by building a more proprietary Solution.

The background features a dark, semi-transparent overlay of various financial data visualizations. These include line graphs with square markers, bar charts, and a grid of numerical data points. The text is white and stands out against the dark background.

Thank You

Q&A



Traders@SMU

© 2025 Southern Methodist University | CONFIDENTIAL: This presentation and its contents are proprietary and confidential information belonging to Traders@SMU. The materials may contain sensitive information protected by applicable laws and regulations. Unauthorized use, disclosure, or distribution of this document or any of its contents is strictly prohibited. If you are not the intended recipient, please notify the sender immediately and delete this document along with any copies in your possession. Any unauthorized review, use, disclosure, or distribution is prohibited and may result in legal action. While every effort has been made to ensure the accuracy and reliability of the information presented, Traders@SMU makes no representations or warranties of any kind, express or implied, regarding its completeness or suitability. All information is provided "as is" without any warranty. This presentation may contain forward-looking statements regarding future events or performance. These statements involve risks and uncertainties that could cause actual results to differ materially from those expressed or implied. In no event shall Traders@SMU or Southern Methodist University be liable for any direct, indirect, incidental, special, consequential, or punitive damages arising out of or related to the use of this presentation or its contents. For questions regarding this presentation or its contents, please contact Traders@SMU.