# Long-Short Equity: A Quantamental Approach

Traders@SMU

April 29th, 2026

# Member Introductions

**Muxin Ge**

**Nolan Trịnh**

**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 |

# I

# 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

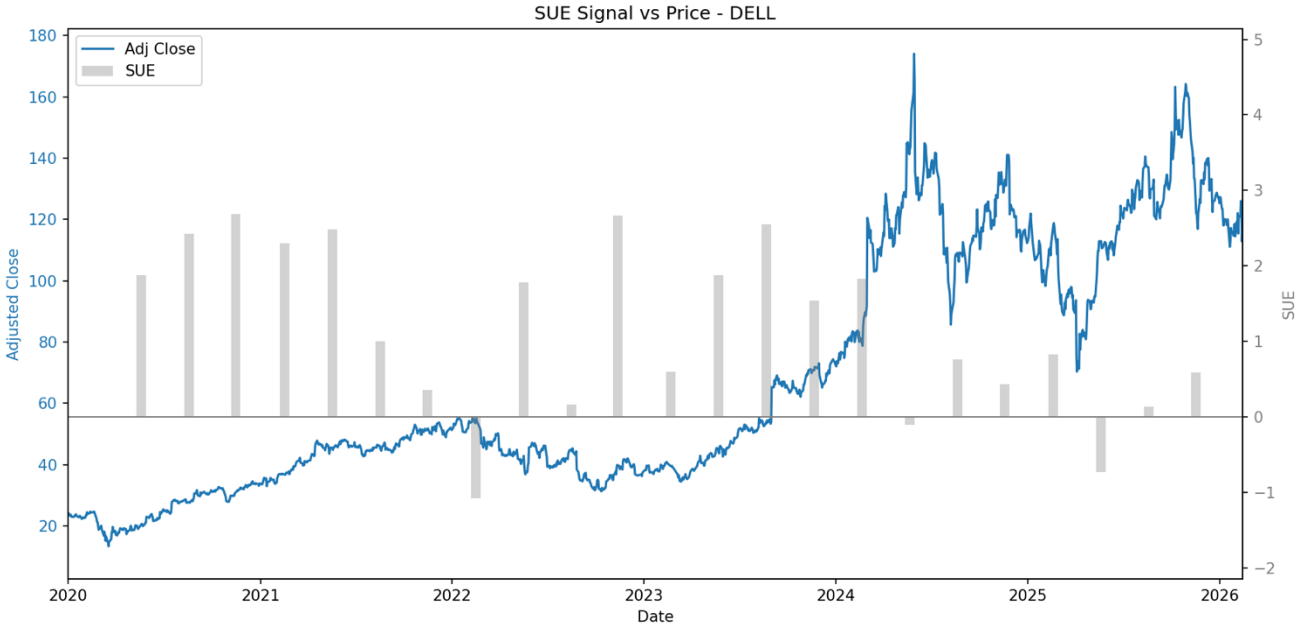
- U.S. Equities, mid-cap and large cap.
- 2-5 week hold period
- 20-day rolling Z-score of stock returns V.S. sector ETF
- Long if Z-score < -2.00
- Short if Z-score > 2.00
- Filter out major news

## 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**

# 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

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

- $i$: stock
- $t$: event (earnings date)
- $\sigma_i$: 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 $[SUE_{1,t}, SUE_{2,t}, \ldots, SUE_{N,t}]$

## 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

$$\alpha_{i,t} = Z_{i,t} = \frac{SUE_{i,t} - \mu_i}{\sigma_i}$$

- $\mu_t$: mean SUE across all stocks at time $t$
- $\sigma_t$: std dev across stocks

## Alpha Matrix (Time x Stocks)

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

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

# 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** λ → smoother, slower changing | **Small** λ → more reactive

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

λ = **controls memory of risk model**

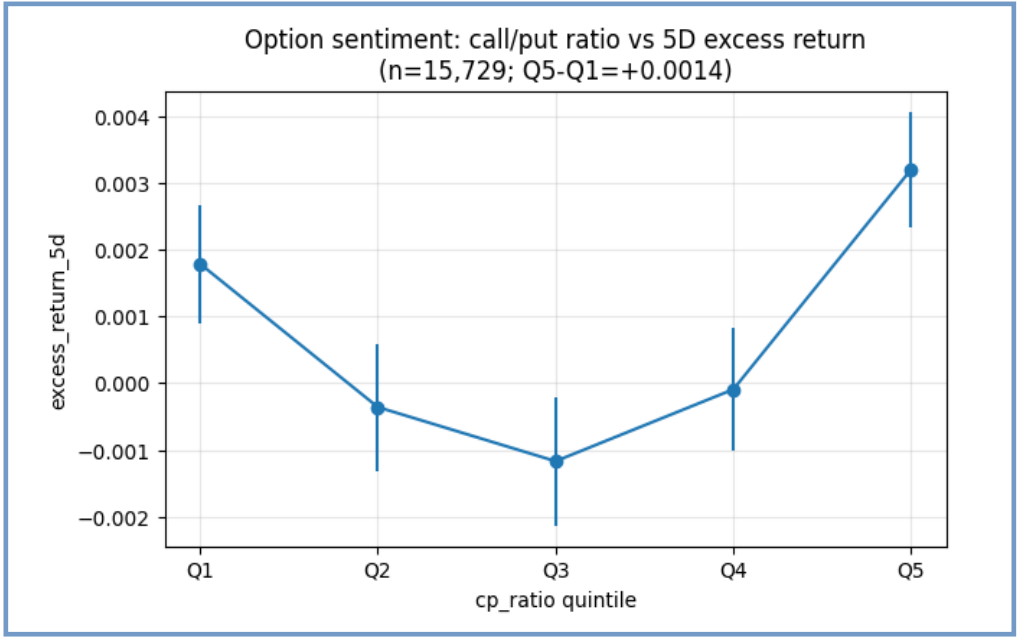
# Pivot

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

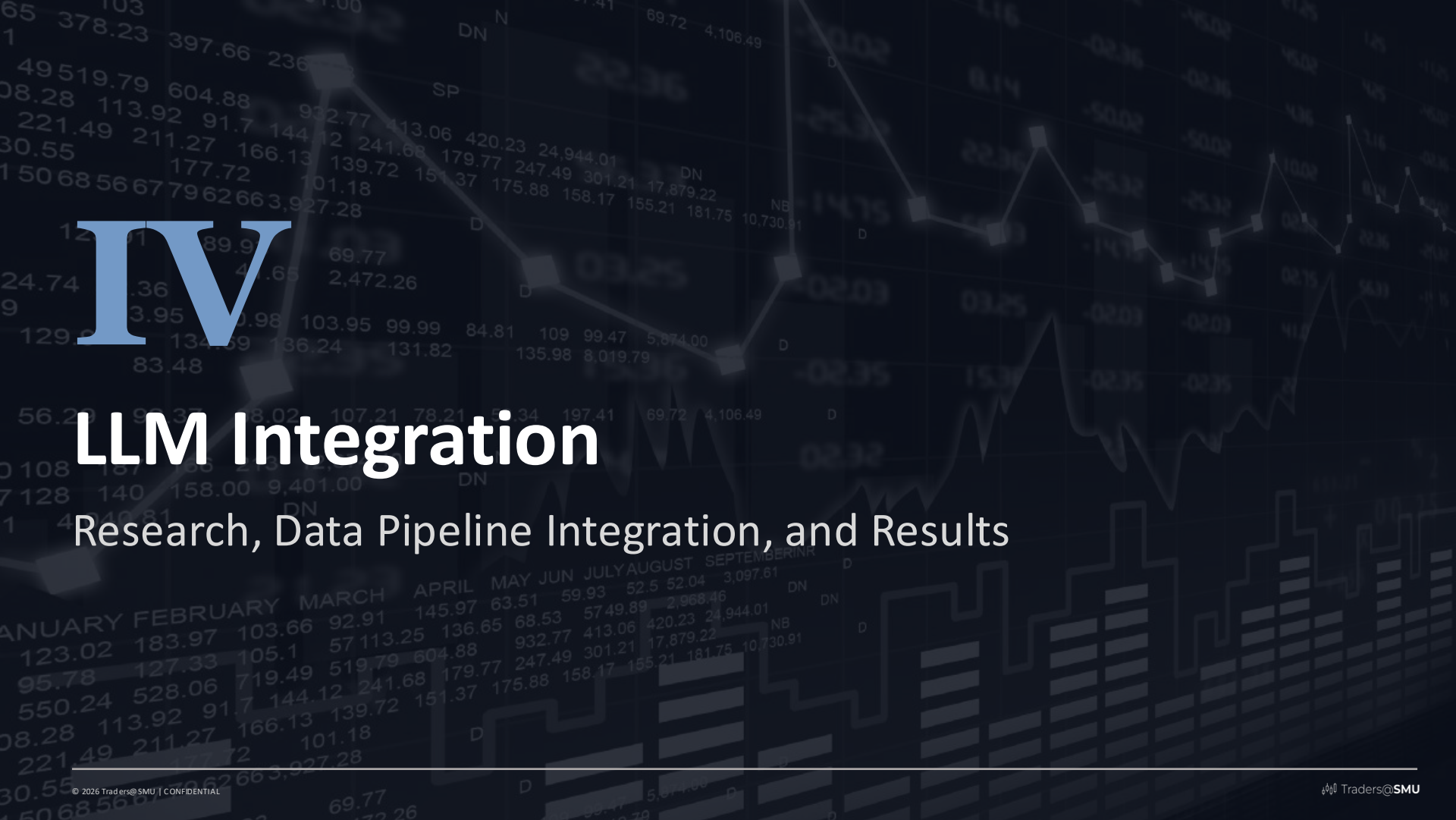
# Quantifying Traditional Approaches

## 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

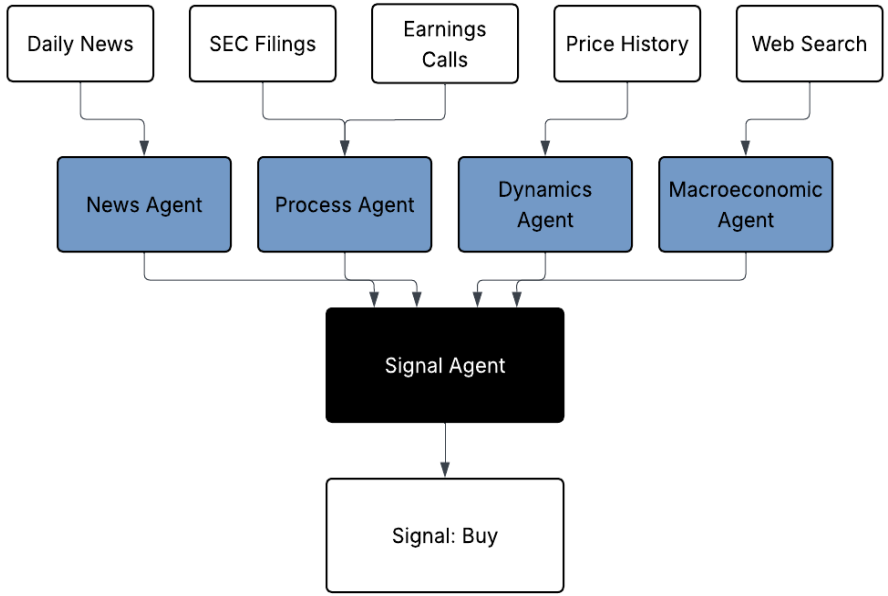
Every stock in Russell 3000 is scanned during every rebalance

**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.

# 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.

# Thank You

Q&A