# Citadel Spinoffs

Final Presentation for: "Data Driven Methods in Finance, IEOR 4576"

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## **Outline of Presentation**

- 1. Introduction to Datasets
- 2. Data Engineering
- 3. Feature Ideation & Engineering
  - a. Technical Factors
    - i. Bollinger Bands
    - ii. SARIMAX
  - b. Alternative Factors
    - i. Analyst Recommendations
    - ii. Starmine Models
- 4. Combination of Models (Black Litterman Model)
- 5. Final Disclaimers

## Introduction to Datasets

#### **Overview of Modelled Data:**

- 1. Stocks (50 assets)
  - a. <u>Fundamental:</u> Valuation, Size, Operating Efficiency, Profitability, Risk, Corporate Activity
  - b. <u>Technicals:</u> Liquidity, Price-Based, Overall Market
  - c. <u>Alternative Factors:</u> Ratings, Revisions, Distributions
  - d. <u>Economic Factors</u>: Inflation, GDP Growth
  - e. <u>Alternative Social Responsibility:</u> ESG Score
- 2. ETFs (50 assets)
  - a. Fundamentals: Scope, Valuation, Size
  - b. Technical: Liquidity, Price-Based, Overall Market
  - c. <u>Alternative:</u> Rating, Revisions, Distributions
  - d. <u>Economic Factors</u>: Inflation, GDP Growth
  - e. Social Responsibility: ESG
- 3. Crypto (10 assets)
  - a. Fundamentals: Scope, Market Size
  - b. <u>Technicals:</u> Liquidity, Price-Based
  - c. <u>Alternative:</u> Scope, Volume of Mining

#### **General Methodology:**

- 1. Preliminary Idea Creation: Academic Papers, Bibliography
- 2. Feasibility Study: Check if forming the factors was achievable
- 3. Feature Creation & Testing: Data Sourcing, Engineering, Testing
- 4. Assumptions Study: Replicability Studies of factors

	Data Provider	Advantages	Disadvantages		
ite	yahoo!	<ul> <li>Free to <u>use</u></li> <li>Well-documented</li> <li>Straightforward API</li> </ul>	<ul> <li>Limited advanced analytical tools</li> <li>Data delays for real-time information</li> </ul>		
	REFINITIV 🧮	<ul> <li>Comprehensive and high- quality data</li> <li>Global market coverage</li> <li>Advanced analytical tools</li> </ul>	<ul> <li>High cost</li> <li>Complexity for new users</li> <li>Limited crypto data compared to stocks and ETFs</li> </ul>		
	FACTSET	<ul> <li>Deep and extensive datasets</li> <li>Advanced portfolio and risk analytics</li> <li>Strong integration capabilities</li> </ul>	<ul> <li>High subscription cost</li> <li>Steeper learning curve</li> <li>Primarily tailored for professional investors and institutions</li> </ul>		

#### Data Leveraged:

- 1. Yahoo Finance: Price Signals were used in conjunction to other platforms
- 2. Refinitiv: Fundamentals, Technicals, Alternative Factors
- 3. FactSet: Sentiment Scoring, Barra Regression
- 4. MarketWatch: Analyst Ratings, Revisions, Distributions

## Data Engineering

### **General Methodology**

- 1. Exporting from relevant datasets using API & SQL queries (Factset, Refinitiv, Yahoo! Finance, MarketWatch)
- 1. Distribution Plot Creation (Data Integrity, Comparative Analysis, Histograms & Box Plots, Time-Series Analysis)
- 1. Data Cleaning (Stage 1)
  - a. Remove non-trading days
  - b. Remove non-trading history

#### 1. Factor Formulation

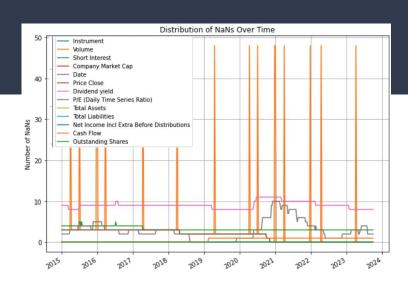
- b. Fundamental Factors
- c. Technical Factors
- d. Economic & Alternative Factors

#### 1. Data Cleaning (Stage 2)

- b. Trimming Outliers
- c. Winsorizing Data
- d. Quality Checks & Validation

Apple_SPY_stock_price.tail(10)									
	Adj Close		Close		н		gh .		
	AAPL	SPY	AAPL	SPY	AAPL	SPY	AAPL		
2021-10-04 13:30:00-04:00	138.751907	427.750092	138.751907	427.750092	139.220001	428.549988	138.535004		
2021-10-04 14:30:00-04:00	138.585007	427.635010	138.585007	427.635010	139.320007	429.220001	138.509995		
2021-10-04 15:30:00-04:00	139.169998	428.700012	139.169998	428.700012	139.229996	429.040009	138.470001		
2021-10-05 09:30:00-04:00	139.869995	433.739990	139.869995	433.739990	140.399994	433.790009	139.410004		







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## Bollinger bands

*Main Idea:* technical analysis tool that signal potential overbought or oversold conditions, aiding traders in identifying reversal points.

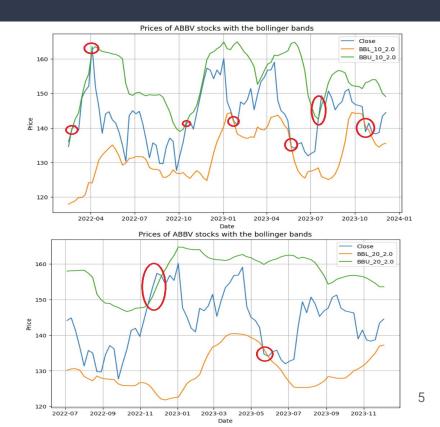
### Implementation:

- 1. Get price history
- 2. Compute the x-day moving average where x is usually 20 or 50
- 3. Compute the lower band by subtracting 2 std to the moving average
- 4. Compute the upper band by adding 2 std to the moving average
- 5. Buy signal when the price is lower than the lower band and sell signal when the price is higher than the upper band

### General framework:

- 1. Bollinger bands: Implement the bollinger bands for all the assets
- 2. Create Bollinger variables: that takes 1 if lower (higher) than the lower band (higher band), 0 otherwise.
- **3. Backtesting:** On rolling weekly periods, regress next Friday's returns with this week's value. We obtained even higher significance using a continuous factor as opposed to (-1, +1, 0) setup:

$$F_{BB} = \frac{P(t) - P_{roll,average}}{\sigma_{roll,average}}$$



### The SARIMAX Factor (pmdarima.arima.auto\_arima)

*Model Explanation:* Stands for Seasonal AutoRegressive Integrated Moving Average with eXogenous factors model. Advanced version of ARIMA, incorporating seasonality and external variables.

### ARIMA Usefulness:

- 1. Adapts to changing market conditions
- 2. Improves accuracy with external data
- 3. Handles non-stationarity data effectively
- 4. It can be used to fit other data than prices & returns

### Seasonal Data:

- 1. Quarterly Earnings Reports
- 2. Holiday Sales Data (especially for retail/consumer companies & ETFs)

### Exogenous:

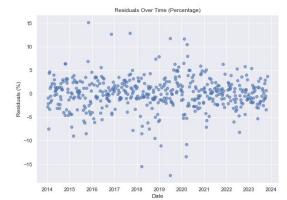
- 1. GDP Growth Rates
- 2. Interest Rates

### Fitting AUTO\_ARIMA:

- 1. Leverage Daily Data to more accurately describe the timeseries.
- 2. Convert to returns, given improved stability over prices
- 3. Automatically Selects relevant Auto-correlation Factors
- 4. Fit to predict the price over next week.

### **General Framework**

- Verify Model Correctness: Iterate through securities to test auto\_arima in conjunction with more manual ARIMA models.
- 2. Deduce Relevant Training Windows:
  - a. Model Fitting: Rolling Windows separated by 13 weeks
  - Model Training: Windows of variable length (30 Weeks 3 Years). Outputs: Optimal Training Window; Modifications based on available trading history (Crypto)
- 3. Store Matrix of Predicted Returns, along with 21-day rolling volatility
- 4. Test Predicted vs Actual Prices



### The SARIMAX Factor (pmdarima.arima.auto\_arima)

#### General Framework (Continued)

- 5. Smoothing Results & Eliminating Impact Days:
- A. Interpolate data for non-trading days
- B. Eliminate impact days from dataset
- C. Include 12-month active T-Bill data



### **Results display:**

- 1. Lower jumps in total
- 2. Smoother tracking of underlying security
- 3. Reduced Outliners overall



**Turning this** 

Into this

### The SARIMAX Factor (pmdarima.arima.auto\_arima)

#### Backtesting Framework:

- 1. Synthesize results from individual securities
- **2. Create monitored factor:** Predicted price of next Friday over the rolling 21-day standard deviation of returns (iteratively):

$$F_{ARIMA} = \frac{P_{predicted}}{\sigma_{21-day,rolling}}$$

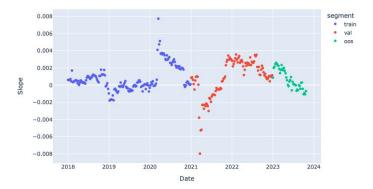
**1. Z-score factors annually:** Cross-sectionally compare the factor of each security over time to prepare data for the linear regression.

$$Z - score, F_{ARIMA} = \frac{F_{ARIMA,i} - F_{ARIMA}}{SD}$$

- 1. Run linear regression, estimating statistical significance of results.
- 1. Create a long-short portfolio, with "± w" on each security, with variable length on top & bottom winners, to perform sensitivity analysis on return over the benchmark index (SPX).

Key Insights & Discussion:

- 1. Long-short weights prevent protect this portfolio against major drawdowns of the market
- 2. Model sensitive to external factors that may show conflicting results across different time periods;
  - a. Low interest rate environment of 2012 2019 adversely affects model performance for post-COVID era.
  - b. Similar sensitivity to unemployment; Low unemployment signals strong market performance pre-COVID, but pushes markets downwards signalling strong economy & stubborn inflation (eliminated).



## Embedding Analyst Recommendations

- **Data**: Analysts recommendations from Refinitiv (idea from <u>Ratings Changes, Ratings Levels, and the</u> <u>Predictive Value of Analysts' Recommendations</u>)
- Attribute a score to each recommendation and combine them all with an average score. The lower the score the more likely the stock's price will go up.
- Backtesting : Regress next week's return with current week's score

SUMMARY GRID											
	Analysts Per level										
	04-Sep-2023	04-Oct-2023	04-Nov-2023	Current							
1-StrongBuy											
2-Buy	12	12	13	13							
3-Hold	14	13	12	13							
4-Sell											
5-StrongSell				-							
Rec Mean	2.4	2.4	2.3	2.3							

Source : Refinitiv (ticker : ABBV)

## **Embedding Analyst Recommendations**

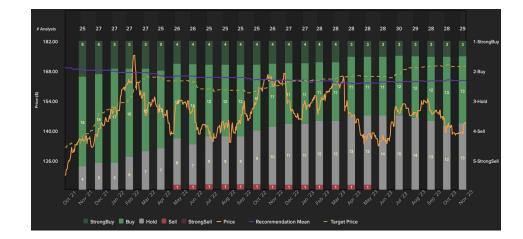
### • Pros:

• Easy to use

• Leverages the work of analysts

### • Cons:

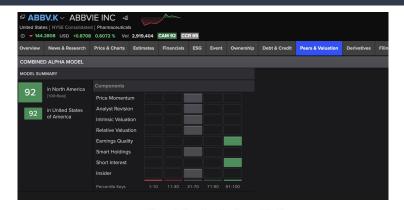
- Very little statistical significance
- Not suited for weekly decision making
- Falls into the herding mentality bias
- Depends on the stock's coverage

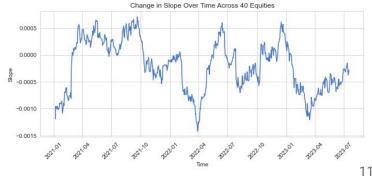


Source : Refinitiv (ticker : ABBV)

## Starmine Reuters Alpha Model

- Main Idea: Leverage Refinitiv's Starmine Alpha model
  - Ranks stock based on various metrics
    - Price Momentum
    - Analyst Valuation
    - Intrinsic Valuation
    - Earnings Quality
    - Short Interest
  - Normalizes Value to be between 1-100
- Pros:
  - Leverage industry insights
  - Completely internal to Reuters
  - Individual Components Statistically Significant
- Cons:
  - Correlated with other signals
    - Causing Multicollinearity
  - Overall not statistically significant





### Combination of Models (Black Litterman Model)

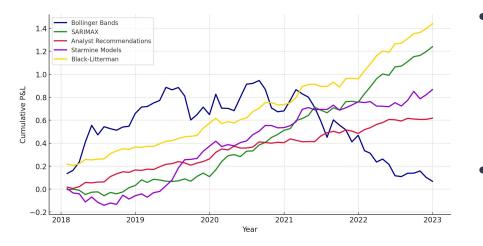
 $\Pi = \lambda \Sigma w_{mkt}$ 

- Π the Implied Excess Equilibrium Return Vector
- λ the risk aversion coefficient
- Σ the covariance matrix of excess returns
- Wmkt the market capitalization weight of the assets

$$E[R] = \left[ \left( \tau \Sigma \right)^{-1} + P' \Omega^{-1} P \right]^{-1} \left[ \left( \tau \Sigma \right)^{-1} \Pi + P' \Omega^{-1} Q \right]$$

- E[R] the new (posterior) Combined Return Vector
- Σ the covariance matrix of excess returns
- P matrix that identifies the assets involved in the views
- τ scalar
- E[R] the new (posterior) Combined Return Vector
- Ω diagonal covariance matrix of error terms from the expressed views (uncertainty in each view)
- Q the View Vector

### Combination of Models (Black Litterman Model)



- Pros:
  - Incorporates Investor Views and confidence levels.
  - Flexibility: Can be adapted to a wide range of asset classes and investment scenarios.
  - Combines Multiple Strategies: Effectively integrates various investment strategies.

### Cons:

- More complex to implement and understand than simpler models like Bollinger Bands or SARIMAX.
- **Dependent on Quality of Inputs** (investor's views and the covariance matrix).
- There's a **risk of overfitting** the model to past data.

### The Fund's Performance

- As we incorporated more robust features over time, we performed better, improving forecasting & decisions performance.
- Last week's poor performance largely affected by the introduction of new factors, presenting an outlier & adversely affecting the semester's results.







## Thank you & Disclaimer

### **The Citadel Spinoffs**



**Disclaimer:** The findings of this presentation should under no circumstances serve to solicit financial decisions, and are solely produced for the class *"IEOR 4576 - Data Driven Methods in Finance"* at Columbia University.

### Thank you for your attention!

**Questions?**