1. Background & Introduction

Trend Following Strategies
Cut short your losses;
let your profits run on.

-David Ricardo
A Simple Example: Channel breakout signal

- Systematically find trends in market prices
- Ride them
- Get out before they revert

Take a long (short) position when a signal breaks out of a certain upper (lower) boundary for a range of values.

FIGURE 1.1 A standard price index for tulip bulb prices. Source: Thompson (2007).
Historical Performance: CTA Smile

Trend following returns tend to perform well during moments when market divergence is the largest.

Periods when markets move the most dramatically provide “trends” suitable for trend following strategies.

Historical Performance: Drawdown

- The **maximum drawdown** for trend following is approximately 25% **lower** than that of the buy-and-hold portfolio.

- The **average of the top five drawdowns** for trend following is roughly $\frac{1}{3}$ **lower** than that of buy-and-hold.

Trend following returns exhibit **positive skewness**. The chance for left tail risk or large drawdowns is relatively small due to the “let profits run and cut short your losses” nature of more small losses as opposed to large drawdowns.
1. When to enter a position
2. How large a position to take on
3. When to exit a position
4. How much risk to allocate to different sectors
2. Literature Review

Trend Following Strategies
The paper gives the evidence of presence of trends in the market over two centuries.

Presence of trends forms the basis for trend following strategies.

In this paper, the signal function is:

$$s_n(t) = \frac{[p(t-1) - \langle p\rangle_{n,t-1}]}{\sigma_n(t-1)}$$

where $\langle p\rangle$ is the exponential moving average.

This sign of the signal function is useful for understanding the position (long or short) taken in the futures market.

The net trend strength used in this paper is:

$$Q_n(t) = \sum \text{sign}[s_n(t')] \times \frac{(p(t' + 1) - p(t'))}{\sigma_n(t - 1)}$$

This is the statistical significance of fictitious profit and loss if we traded everyday based on the position taken based on sign of signal function.
Two centuries of trend following - Results

- A t-stat of **5.9** for trend following has been observed for a diversified pool of futures.
- Over two centuries, the t-statistic is around **10**.
- We can reject the null hypothesis because of the high value of the t-statistic.
- The highest values of the t-statistic were seen with commodities data over the last 50 years. However, all asset classes showed high t-stat values.
- The paper conclusively shows that: long term trends exist across all asset classes and are stable in time.

Fig: Fictitious P&L for a pool of futures
This paper introduces the two common ways of measuring trend strengths and compares them on futures data. The two strategies are time series momentum (TSMOM) and moving average crossover (MACROSS). A TSMOM strategy goes long when prices have been moving up, and short when prices have been moving down. The simplest TSMOM signal is the past return over some time period, say $m$ months or days:

$$TSMOM_t^m = return_{t-m,t}$$

The MACROSS strategy first computes two moving averages (MA) of prices, which we call $MA^{fast}$ and $MA^{slow}$. The fast MA puts more weight on recent prices, whereas the slow MA puts more weight on past prices. The MACROSS strategy depends on which MA is higher: the fast one or the slow one.

Transfer of Momentum Strategy

Moving Average Crossover Strategy
This paper also writes the MACROSS strategy in the form of weights and then chooses weights in different ways.

Different forms of weights include exponential weighted moving average crossover. Weights can also be taken from ordinary least squares.
The paper compared some of these strategies on futures data.

\[
signal_t^{\text{TSMOM}(n)} = P_t - P_{t-n}
\]

\[
signal_t^{\text{MACROSS}(m,M)} = \sum_{s=1}^{m} w_s^m P_{t-s+1} - \sum_{s=1}^{M} w_s^M P_{t-s+1}
\]

<table>
<thead>
<tr>
<th>Signal Name</th>
<th>Annual Returns (Excess of Cash)</th>
<th>Annualized Volatility</th>
<th>Sharpe Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>MACROSS(3,12)</td>
<td>10.3%</td>
<td>10.2%</td>
<td>1.01</td>
</tr>
<tr>
<td>MACROSS(8,32)</td>
<td>10.9%</td>
<td>10.3%</td>
<td>1.06</td>
</tr>
<tr>
<td>MACROSS(32,128)</td>
<td>12.8%</td>
<td>9.7%</td>
<td>1.33</td>
</tr>
<tr>
<td>TSMOM(22)</td>
<td>9.8%</td>
<td>10.1%</td>
<td>0.97</td>
</tr>
<tr>
<td>TSMOM(66)</td>
<td>12.1%</td>
<td>10.1%</td>
<td>1.20</td>
</tr>
<tr>
<td>TSMOM(260)</td>
<td>14.2%</td>
<td>9.8%</td>
<td>1.45</td>
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</tbody>
</table>

**Note:** The Sharpe Ratios are before transaction costs.
3. Datasets

Futures of Commodities
Datasets of Commodities Futures

<table>
<thead>
<tr>
<th>Energy</th>
<th>Metals</th>
<th>Agriculture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude Oil</td>
<td>Gold</td>
<td>Corn</td>
</tr>
<tr>
<td>Natural Gas</td>
<td>Silver</td>
<td>Wheat</td>
</tr>
<tr>
<td>Gasoline</td>
<td>Copper</td>
<td>Soybean</td>
</tr>
<tr>
<td>(Refined)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Time Frame:** 1-12 months Expiration  
**Source:** Quandl
Dataset Exploration: Moving Average Strategy Plot

Main Task
Data Preprocessing
Feature Engineering

Model
Using Machine Learning Techniques to not only identify these signals but also evaluate the strength of the signal
A higher SNR indicates a higher quality of trend, or higher price divergence.

The price trend with low SNR appears to be very noisy. The signal for trading is weak.
4. Future Work

Signals Generations and Trade Executions
Plan for the Semester

1. Alpha Prediction
   a. Select and clean a small number of time series, generating simple features and labels
   b. Use regression to predict returns based on those features

2. Trading System
   a. Generate covariance matrix based on empirical data
   b. Use Modern Portfolio Theory to build a portfolio of contracts at each timestep
   c. Evaluate effectiveness based on returns, Sharpe ratio

3. Increase robustness
   a. Introduce trading frictions (transaction costs, observe/trade delay, etc.)
   b. Generate more features to use in the return prediction model (price-based or external)
   c. Modify learning labels to consider returns of a longer time frame
   d. Use a more sophisticated return prediction algorithm (i.e. artificial neural network)
Modern Portfolio Theory

$n$  number of assets in the universe,
$w$  length-$n$ vector representing allocation to each asset (typically sums to 100%)
$r$  length-$n$ vector representing predicted returns of each asset
$C$  $n \times n$ covariance matrix

Expected portfolio return is $w^T r$
Expected portfolio variance is $w^T C w$

Straightforward convex optimization problems to:
- Constrain variance (upper bound) and maximize return
- Constrain return (lower bound) and minimize variance
- In certain cases, can also maximize explicitly for Sharpe ratio
Any Questions?