Trend Following Strategies

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1. Background & Introduction

Trend Following Strategies

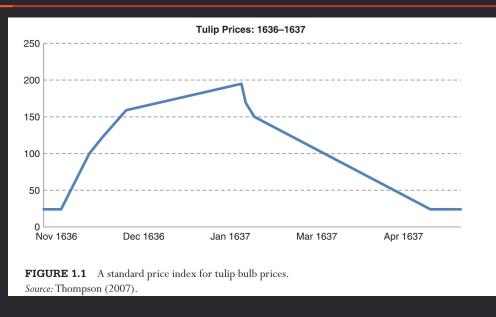




Cut short your losses; let your profits run on.

-David Ricardo

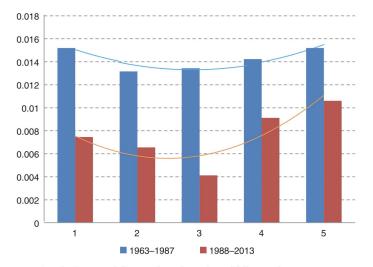
A Simple Example: Channel breakout signal



- 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.

Historical Performance: CTA Smile



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

FIGURE 1.12 The "CTA Smile": Quintile analysis of trend following for 1913–1937, 1938–1962, 1963–1987, and 1988–2013. Returns are sorted by quintiles of equity performance from 1 (worst) to 5 (best).

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

Historical Performance: Drawdown

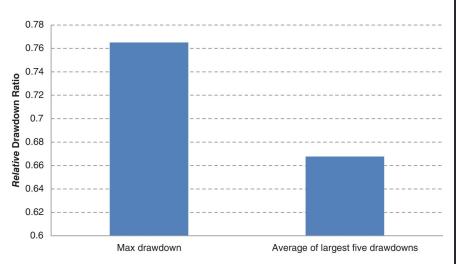


FIGURE 1.13 The maximum and average of the largest five relative drawdowns as a percentage for trend following relative to the buy-and-hold portfolio. The maximum drawdown of trend following is 75 percent of the magnitude of the maximum drawdown for the buy-and-hold portfolio.

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 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.

Trading Framework

- 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



Two centuries of trend following (2014) - Y. Lempérière, C. Deremble, P. Seager, M. Potters

- 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: $s_n(t) = [p(t - 1) - \langle p \rangle_{n,t-1}] / \sigma_n(t - 1)$ 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: $Q_n(t) = \Box sum [sign[s_n(t')] \times (p(t' + 1) - p(t')) / \sigma_n(t - 1)]$
- 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

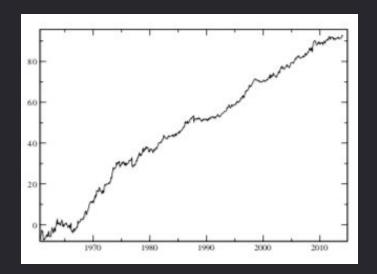


Fig: Fictitious P&L for a pool of futures

- 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.

Which Trend Is Your Friend? (2015) - Ari Levine and Lasse Heje Pedersen

- This paper introduces the two common ways of measuring trend strengths \bullet and compares them on futures data
- The two strategies are time series momentum (TSMOM) and moving average igodolcrossover (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^m_t = 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.

Which Trend Is Your Friend? (2015) - Ari Levine and Lasse Heje Pedersen



Transfer of Momentum Strategy

Moving Average Crossover Strategy

Which Trend Is Your Friend? (2015) - Ari Levine and Lasse Heje Pedersen

• This paper also writes the MACROSS strategy in the form of weights and then chooses weights in different ways.

$$MA_{t}^{fast} = \sum_{s=1}^{\infty} w_{s}^{fast} P_{t-s+1}$$

$$MA_{t}^{slow} = \sum_{s=1}^{\infty} w_{s}^{slow} P_{t-s+1}$$

$$\sum_{s=1}^{s} w_{j}^{fast} \ge \sum_{j=1}^{s} w_{j}^{slow} \text{ for all } s$$

• Different forms of weights include exponential weighted moving average crossover. Weights can also be taken from ordinary least squares.

Which Trend Is Your Friend? (2015) - Results

• The paper compared some of these strategies on futures data.

$signal_t^{TSMOM(n)} = P_t - P_{t-n} \qquad signal_t^{MACROSS(m,M)} = \sum_{s=1} w_s^m P_{t-s+1} - \sum_{s=1} w_s^M P_{t-s+1}$				
Signal Name	Annual Returns (Excess of Cash)	Annualized Volatility	Sharpe Ratio	
MACROSS(3,12)	10.3%	10.2%	1.01	
MACROSS(8,32)	10.9%	10.3%	1.06	
MACROSS(32,128)	12.8%	9.7%	1.33	
TSMOM(22)	9.8%	10.1%	0.97	
TSMOM(66)	12.1%	10.1%	1.20	
TSMOM(260)	14.2%	9.8%	1.45	

• <u>Note</u>: The Sharpe Ratios are before transaction costs.

3. Datasets

Futures of Commodities



Datasets of Commodities Futures

Energy	Metals
Crude Oil	Gold
Natural Gas	Silver
Gasoline (Refined)	Copper

Agriculture

Corn

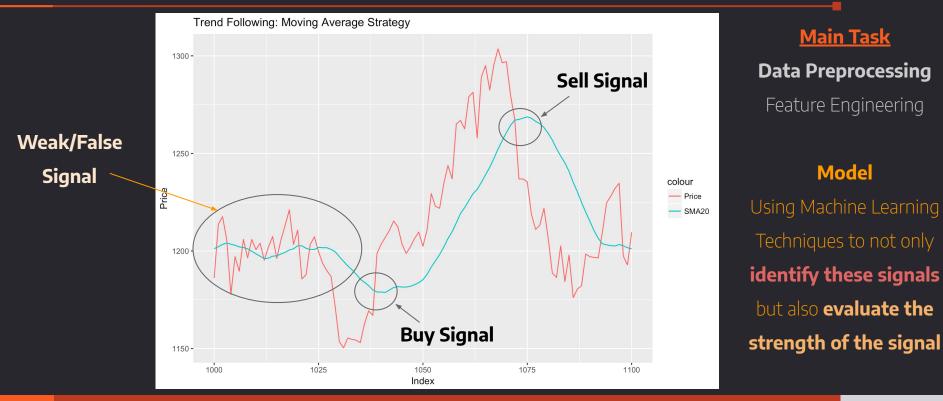
Wheat

Soybean

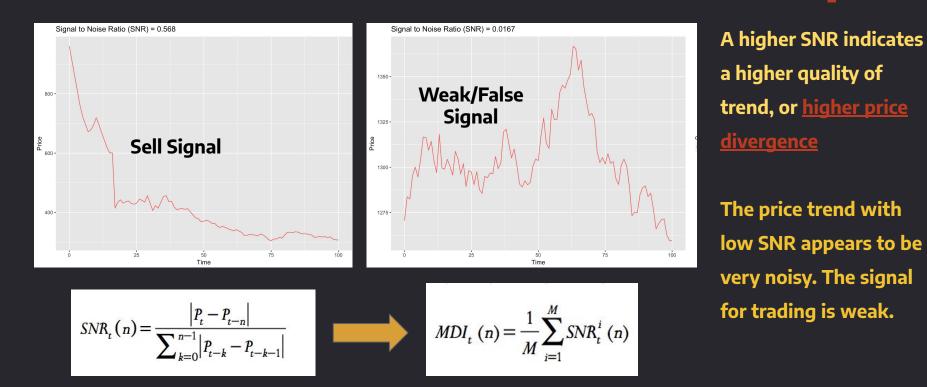
Time Frame: 1-12 months Expiration Source: Quandl



Dataset Exploration: Moving Average Strategy Plot



Signal Generation: Signal to Noise Ratio (SNR)





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
 - D. 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.)
 - D. 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* × *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

