InferTrade

PREDICTIVE RESEARCH TOOLS

Predictive Relationship: Change Relationship

Contents

1 Relationship Description

In a change relationship, recent changes in the current value of the signal directly affects future changes in the price:

$$\Delta p_{+1} \propto k \Delta S_t + c \tag{1}$$

where Δp_{t+1} represents the future percentage price change, ΔS_t represents the previous percentage change in the research signal at current time t, k is a scalar, and c is a constant.

Intuitively, assuming a positive coefficient for k, this means that when the signal is high it is good to buy the market, as the price will tend to drift higher. When the signal is low, it is good to sell the market as the price will tend to drift lower.

An example of a time series that might show a predictive change relationship would be interest rate:

interest rate falls -> recent change in interest rate is high -> price of the SP 500 goes up because investors are allocating capital towards higher return generating assets

We could also see a change component to price forecasts or fair value models if an analyst or model is updated infrequently, as a recent positive change could indicate incorporation of fresh news or information. However if the market price has moved stably then the new information may already be fully incorporated in the price.

Similarly, a technical positioning indicator as a signal may be more likely to show a change relationship, whereby changes in the value of a signal drive the price, because a stable level of interest may not move the market. We would typically not expect a signal that is a price forecast to show a predictive change relationship, as a price forecast is typically relative to the current price (a difference relationship).

2 Trading Strategy Description

A predictive change relationship can be reflected in many kinds of rules. InferTrade uses a 120 period (6 months for daily data) rolling regression of the percentage change in the signal from the prior day against next day's price change as a benchmark. This trading rule recommends taking a position sized as a percentage of the capital you have allocated to trading this particular market.

This rule will show higher returns than usual after optimisation if a significant change relationship is present between the price and signal series. The following equation shows how a change regression trading rule calculates a position sizing:

$$z_t = k_1 \left(\frac{r_t}{r_{t-1}} - 1 \right) + k_2 + \epsilon_{t+1} \tag{2}$$

where z_t is the recommended strategy allocation at time t, r_t is the research value at time t, k_1 is the change coefficient and k_2 is the static coefficient. The bracketed term calculates the percentage change in the value of the research signal from time t to $t-1$.

with the error symmetric such that

$$E_t^{model}[\Delta p_t + 1] = k_1 \left(\frac{r_t}{r_{t-1}} - 1 \right) + k_2 \tag{3}$$

where $E_t^{model}[\Delta p_{t+1}]$ is the predicted next day percentage price change, r_t is the research value at time t, and k_1 and k_2 are the change and static coefficients. ϵ_t represents the in sample regression error between the model predicted and observed price change for time t, such that $\epsilon_{t+1} = E_{t-1}^{model}[\Delta p_t] - \Delta p_t$.

To give a suggested portfolio allocation z_t for the market, e.g. "invest 5% of strategy allocation into the security", the regression forecast's expected next day % price move is divided by the square of the Standard Root Mean Squared Percentage Prediction Error $\varepsilon^2_{rms_t}$ in our above regression:

$$z_t = \begin{cases} \frac{\Delta p_{t+1}}{\varepsilon^2_{rms_t}} & \text{if } t > L, \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where z_t is the suggested allocation as a percentage of the capital which you have allocated to trading this market at time t.

Worked example for liquid market: current share price is $50, regression coefficients are 0.00005 for change and 0.0 for the constant, with $1,000 allocated to this single-stock strategy. The current research series - the interest rate - is +5, with a RMS prediction error from the regression of 5%. In this situation the strategy recipe recommends an investment of $0.00005 * 5/(0.05)^2 = 10\%$ be allocated. So $1,000 * 10% = $100 would be allocated, so we would buy $\frac{\$100}{\$100} = 2$ shares. We see from this example the expected gain over the next day is 2.5 basis points (minus trading costs), versus 500 basis points of daily risk, so in practice this kind of strategy is most useful where the signal and price both has a predictive edge and is stable (auto-correlated) in recommendation over time, so that the 'edge' from multiple time steps can compound linearly without incurring additional bid-offer spreads whilst the 'risk' aggregates scales with the square-root of time (for random walk).

(Note that if the magnitude of the error term is smaller than the magnitude of the price change prediction, i.e. $|\varepsilon_{rms_t}| < |\Delta p_{t+1}|$, dividing Δp_{t+1} by $\varepsilon^2_{rms_t}$ would result in $z_t > 1$. Limits can then be applied to cap the allocation. E.g. between 0% and 100% if short selling is prohibited. In practice it is generally unlikely that in liquid markets a genuine statistical trading signal this strong will be found.)

3 Rule Parameters

Below is a table summarizing the parameters specific to this trading rule.

Parameter Name	Default Value	Description	Symbol
Regression Length	120	This is the number of previous days used to estimate the regression coefficients.	L

Note that rule parameters are fixed to their default values for this and any other relationships optimised on simplified mode. For estimating the regression coefficients, a rolling window is used, so that at time t, the regression data uses research data from time t-121 to t-1 to calculate 120 research changes as the regression's independent variable. Price data from t-120 to t is used to calculate 120 next day price changes as the regression's dependent variable.

4 Glossary

- **Bullish:** Positive outlook on the market. Expectation of positive returns.
- **Bearish:** Negative outlook on the market. Expectation of negative returns.
- **Allocation:** The allocation is the fractional amount of the portfolios value used to determine the size of the trading position.
- **Parameter:** Value used by the trading rule in the calculation for trading position
- **Trading Rule:** Strategy to determine when to buy, hold or sell a position.

Further Links

1. InferTrade: `https://www.infertrade.com`
2. Privacy Policy/Legal notice: `https://www.infertrade.com/privacy-policy`
3. InferStat Ltd: `https://www.inferstat.com`

Appendix

Calculating Regression Error

This PDF omits any explanation of how the regression coefficients k_1 and k_2 are calculated as we are using a standard regression for calculation of both the coefficients and standard error. For InferTrade we used the open source *sklearn* Python library. The same can be achieved in Microsoft Excel by using the *FORECAST.LINEAR* function.

As a worked illustration of the error calculation, assume that InferTrade predicted that a security would increase in price by 0.1% between yesterday and today, and the price actually decreased by 4.9%. In this example, $\Delta p_t = +0.1\%$, and $\Delta o_t = -4.9\%$, giving $\Delta P_t - \Delta p_t = 0.1\% - 4.9\% = -5\% = -0.05$. This value is then squared to give $(\Delta p_t - \Delta o_t)^2 = (-0.05)^2 = 0.0025$. To obtain $\varepsilon^2_{rms_t}$ for day t, this calculation is repeated for every day from day $i = t - L$ to day $i = t$, with values summed before dividing by the regression length L.