Value Speculating-an effective and interpretable small-cap quantitative equity strategy

Introduction: Quantitative investment, Value speculating, Small-cap equity strategy

- **Quantitative investment**: Quantitative investment involves using mathematical models and algorithms to make investment decisions. It relies on data analysis and statistical methods to identify and exploit market inefficiencies.
- **Value speculating**: Value speculating is a strategy that focuses on finding fundamentally sound stocks with small market capitalization. It aims to identify undervalued stocks that have the potential for significant price appreciation.
- **Small-cap equity strategy**: A small-cap equity strategy involves investing in stocks of companies with small market capitalization. Small-cap stocks are generally considered to have higher growth potential but also higher risk compared to large-cap stocks.

Value investing vs Value speculating

- **Value investing**: Value investing is a strategy that involves investing in undervalued stocks based on their intrinsic value. It focuses on finding stocks that are trading at a discount to their estimated intrinsic value. Typically, investors would hold stocks for a long time.
- **Value speculating**: Value speculating, as mentioned earlier, is a variation of value investing that specifically targets small-cap stocks. It seeks to identify fundamentally sound stocks with the smallest market capitalization.
- **Fundamental sound stocks**: Fundamentally sound stocks are those that have strong financials, favorable growth prospects, and a competitive advantage in their industry. These stocks are considered to have the potential for long-term success.
- **Smallest market cap**: The smallest market capitalization refers to the companies with the lowest total value of their outstanding shares. These stocks are typically considered to have higher growth potential but may also carry greater risk.

A Simple Example: Universe selection, Factor extraction, Ranks and scores, Portfolio construction, Rebalancing

- **Universe selection**: The first step in a quantitative strategy is to define the universe of stocks or assets that will be considered for investment. This involves determining the criteria for inclusion and exclusion, such as excluding paused and ST equities in the Chinese security market.

```
stocks = get_all_securities(date=context.previous_date).index.tolist()
current_data = get_current_data()
is_st = pd.Series([current_data[s].is_st for s in stocks], index=stocks)
paused = pd.Series([current_data[s].paused for s in stocks], index=stocks)
stocks = is_st[(~is_st)&(~paused)].index.tolist()
```

A Simple Example: Universe selection, Factor extraction, Ranks and scores, Portfolio construction, Rebalancing

- **Factor extraction**: Factor extraction involves identifying and calculating relevant factors or variables that can be used to evaluate the stocks in the universe. For example, extracting the 1/pb (price-to-book ratio) and ROE (return on equity) of each stock.

```
q1 = query(indicator.code, valuation.pb_ratio, valuation.market_cap,
indicator.roe)

df1 = get_fundamentals( q1,date = context.previous_date)
```

A Simple Example: Universe selection, Factor extraction, Ranks and scores, Portfolio construction, Rebalancing

- **Ranks and scores**: Once the factors are extracted, they are used to rank the stocks in the universe. The rankings are then aggregated to calculate scores for each stock, representing their attractiveness based on the selected factors.

```
df1['1/pb'] = 1/ df1['pb_ratio']

df1['point'] = df1[['roe', '1/pb']].rank().T.apply(sum)

df1.sort_values(by = 'point',ascending = False , inplace = True)

df1 = df1[:150]

stocks = df1['code'].values.tolist()
```

A Simple Example: Universe selection, Factor extraction, Ranks and scores, Portfolio construction, Rebalancing

- **Portfolio construction**: Based on the scores, the top-performing stocks are selected to construct a portfolio. The number of stocks and the weightings can vary depending on the strategy and risk appetite.

```
df1.sort_values('market_cap', ascending = True,inplace = True )

df1 = df1[:10]

pool = df1['code'].values.tolist()
```

A Simple Example: Universe selection, Factor extraction, Ranks and scores, Portfolio construction, Rebalancing

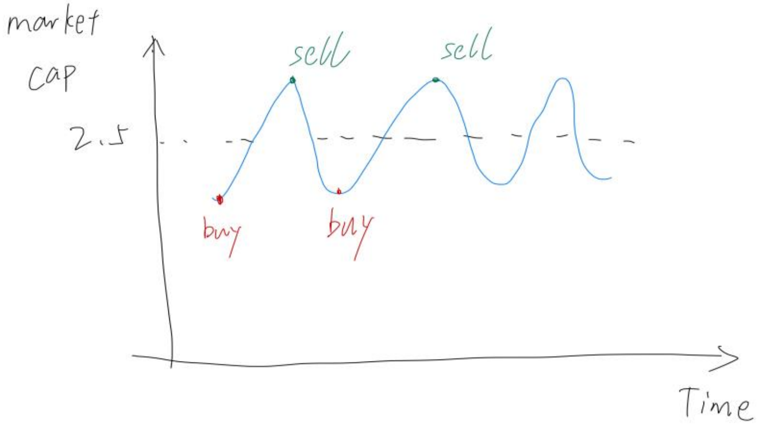
- **Rebalancing**: Rebalancing is the process of periodically adjusting the portfolio composition to maintain the desired asset allocation and risk profile. It involves selling stocks that no longer meet the selection criteria and buying new stocks that meet the criteria.

```
cash = context.portfolio.total_value/len(pool)

hold_stock = context.portfolio.positions.keys()

for s in hold_stock:

        if s not in pool:

                order_target(s,0)

for s in pool:

        if s not in hold_stock:

                order_target_value(s,cash)
```

Sorting by Market Cap

Using market cap for stock selection

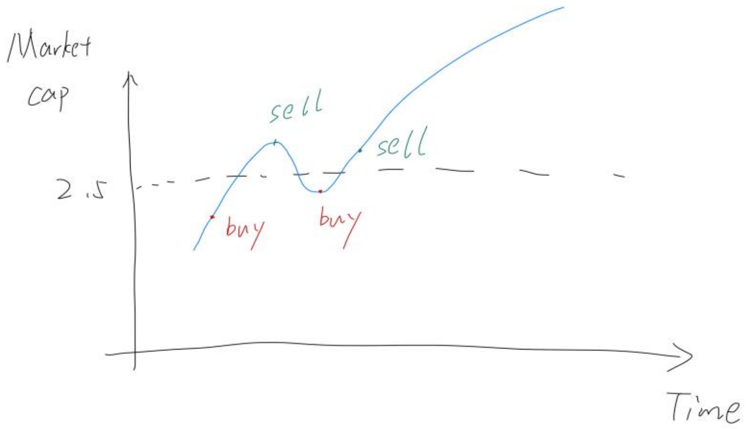
- **Definition of market cap**: Market cap is the total value of a company's outstanding shares, calculated by multiplying the number of shares by the current stock price
- **Relationship with price**: If the stock price rises, the market cap also increases, and vice versa. This can impact the ranking of stocks based on market cap
- **Mean-reversion strategy**: When a stock‘s market cap exceeds a certain threshold (Rank No. 10, 2.5 billion), it is sold. When the market cap decreases below the threshold, the stock is bought. This strategy aims to take advantage of fluctuations in stock prices



Situation 1: Mean Reversion vs Trend Following

Choosing between momentum and SMB factors

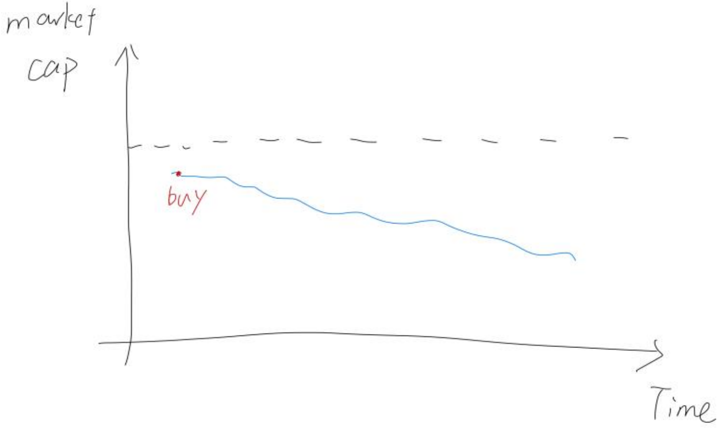
- **Momentum factors**: Trend Following
- **SMB factor**: Mean Reversion
- **Conflict:** difficulty in leveraging two factor simultaneously
- **SMB > Momentum in China**



Situation 2: Leverage Fundamental Soundness

Why we need to identify stocks with fundamental strength

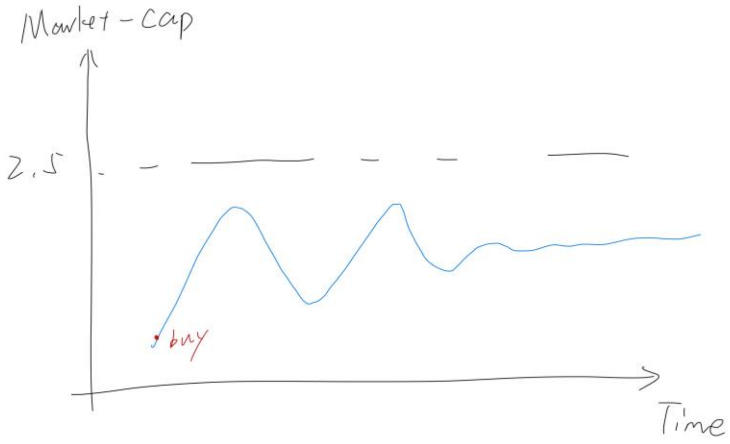
- **Probability of price plummeting**:
  Fundamentally sound stocks have a lower probability of experiencing significant price drops. Such situation tends to happen when the whole market plummet.



Situation 3: Drawback of the Model

Sell stocks in time

- **Selling rule for upper limit price**: If a stock reaches the upper limit but does not continue to do so on the second day, it is considered a sell signal.
- **Solving the flaw with minute-resolution data**: By using minute-resolution price data, we can better track the movement of stock prices during yesterday and make more informed decisions.



Explaining the SMB factor

- **Liquidity advantage**: Small-cap stocks have a liquidity advantage, which means that even a small influx of capital can drive their stock prices up significantly. This can lead to higher returns compared to large-cap stocks.
- **Investor sentiment and small companies**: Investors are often drawn to small companies because they have the potential for significant growth and can capture the imagination of investors. This can lead to higher volatility and larger fluctuations in small-cap stock prices.

Photo by Chris Li on Unsplash

Extended Version of Previous Framework

```
df1 = get_fundamentals( q1,date = context.previous_date)

df1['point1'] = df1[['xxxx', 'xxxxxxx']].rank().T.apply(sum)
df1.sort_values(by = 'point1',ascending = False , inplace = True)

df1 = df1[:df1.shape[0]//2]



df1['point2'] = df1[['xxxx', 'xxxxxxx']].rank().T.apply(sum)
df1.sort_values(by = 'point2',ascending = False , inplace = True)

df1 = df1[:df1.shape[0]//2]

......

df1.sort_values('market_cap', ascending = True,inplace = True )

df1 = df1[:10]
```

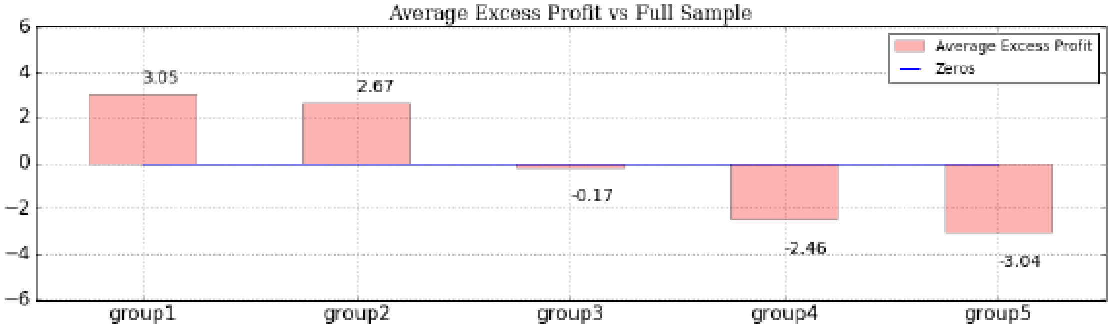
Determining Fundamental Soundness

Analyzing factors for soundness

- **Rank IC and Rank IR**:
- **Performance analysis of factors-Monotonicity**: We divide the universe of stocks into groups based on percentile ranks of factors and analyze the performance of each group.

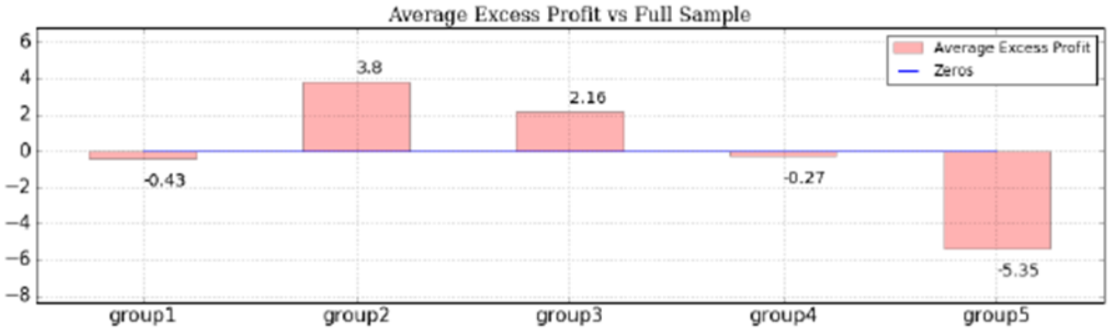
Choosing the best and Risk exclusion

What can we find from group analysis: **Operating Revenue Grow Rate**



Choosing the best and Risk exclusion

What can we find from group analysis: **Inventory Turnover Days**



Correlation

Experience from linear regression

- **Avoid putting highly correlated factors together**
- **Combine weekly correlated factors with high rank IC**

```
df1['point1'] = df1[['adjusted_profit_to_profit','ocf_to_revenue']].rank().T.apply(sum)
```

Persistence

If the factor performs well in T, it will also perform well in T+1.

- **Leverage insider trading:** Imagine a situation where the Q2 earnings preview is released in August and the stock price soars, some insiders have already bought some stocks. However, chances are that we can buy the stocks in May when we obtain the Q1 data. As long as the financial performance of the company is persistent, we can buy stocks in advance.

Validation of Strategy

Testing the effectiveness of the value speculating strategy

- **Use New Data, rather than Cross-Validation**: Only use cross-validation when we lack funds
- **Stock Simulator Testing**: Test for at least 6 months and observe max drawdown of excess returns
- **Stress Testing in Backtesting**: Only keep strategies that perform well when the SMB is not effective and when the whole market plummet.
- **Black Swan Events**: Black swan events are unpredictable and rare events that have a significant impact on financial markets. It is important to consider how the value speculating strategy may perform during such events. By analyzing historical black swan events and their effects on the market, we can better understand the strategy's risk exposure and potential mitigation strategies.

Black Swan Events

Diversification vs Uncertainty

- **No Model Performs Well All The Time**
- **Diversification: Invest in other markets**
- **If you invest in stocks, a 20% drawdown is what you must take.**