# Active Portfolio Benchmarking Model: Optimizing Investment Decisions Based on Sector-Anchored Individual Stock Strategies under Strong Constraints 

Cheng Ruoyu, Ji Cheng, Meng Xianglin<br>China Reform Securities Co., Ltd., Beijing, 100020, China

Keywords: Active portfolio benchmark, anchor stock of value, anchor stock


#### Abstract

Based on the quarterly updated financial indicators, we defined the anchor stock for value and growth under GICS classifications. According to industry, style, structured data, regulation and trading environment, we built a benchmark model for active portfolio in A shares. This paper finds that this benchmark model achieved higher monthly return with lower risk compared to passive index. In the meantime, this model can better perform value investment strategy in the long-run. The active growth model realized a significant higher return than passive index during the year 2014-2015.


## 1. Introduction

In the practice of active investment management in the Chinese securities market, benchmarks such as the passive market index like the Shanghai Shenzhen 300 Index or passive sector indices remain the most widely applied measures in terms of scale and scope for performance evaluation. As understanding of active investment management deepens among Chinese market investors, contributors, and regulatory bodies, there should exist an evolving benchmark model capable of progressively refining the subjective forecasts of a range of virtualized factors or investment strategies into very specific stocks. This facilitates precise calculations of returns and risks for professional market participants, enhancing the operational feasibility of portfolio adjustments and risk management.

### 1.1. Active Portfolio Management Model Development

Markowitz (1952) early proposed that the prediction of risk and return should combine statistical tools with subjective investment judgments. Grinold and Kahn (1994) also suggested that effective investment strategies depend on the integration of investment intuition and statistical techniques. From the monthly R2 statistics, various factor models explain on average between $30 \%$ to $40 \%$ of portfolio returns. According to Fama and French (2018), time-series quantitative factor models are as effective as fixed-slope models in terms of effectiveness. MSCI (2018) indicated that statistical factor models serve several purposes in investment practice: risk analysis, portfolio construction, performance attribution, strategy backtesting, portfolio risk management, regulation and investment transparency, and hedging. From a traditional perspective (Grinold, 1994), the basic elements of active portfolio management include returns above benchmark portfolios, with constraints on risk,
return, and information ratio based on investor preferences. ${ }^{[1-2]}$

### 1.2. Introduction to common stock indices used in China market practice

The performance benchmarks of stock funds in the Chinese market have undergone a series of evolutions. Taking the Huaxin Innovative Securities Investment Fund (code "040001.OF") as an example (Huaxin Fund, 2002), in the earliest year with accessible fund annual reports, 2001, its comparative performance utilized the Shanghai Composite Index and the Shenzhen Composite Index. From 2004 to 2010, a $75 \%$ weight was applied to the returns of the CITIC S\&P 300 Index and $25 \%$ to the returns of the CITIC S\&P Bond Index. According to the 2016 annual report (Huaxin Fund, 2016), this was revised to " $75 \% \times$ Shanghai-Shenzhen 300 Index returns $+25 \% \times$ CITIC Treasury Bond Total Wealth Index returns." As of October 2018, 99\% of the performance benchmarks for all open-end stock funds in the Chinese market on the Wind Information terminal consist of a linear weighted combination of up to three market-type indices and rate-of-return indices resembling cash instruments. Among these, the most widely used index for the equity portion is the CSI 300 Index. ${ }^{[3-4]}$

## 2. Overview of classical theories and dominant benchmark models

## 2.1. "Anchors" in portfolio management

The market portfolio within the framework of the Capital Asset Pricing Model (CAPM) serves as the singular anchor against which any investment portfolio can be priced, with beta measuring the risk relative to this market portfolio (Siddiqi, 2015). Over the past two decades, dominant benchmarks in domestic and international portfolio management such as the S\&P 500 Index, Shanghai Composite Index, or the CSI 300 Index are composed of market capitalization-weighted portfolios. Market capitalization-weighted portfolios, unlike value-weighted portfolios based on various financial metrics, tend to overreact to specific events, leading to overpricing of stocks favored by market participants or neglecting fundamental analysis, thus incorporating stocks at risk of significant price declines (Haugen, 1995). ${ }^{[5-6]}$

This paper contends that market capitalization-weighted portfolios lack comprehensive value analysis and are unsuitable as anchors for evaluating actively managed portfolios. Building upon Fama and French's (2015) demonstration that value stocks exhibit a return premium over growth stocks and lower volatility, superior active benchmark portfolios can be constructed by actively analyzing stocks across different sectors based on distinct characteristics such as value and growth.

### 2.2. Benchmarking framework for managing the active investment process

In the given industry context, anchoring individual stocks with a specific factor or combination of factors serves as the basis for valuing other stocks within the sector, and for determining composite weight allocations. ${ }^{[7]}$
(1) Core Assumptions
(1) Within the sample space, a greater number of stocks and larger market capitalization are indicative of higher value. Stocks ranking in the top $50 \%$ based on liquidity or net profit over the past six months effectively capture the major excess return potential across the market.
(2) Fundamental corporate data such as profit and revenue will dictate the market capitalization proportion relative to the industry and overall market.
(2) Sample Space
(1) Sample Space: For a given period, constituent stocks are the latest set adjusted periodically
from the CSI Index, 2018, including the CSI 300, CSI 500, and CSI 1000 indices.
(2) Fundamental Data: Market trends, financials, and corporate actions over the past 12 months.
(3) Time Variables: The benchmark portfolio adjusts regularly, starting each year's May 31st and November 30th, on the first trading day thereafter. Given that the CSI 1000 Index was introduced in November 2014, and with significant microstructural changes in market regulation and liquidity since mid-2014, this study selects May 2007 and May 2014 as the respective starting points for empirical case calculation. ${ }^{[8-9]}$

### 2.3. Financial forecasting indicators

From an investment perspective over the long term, this paper argues that the proportion of annual net profit within the industry is most suitable for evaluating the relative value of a company in that sector, while revenue and operating cash flow can serve as alternatives when net profit data is anomalous or unavailable. Taking Apple Inc., a US-listed company in the fourth quarter of 2017, as an example (Counterpoint, 2018), the iPhone series contributed $18 \%$ of revenue in the smartphone market but accounted for $86 \%$ of profits. ${ }^{[10]}$

This paper assumes each company belongs solely to a major industry category, while employing net profit and its expected growth rate in absolute terms for proportional calculations within the industry.

In May of each year, this document forecasts the full-year net profit. Initially, it derives a parameter variable by comparing the full-year proportion of the previous year's first quarter net profit to $35 \%$ and selecting the smaller value. It then calculates the year-on-year value of the first quarter net profit for the current year compared to the previous year's first quarter, obtaining an index variable. This process yields the forecasted full-year net profit for the current year:

$$
\begin{align*}
\text { profit_es }_{y e a r} & =\text { profit }_{q 1}+\left(\text { profit }_{\text {year_pre }}-\text { profit }_{q 1 \_p r e}\right) *\left(1-\text { para }_{q 1 \_q}\right. \\
& \left.+ \text { para }_{q 1_{q 4}} * \text { growth }_{q 1_{-} y o y}\right) \tag{1}
\end{align*}
$$

profit_es $y_{\text {year }}$ represents the annual net profit forecast for the year, profit $q_{1}$ denotes the net profit forecast for the first quarter of the year, profit ${ }_{q 1_{-}}$pre represents the net profit forecast for the first quarter of the previous year, and profit year_pre represents the net profit for the previous fiscal year. The primary premise is that the variance in first-quarter data should ideally fall within a range representing at least one-quarter or up to $65 \%$ of the annual impact on the financial data for the remaining three quarters of the year. In instances where data calculation yields missing values, the conservative approach substitutes with $95 \%$ of the previous year's annual net profit data. Further computations derive the projected growth in net profit for the current year:

$$
\begin{equation*}
\text { diff_profit_es }_{\text {year }}=\text { profit_es } \text { year }- \text { profit }_{\text {year_pre }} \tag{2}
\end{equation*}
$$

In November, this paper updates the annual net profit forecast for the current year. First obtain the previous year's first three quarters of net profit for the full year share, and $75 \%$ compared to take the smaller worth to the parameter variable growth $_{\text {3 }_{1} y o y}$; and then calculate the year's first three quarters of net profit year-on-year last year's first three quarters of net profit is worth to the indicator variable; the year's net profit forecast value is:

$$
\begin{gather*}
\text { profit_es }_{y_{\text {eear }}}=\text { profit }_{q 3}+\left(\text { profit }_{\text {year_pre }}-\text { profit }_{q 3_{\_} \text {pre }}\right) *(1 \\
\left.- \text { para }_{q 3_{\_} q 4}+\text { para }_{q 3_{-} q 4} * \text { growth }_{q 3_{\_} y o y}\right) \tag{3}
\end{gather*}
$$

Where profit_es ${ }_{\text {year }}$ is the current year's net profit forecast, profit ${ }_{q 3}$ is the first three
quarters of the previous year's net profit forecast, profit $_{q 3}$ is the first three quarters of the previous year's net profit forecast, profit year_pre is the previous year's annual net profit. The main logic is that the change in the value of the first three quarters of the data should be at least in the range of the first three quarters of the proportion of the year or a minimum of $25 \%$ of the proportion of the fourth quarter of the current year's financial data have an impact. If there are missing values in the above data calculation process, $95 \%$ of the previous year's net profit data is used as a prudent proxy. Forecast the year-on-year growth value of net profit for the current year:

$$
\begin{equation*}
\text { diff_profit_es }_{\text {year }}=\text { profit_es } e s_{\text {year }}-\text { profit } t_{\text {year_pre }} \tag{4}
\end{equation*}
$$

In cases where positive values cannot be computed in the aforementioned steps, the forecasted values for operating cash flow and revenue for the current year are calculated using the same procedure. Given that corporate revenue data is likely disclosed normally and is positive, it ensures obtaining a positive forecasted value for the current year and the year-on-year growth forecast.

## 3. Empirical case studies

### 3.1. Initialization of the baseline model: data, significant variables and parameter design

(1) Time series data for the benchmark model

According to Wind Information data, this article utilizes daily opening and closing prices, as well as trading volumes, of all A-share stocks from May 30, 2007, to May 30, 2014, and from May 30, 2014, to November 5, 2018. It also incorporates quarterly financial information regularly updated and collected via the DZH Information Terminal. Data on stock dividends, bonus issues, and other corporate actions are utilized to compute adjusted stock prices. The inaugural disclosure of the CSI 1000 Index was in November 2014; therefore, this article uses May 31, 2014, the date of the last disclosure prior to that, as the initial backtesting date for the active benchmark portfolio. ${ }^{[11]}$
(2) Strategy analysis and optimization process for portfolio allocation

The fundamental financial metrics used for strategic analysis include current year net profit forecast, total revenue forecast, and operational cash flow forecast. These metrics are derived from quarterly financial statements of listed companies, specifically "net profit (excluding minority shareholders' income)," "operating revenue," and "net cash flow from operating activities." Absolute changes in current year net profit, total revenue, and operating cash flow are obtained by subtracting year-end data from the previous year, as outlined in the original dataset. ${ }^{[12]}$

In the 9 periods focusing on growth anchors in the financial sector, China Ping An and China Construction Bank appeared 4 times and 2 times respectively. When using $1 \%$ and $3 \%$ as cutoff values for selecting anchoring coefficients within the industry, the numbers of financial stocks with coefficients exceeding $1 \%$ and $3 \%$ were significantly lower compared to those with value-oriented coefficients. However, the total value represented by stocks exceeding these thresholds declined gradually across periods while consistently maintaining a level above $94 \%$. Thus, the study posits that stocks with anchoring coefficients representing more than $0.11 \%$ of the total stock value adequately capture incremental value created by enterprises within their respective industries. ${ }^{[13]}$

Among the 11 primary industries, the industrial sector boasted the largest number of stocks, exceeding 440, while the telecommunications services sector had the fewest, with only 3 stocks. Throughout the nine half-year periods from May 2014 to May 2018, value anchors were consistently calculable across all industries, although some industries occasionally lacked data for growth anchors due to stagnation or decline in overall operational conditions during this period. ${ }^{[14]}$

Based on combinations of value and growth across the 11 industries, this study established comprehensive market value and growth portfolios. The market value portfolio consistently
comprised 640 stocks, with an average relative coefficient (indicating forecasted net profit or analogous metrics relative to anchored stocks) ranging from $1.3 \%$ to $1.7 \%$. As of late May 2018, the top 20 stocks by relative coefficient included 13 from the financial sector, collectively representing approximately $84 \%$ of the total coefficient value, up from around $80 \%$ at the end of 2014 . The average holding of stocks in the market growth portfolio was 487, achieving sufficient diversification. The average relative coefficient in the growth portfolio was $2.6 \%$, higher than the $1.5 \%$ seen in the value portfolio. Notably, the proportion of the financial sector within the growth portfolio decreased significantly, with the number of financial stocks varying between 1 and 7 among different periods, and anchoring stocks rarely being from the financial sector. ${ }^{[15]}$

### 3.2. Active Benchmark Portfolio Construction, Adjustment Process

(1) Analysis of portfolio adjustments

Given the initial time point, the actively managed benchmark portfolio calculates optimal allocation ratios for each stock based on anchored stocks. Subsequently, it determines the target holdings of the actively managed benchmark portfolio according to strategic signals. It compares these with existing holdings, computes the differential items, and generates a plan for portfolio adjustments (trades). Portfolio adjustments starting on day T are executed daily over the following five trading days, with each day transacting $20 \%$ of the quantity; transaction prices are based on the average of each day's opening and closing prices. ${ }^{[16]}$

Table 1: Sector and Market Anchor Portfolio Position Adjustment Program before and after three positions

| Value Anchor Portfolio | Average of Non-Building Positions | Growth Anchor Portfolio | Average of Non-Building Positions |
| :---: | :---: | :---: | :---: |
| Full Market Value Anchors | 14.6 percent | All Markets Growth Anchors | 73.5\% |
|  | Top three buy positions |  | Top 3 Buy Positions |
| Information Technology | 39.06 | Utilities | 91.2 percent |
| Materials | 37.23 | Energy | 87.8 percent |
| Utilities | 23.11 | Real Estate | 84.6 |
|  | Bottom three buy positions |  | Bottom three buy positions |
| Industrials | 14.58 | Materials | 77.9 |
| All Markets | 14.56 | All Markets | 73.5\% |
| Finance | 5.38 percent | Telecom Services | 62.6\%-75.7 |
| All Markets Value Anchor | -18.9 percent | All Markets Growth Anchors | -75.7 |
|  | Top three sell positions |  | Top three sell positions |
| Financial | 5.89\% -16.11 | Telecom Services | 63.2\%-75.7 |
| Industrial | -16.11 | All Markets | 75.7\% -78.3 |
| Consumer Discretionary | -16.98 | Materials | -78.3 |
|  | Bottom three sell positions |  | Bottom three selling positions |
| Utilities | -23.3\% -37.7 | Real Estate | -85.2\% -86.6 |
| Materials | -37.7 percent | Energy | 86.6\% -90.8\% |
| Information Technology | -39.9 percent | Utilities | -90.8 |

According to Table 1, excluding the initial position-building period in the first quarter, the average buy positions of the 11 industry value portfolios are $20.7 \%$ semi-annually, while the average sell positions are $21.4 \%$. Within the industry value portfolios, the financial sector portfolio exhibits the lowest semi-annual rebalancing proportion, approximately $5.5 \%$, whereas the information technology sector portfolio shows the highest, exceeding $39 \%$. This reflects the relatively stable and predictable net profits of individual stocks in the financial sector compared to the significant variations in net profits of stocks in the information technology sector.

In contrast to the value portfolios, the growth portfolios demonstrate significantly higher rebalancing extents, with average buy and sell positions exceeding $81 \%$ per period. The telecommunications sector exhibits the lowest average rebalancing proportion within the industry, with only three stocks; the utilities sector, conversely, features the highest average rebalancing proportion, likely due to ongoing new project investments affecting net profit and related data significantly. ${ }^{[17]}$

The average portfolio adjustment proportions of the entire market's value and growth portfolios are both lower than the average of the 11 industry portfolios. This is believed to stem from the high proportion of net profits attributable to the financial industry in the overall market, establishing a value anchor from an industry perspective and thereby reducing the proportion of portfolio adjustments per period.

The benchmark model should be capable of daily retaining trading plans and records. From a stock perspective, the top 20 stocks in the value portfolios average a $60 \%$ share of realized gains, whereas the top 20 stocks in the growth portfolios average only a $20 \%$ share of realized gains.
(2) Portfolio net worth and retracement analysis

The latest (as of November 5, 2018) holdings of industry value portfolios show significant outperformance in book profit and loss compared to growth portfolios within the same industry. Examining individual stock $\mathrm{P} / \mathrm{L}$ as a percentage of net asset value, the maximum in the value portfolio averages $17.4 \%$, nearly ten times that of the growth portfolio's $1.7 \%$, while the minimum in the value portfolio averages $-1.5 \%$, less than half of the growth portfolio's $-3.2 \%$. On a single-stock basis, the top profit-making stock in the value portfolio averages $48.3 \%$ of the total profit, reflecting cumulative stable long-term holding returns in excellent industry stocks. Due to more frequent portfolio adjustments, the growth portfolio exhibits a significantly lower average of $16.7 \%$ for maximum profits compared to an average of $-33.2 \%$ for maximum losses.

In terms of absolute book profits, the top 5 profitable stocks in the value portfolio collectively account for $91.8 \%$ of profits, and the top 10 account for $99.9 \%$. As these profitable stocks anchor high industry value and relative value coefficients, they indirectly affirm the dominant role of industry value anchors in portfolio returns, echoing insights from the German DAX market index (Hilpisch, 2014), where the largest 9 stocks explain $97.7 \%$ of index price movements. Conversely, neither the maximum profit/loss values nor the sums of profits from the top 5 or 10 stocks in the growth portfolio exceed $30 \%$ in explaining book profits. The main reason for the growth portfolio's inability to demonstrate significant book profits lies in the majority of investment gains converting to realized profits through biannual adjustments. ${ }^{[18]}$

## 4. Conclusions and outlook

The present study proposes a strategy for allocating stocks within an industry based on fundamental data (such as financial indicators), constructing a benchmark model for industry and market actively from both value and growth perspectives. Research indicates that industry-specific value anchor and growth anchor stocks better match the risk of portfolio holdings compared to factor models. Value portfolios, reflecting long-term investment returns more effectively through
holdings' floating profit and loss data, are found to be more accurate. However, the active benchmark model has considerable room for improvement. Using only annual forecasts of net profit, total revenue, and operating cash flow net amount may inadequately capture all critical factors influencing enterprise value and growth. Further stock valuation calculations should incorporate, but not be limited to, momentum, capital structure, operational business, human resources, and information systems forecasts. The current portfolio allocation strategy fails to consider varying financial indicators (e.g., P/E ratio or P/B ratio) among industry peers. Empirical results also reveal that active value portfolios across A-share markets have significantly outperformed growth portfolios in both risk and return over the past four years. The study anticipates that top-ranking companies in industry profits and revenues will continue to expand their share of industry value increment in the future. If this hypothesis holds, it will strongly support the risk-adjusted return of actively managed benchmark portfolios converging towards theoretically optimal levels.

## References

[1] Boxwell Jr JRobert, 1994, Benchmarking for Competitive Advantage [M]. McGraw-Hill.
[2] Counterpoint, 2018, Monthly market pulse[R]. Counterpoint Research.
[3] E. J V, Tierney DBailey, 1988, Benchmark Portfolios and the Manager. Journal of Applied Corporate Finance, (4): 25-32.
[4] Eugene F. Fama R. FrenchKenneth. 1993, Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, (2):3-56.
[5] HilpischYves, 2014, Python for Finance [M]. O'Reilly.
[6] KahnC. Grinold and Ronald N.Richard, 1999, Active Portfolio Management: a Quantitative Approach[M]. McGraw-Hill Education.
[7] Morgan Stanley Capital International, November 2018, MSCI ACWI INDEX (USD) [R].
[8] S\&P Dow Jones Indices Limited, 2018, S\&P Dow Jones Indices [R].
[9] CSI Indexes Ltd, 2014, Smart Beta Strategy Indexes [R].
[10] CSI Indexes Ltd, August 2018, CSI 300 Index Program [R].
[11] CSI Indexes Ltd, 2018, CSI 800 Style Index Series Compilation Program [R].
[12] CSI Indexes Ltd, 2018, CSI 300 Segmented Industry Index Program [R].
[13] CSI Indexes Ltd, 2018, CSI Series Index Calculation and Maintenance Rules [R].
[14] CSI Indexes Limited, 2014, Application of Benchmarks in Investment Management [R].
[15] Hua An Fund Management Co Ltd, 2002, Hua An Innovative Securities Investment Fund 2001 Annual Report [R].
[16] Hua An Fund Management Co Ltd, 2017, Hua An Innovative Securities Investment Fund 2016 Annual Report [R].
[17] China Securities Regulatory Commission, 2007, Administrative Measures for Information Disclosure of Listed Companies [R].
[18] China Securities Regulatory Commission, 2012, Guidelines on Industry Classification of Listed Companies (2012 Revision) [R].

