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A Comprehensive Study on Smart Beta Strategies in the A-share Market

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Abstract[1]

In this paper, we explore how smart beta strategies are applied in the Chinese A-share market. Specifically, we empirically examine several popular smart beta strategies, including Mean-Variance Optimization (MVO), Minimum-Variance Portfolio, Equal Weighting, Risk Parity Strategy, and Fundamental Indexation, and we do so using the Shanghai Stock Exchange (SSE) 50 index and SSE sector indices as our comparison benchmarks. We find that all smart beta strategies outperform these benchmarks from year 2006 to year 2015, and that all smart beta strategies outperform the SSE 50 index by an average of 2.57% per year. In turn, these strategies improve the Sharpe Ratio by 46.2% on average.

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A Comprehensive Study on Smart Beta Strategies in the A-share Market

Abstract

In this paper, we explore how smart beta strategies are applied in the Chinese A-share market. Specifically, we empirically examine several popular smart beta strategies, including Mean-Variance Optimization (MVO), Minimum-Variance Portfolio, Equal Weighting, Risk Parity Strategy, and Fundamental Indexation, and we do so using the Shanghai Stock Exchange (SSE) 50 index and SSE sector indices as our comparison benchmarks. We find that all smart beta strategies outperform these benchmarks from year 2006 to year 2015, and that all smart beta strategies outperform the SSE 50 index by an average of 2.57% per year. In turn, these strategies improve the Sharpe Ratio by 46.2% on average.

JEL Classification: G11, G15

Keywords: Smart beta strategies, Value-weighted index, Chinese A-share market

1. Introduction

Since Capital Asset Pricing Theory (CAPM) was developed in the 1960s, it has been assumed that only beta risk could generate risk premium for all market investors and that all unsystematic risk could be diversified. What investors needed to invest, then, was just a holding "market portfolio" or capitalization-weighted portfolio (i.e., beta investment), which is mean-variance optimal (Markowitz, 1952). In the following 20 years, many scholars identified other risk factors besides beta risk that can bring higher returns to investors[2]. Empirical studies have also shown that portfolios with additional risk factors can produce higher abnormal returns than market capitalization-weighted indices, suggesting that market value indices are not mean-variance optimal. Thus, it is possible to build more mean-variance efficient portfolios other than traditional market value indices.

A growing number of institutional investors recognize the shortcomings of traditional market value indices. Moreover, responding to dramatic fluctuations in the stock market and the impact of inefficient markets, investors seek investment methods with higher returns than passive investment and also seek lower volatility than active investment. As a result, investors have started to adopt smart beta strategies as investment vehicles. As the name "smart beta" implies, these new investment vehicles are "smarter" than original beta investments, as they achieve either higher returns or lower volatility.

Although there is no consensus among investors on the definition of "smart beta strategy," the one common characteristic that all smart beta strategies or indices share is that they are rules-based. The smart beta strategy integrates the ideas of both active and passive portfolio management, weighting the assets by using methods other than market value-weighted methods. One definition is proposed by Research Affiliates (RAFI) in 2014: *The smart beta is a category of valuation-indifferent strategies that consciously and deliberately break the link between the price of an asset and its weight in the portfolio,*

[2] For example, Black, Jensen, and Scholes (1972) found that shares with low betas have excess returns while those with high betas have negative excess returns. Haugen and Heins (1975) found that low-volatility stocks have abnormal returns, and Haugen and Baker (1991) pointed out that the performance of the minimum-variance index is superior to that of the cap-weighted index. Also, Basu (1983) proposed that value-based portfolios could outperform the market value index, and Banz (1981) observed the significance of "size effects." Fama and French (1992) developed a three-factor asset pricing model by incorporating the value factor and size factor into the single-factor CAPM model. Carhart (1997) then added the momentum factor into this pricing model, which developed it into a four-factor model.

seeking to earn excess return over the cap-weighted benchmark by no longer weighting assets proportional to their popularity, while retaining most of the positive attributes of passive indexing (Arnott and Kose, 2014)[3].

In the U.S. market, although smart beta products have only existed for a decade, they have developed dramatically. Smart Beta Exchange-Traded Funds (ETF) not only remain the core features of traditional ETFs like low cost and transparent management, but also control risk and enhance returns better than cap-weighted ETFs because of their improved weighting methods. By the end of 2016, 600 Smart Beta ETFs in the U.S. existed, and assets under management (AUM) reached $400 billion, accounting for 30% of the number and 40% of AUM of ETFs in the U.S. *Blackrock*, an American global investment management corporation that is the world's biggest provider of Smart Beta ETFs, predicted that AUM will exceed $1 trillion by 2020. In contrast to those products developed in mature markets, the overall size and variety of smart beta products in the Chinese A-share market are obviously lagging. By the end of 2016, only about 50 smart beta funds in the Chinese A-share market existed, but the increasing trend is very significant.

Although smart beta strategies in the U.S. stock market have been extensively studied, studies of similar strategies in the A-share market are limited. In this paper, we investigate several popular smart beta strategies' performance in the A-share market. Based on the sample of Shanghai Stock Exchange 50 index (SSE 50 index, hereafter) in the Chinese A-share market from January 2006 to December 2015, we implement five popular smart beta strategies and find that all five strategies achieve higher Sharpe Ratios than their corresponding market value-weighted indices.

Specifically, all smart beta strategies outperform the SSE 50 index by an average of 2.57% per year. Also, the smart beta strategies improve the Sharpe Ratio by 46.2%, on average. Our research and empirical findings add to the growing body of literature on the effective implementation of smart beta strategies in different financial markets. The emerging market and the developed market differ in several dimensions, including the regulatory environment, the development of capital markets, stock market integration,

[3] The article "What 'Smart Beta' means to us" can also be found at the following link: https://www.researchaffiliates.com/en_us/publications/articles/292_what_smart_beta_means_to_us.html

international diversification, and others (e.g. Korajczyk, 1996, Djankov, McLiesh and Shleifer, 2007, Cao, Jin and Fu, 2017, and other papers cited therein); therefore, we re-examine popular smart beta strategies in emerging markets, especially the Chinese A-share market. Our empirical evidence is promising, and we are optimistic about the feasibility and future development of smart beta strategies in the A-share market.

The remainder of the paper is organized as follows. In Section 2, we introduce the data and smart beta strategies that we used in this paper, as well as discuss performance measures. In Section 3, we present our empirical comparisons among different smart beta strategies and traditional market value indices in the A-share market. We then conclude our paper with Section 4.

2. Data and Smart Beta Strategies

2.1. Data

The sample contains all the information of the SSE 50 index members in the Shanghai Stock Exchange from January 2006 to December 2015. The SSE 50 index consists of the 50 largest stocks from the Shanghai Stock Exchange. In order to test the applicability of smart beta strategies across different industries, we take each of the SSE Sector Indices as an additional benchmark to carry out our empirical research.

Based on the China Securities Index Company and the WIND Database, we obtain both the market transaction data of indices and their corresponding constituent stocks from the year in which the index was created to 2006. We then adjust the stock price and obtain the actual price change by using the forward answer authority pattern. Finally, we obtain financial data such as book value, revenue, cash flows, dividends, and others from the Phoenix Finance website.

2.2. Smart Beta Strategies

Throughout our paper, we analyze five popular smart beta strategies: mean-variance optimization (MVO), minimum-variance portfolio, equal weighting, risk parity strategy, and fundamental indexation. To estimate the sample covariance matrix and sample mean return, we implement the daily price change in the previous year to estimate these two parameters, so we may further estimate the weights in the following period for each rebalancing date.

Due to the strong short-sales limitations in the Chinese stock market, all the smart beta strategies we constructed for our empirical research are not under any short-sales constraints, which is equivalent to adding non-negative weight constraints to the corresponding optimizations.

2.2.1. Mean-Variance Optimization

This strategy is derived from portfolio theory (Markowitz, 1952), which allows investors to efficiently allocate assets by considering trade-offs between risk and return. A constructed portfolio would have the minimum variance for a given specific mean return. The optimal weight vector is the solution to the following linear programming equation:

$$
\begin{aligned}
&\min w^T \Sigma w \\
&s.t. \\
&\sum_{i=1}^{N} w_i = 1, \\
&R^T w = \mu
\end{aligned}
$$

for which w denotes the vector of portfolio weights, Σ denotes the covariance matrix for the portfolio excess returns, *R* denotes the vector of returns and μ denotes the expected return of the portfolio.

2.2.2. Minimum-Variance Portfolio

One criticism of the mean variance portfolio is the sensitive input: the expected return. The minimum-variance portfolio is a modified portfolio strategy, which achieves the lowest risk among all the portfolio choices. For example, Haugen and Baker (1991), Clarke, de Silva, and Thorley (2006), and Jin and Wang (2016) all examined the minimum-variance strategy and illustrated that this strategy could perform better than the cap-weighted strategy. Without the restriction of the expected return, the mathematical expression mentioned can be rewritten as:

$$\min w^T \Sigma w$$
$$s.t.$$
$$\sum_{i=1}^{N} w_i = 1$$

for which w is the vector of portfolio weights, and Σ is the covariance matrix for the portfolio returns.

As shown in the linear programming equation, the solution of this strategy only depends on the covariance matrix, which could be calculated from the historical data of the assets' returns.

2.2.3. Equal weighting

This strategy only has one parameter, N, which denotes the number of selected stocks. The weight of each stock equals 1/N.

The benefit of the equal weighting strategy is that the systematic issue of overweighting overpriced stocks and underweighting underpriced stocks in traditional market value indexes is changed to be random. This method avoids the preference for popular stocks of market value indexes and captures the benefits of smaller cap stocks at the same time. In January 2003, the S&P 500 Equal Weight Index (EWI) was created. The performance of equal weighting has been obviously impressive. For instance, over the past five years, when compared to the traditional S&P 500's return of 23.3%, the S&P 500 EWI achieved a return of 26.8%. From 2003 to 2015, if investors invested $1,000 in the traditional S&P 500 index, these investors would gain $2,937. During this same period, investors would obtain $3,886 with the same investment in the S&P 500 EWI.

2.2.4. Risk Parity Strategy

The risk parity strategy originated in 1996, and the famous U.S. hedge fund Bridgewater Associates established the first risk parity fund, the All Weather fund. When the tech-stock bubble burst between 2000 and 2002, the performance of Risk Parity was outstanding. As a result, this strategy gradually gained popularity among institutional investors. The financial crisis in 2008 demonstrated its success once again. In addition, more and more insurance companies and pension funds have adopted the risk parity strategy.

As a weighting approach to construct diversified portfolios, risk parity reflects asset allocation and is based on risk-driven allocation, rather than based on capital-driven allocation, as is the case with traditional portfolios. Thus, risk parity pays a large proportion of attention to risk management.

Similar to the minimum-variance strategy, the risk parity method merely takes risk into consideration. However, the minimum-variance portfolio, which is based on the covariance matrix to weigh assets, tends to give more weight to assets with low volatility and weak correlations with other assets, which exposes the portfolio to the unexpected risk of the heavy-weighted components. To better control for the uncertainties of these individual assets, researchers devised the concept of risk contribution. Qian (2006) illustrated that the risk parity strategy weights the components in the portfolios with an identical risk contribution, so the portfolios would avoid suffering great losses from specific assets.

Maillard, Roncalli, and Teiletche (2010) assumed that correlations between any two assets were identical, constructed the Equally Weighted Risk Construction portfolio (ERC), and deduced that the weights in ERC portfolios should satisfy the following equation:

$$w_i = \frac{\sigma_i^{-1}}{\sum_{j=1}^{N} \sigma_j^{-1}}$$

When we rebalance the index, we use daily transaction data from the last year to calculate the mean and covariance matrixes of constituent stocks and decide upon the weights in the next period.

This simple method does not take the correlation among assets into account. If the relative risk of assets to the remaining portfolio is considered, then the risk contribution of one component to the portfolio would be labeled as a Total Risk Contribution (TRC) and any two of the TRCs would be equal. The mathematical expression is:

$$Min\sum_{i=1}^{N}\sum_{j=1}^{N}(TRC_i - TRC_j)^2$$

$$TRC_i = w_i\sigma_{i,p} = w_i\Sigma_i$$

for which Σ_i denotes the ith row of the covariance matrix.

2.2.5. Fundamental Indexation

Introduced by Arnott, Hsu, and Moore (2005), the fundamental weighting method uses the fundamental factor in the financial statement to set the weights for different portfolios. Any single financial indicator has its specific shortcomings. For example, many companies do not pay dividends, and dividends cannot reflect intrinsic value well. Hence, a dividend-weighted index will remove many companies. We choose to integrate several aspects of fundamental indicators to broaden our consideration set. The items we choose are the book value, the revenue, the cash flow, and the dividends, and they are equally weighted to form the comprehensive fundamental factor:

$$F_i = \frac{\frac{Equity_i}{\sum Equity} + \frac{CF_i}{\sum CF} + \frac{Revenue_i}{\sum Revenue} + \frac{Dividend_i}{\sum Dividend}}{4}$$

Similar to the cap-weighted method, the expression of the fundamental indexation is:

$$\mathrm{w_i} = \frac{F_i}{\sum_{j=1}^{N} F_j}$$

for which $\mathrm{w_i}$ denotes the normalized portfolio weights, and $\mathrm{F_i}$ denotes the fundamental factor.[4]

[4] By the end of year *t-1*, we collect the financial data of the corporations in SSE 50, including the Book Value (Equity), Cash Flow, Revenue, and Gross Dividend (Dividend), and then calculate the fundamental

The fundamental index outperformed the S&P 500 by an average of 1.97% per year from 1962 to 2004. Regardless of interest regimes, business cycles, and bear or bull stock markets, the performance of this strategy is good. The authors attribute the excess return of the fundamental indexes over the cap-weighted index to superior index construction, additional exposure to distress risk, and price inefficiency, or a mixture of these factors (Arnott, Hsu and Moore, 2005)

2.3. Performance Measures

Throughout our paper, we used several popular performance measures to evaluate the different smart beta strategies' performance, including the holding period return (HPR), the Sharpe ratio, the tracking error, and the information ratio.

The holding period return (HPR) of indices reports the accumulated returns when holding the underlying assets. Both payout dividends and price movements are incorporated in the HPR. In our empirical research on SSE 50 and Sector indices, our starting dates are January 5th 2004 and January 9th 2009, respectively. The definition of the HPR is as follows:

$$HPR = \frac{P_t}{P_0} - 1$$

for which P_is are the adjusted closing prices of the underlying assets.[5]

The Sharpe ratio measures the premium per unit of risk, which is defined as the excess return (annualized return of the portfolio r_p minus the risk-free rate r_f) divided by the risk (annualized volatility, σ_p). We implement 3.5%, the return of a ten-year treasury bond in China, as the risk-free rate, r_f.

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factor F_i for individual stocks. After obtaining all the fundamental factors F_is, we normalize the weights because the summation of the portfolio weights should be 100% (i.e., $w_i = F_i/\sum F_j$).

[5] The adjusted closing prices P_is are adjusted for stock splits, dividends, and rights offerings.

$$\text{Sharpe } Ratio = \frac{r_p - r_f}{\sigma_{\mathrm{p}}}$$

The tracking error is the annualized standard deviation of the difference between the daily returns of each smart beta index and benchmark index. The tracking error measures how closely the strategies follow the benchmark, and ($r_p - r_B$) is also known as an active return.

$$TE = \sigma_{r_P - r_B} = \sqrt{\mathrm{Var}(\mathrm{r_P} - r_B)}$$

The information ratio measures the risk premium from the tracking error perspective. The higher the information ratio, the higher the active return of each strategy adjusted for each unit of tracking error.

$$IR = \frac{\mathrm{E}(r_p - r_B)}{TE}$$

3. Empirical Results

In this section, we present the empirical results of the different smart beta strategies in the A-share market. We implement the standard "rolling horizon" approach: for every semi-annual, we calculate the portfolio weights according to the algorithms in Section 2.2. To estimate the sample covariance matrix and sample mean return, we implement the daily price change in the previous year to estimate these two parameters, so we may further estimate the weights in the following period for each rebalancing date. Using the obtained portfolio weights, we hold the portfolios for the following six months and record the monthly returns. In Section 3.1, we examine the performance of the smart beta strategies on the SSE 50 index, and then use Section 3.2 to further test these strategies' performance on SSE sector indices.

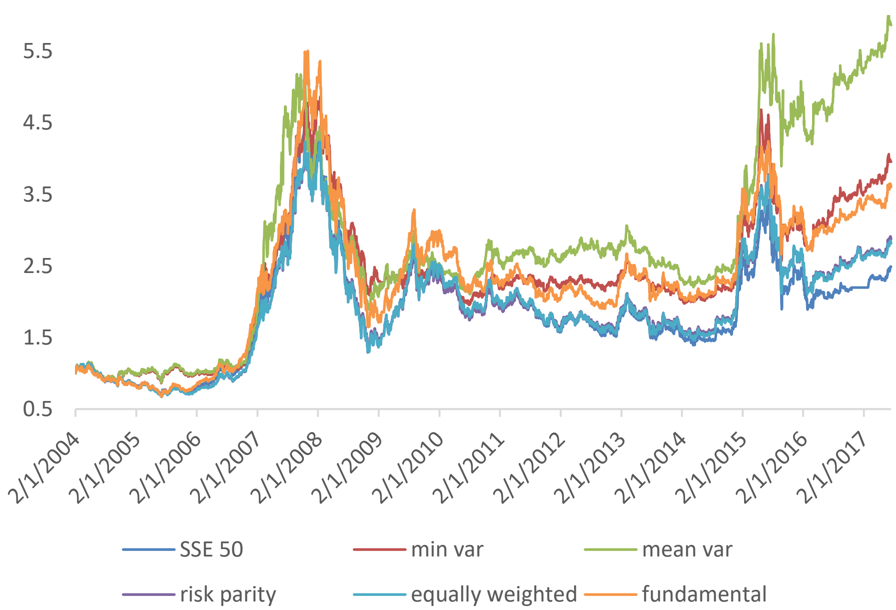
3.1. Performance of the Smart Beta Strategies on SSE 50 index

In Section 3.1., we implement the different smart beta strategies on the SSE 50 stock universe. In Table 1, we report the summary statistics, and we use Figure 1 to show the time series of the accumulative returns of the portfolios that we constructed using several smart beta strategies and the value-weighted index. Overall, the total returns of smart beta portfolios are better than the total return of the SSE 50 Index, which illustrates that these smart beta strategies all outperform the traditional cap-weighted index in the A-share market in the long term.

Table 1: Summary statistics of smart beta strategies on the A-share market

	SSE 50	Min V	Mean V	RP	EW	FW
HPR	148.69%	295.36%	486.46%	187.34%	181.73%	260.09%
Annualized Return	11.00%	13.19%	16.99%	11.78%	11.97%	13.93%
Annualized Volatility	28.33%	23.04%	26.25%	27.13%	28.37%	28.67%
Sharpe Ratio	0.26	0.42	0.51	0.31	0.30	0.36
Tracking Error	--	1.62%	1.78%	1.50%	1.53%	1.57%
Information Ratio	--	1.35	3.36	0.52	0.63	1.87

Figure 1: Performance of smart beta strategies on the A-share market



Of all the smart beta strategies, the mean variance portfolio achieves the highest annualized return of 16.99% and the highest Sharpe ratio of 51%. The other smart beta strategies also outperform the value-weighted index in terms of the annualized return and the Sharpe ratio. Specifically, all smart beta strategies outperform the SSE 50 index by an average of 2.57% per year, and the strategies improve the Sharpe ratio by 46.2%, on average.

The annualized volatilities of the fundamental weighting and equally weighting strategies are the largest. The volatilities of the other three smart beta strategies are all smaller than the volatility of SSE 50, and the minimum variance strategy experiences the least fluctuation. The Sharpe ratio of the SSE 50 index is the smallest and that of mean-variance is the largest, which confirms again that the cap-weighted portfolio is not the optimal one. In sum, the risk-adjusted returns of the smart beta indexes are all better than that of the cap-weighted index.

The tracking errors of the mean variance portfolio are the largest, which shows that the mean variance is injected with the largest number of non-market-beta sources of equity premium. Also, the mean variance portfolio has the largest information ratio and, in turn, has the highest value-added return per unit of benchmark risk, which arises from deviating from the SSE 50 index.

Next, we explore the robustness and performances of the smart beta strategies in the bearish and bullish markets. To further implement the smart beta strategies in real practice, robustness (i.e., the capacity of smart beta strategies to perform effectively in the changing environment) becomes an important issue, as investors may express related concerns (Amenc et al. 2015). We follow the literature — Fabozzi and Francis (1977), Hsu, Kalesnik, and Li (2012), and Amenc et al. (2015) and papers cited therein — to further empirically examine the performance of smart beta strategies in bearish and bullish markets.

Table 2: HPR of different strategies in bearish and bullish markets

	Type	SSE 50	Min V	Mean V	RP	EW	FW
2004.1.2-2005.6.6	bearish	-29.08%	-9.60%	-7.96%	-30.00%	-31.51%	-30.96%
2005.6.6-2007.10.16	bullish	559.75%	425.16%	471.35%	499.55%	518.51%	690.01%
2007.10.16-2008.10.28	bearish	-71.39%	-54.26%	-62.58%	-66.73%	-67.98%	-68.63%

2008.10.28-2009.8.4	bullish	107.60%	25.18%	48.49%	92.78%	105.21%	90.82%
2009.8.4-2012.12.4	bearish	-44.99%	-17.06%	-10.63%	-38.22%	-41.52%	-38.10%
2012.12.4-2013.2.18	bullish	30.31%	12.80%	14.07%	21.95%	23.25%	26.22%
2013.2.18-2013.6.25	bearish	-24.21%	-15.79%	-15.53%	-21.09%	-23.07%	-21.43%
2013.6.25-2013.9.12	bullish	16.10%	4.97%	2.68%	14.05%	17.65%	18.04%
2013.9.12-2014.3.12	bearish	-19.97%	-9.94%	-13.55%	-15.81%	-17.93%	-14.34%
2014.3.12-2015.6.12	bullish	136.15%	108.81%	127.54%	132.88%	139.10%	98.31%
2015.6..12-2017.6.13	bearish	-24.93%	-6.48%	15.39%	-19.72%	-20.93%	-10.42%

According to the A-share market performance from 2004 to 2017, we divide the entire stage into 11 periods that include six bull market periods and five bear market periods, so we may further compare the performance of different strategies, as shown in Table 2.

Trends across all portfolios are roughly the same. In bearish markets, the performance of the equally weighting portfolio is similar with that of the SSE 50 index. Also, the performance of the minimum variance and the mean variance portfolios are quite similar. In bullish markets, the performance of the minimum variance and mean variance portfolios do not stand out because of the volatility restriction. However, in bearish markets, which benefit from the control of volatility, they perform significantly better than the cap-weighted index and the equally weighting portfolio.

Table 3: Effect of changes of μ on the mean variance strategy

μ	0	10%	20%
Annualized Return	17.55%	16.99%	17.98%
Annualized Volatility	26.62%	26.25%	26.73%
Sharpe Ratio	52.78%	51.39%	54.16%

Among these five smart beta strategies, the performance of the mean variance portfolio is the best in the A-share market, but it can be affected by the parameter μ. Thus, we change the constraint constant of μ from 10% to 0% and 20%, respectively, so we may examine the sensitivity of parameter μ, as shown in Table 3.

We find that, along with the parameter μ changes, the performance of the mean variance portfolio also changes but still performs better than other strategies. Moreover, the Sharpe ratio improves by nearly 5.4% when the parameter μ changes from 10% to 20%, indicating that the impact is relatively limited.

3.2. Performance of Smart Beta Strategies on SSE Sector Indices

To further study performance and test the applicability of smart beta strategies in the A-share market, we implement minimum variance, mean variance, equally weighting, risk parity, and fundamental weighting strategies to nine SSE sectors: Consumer Staples, Energy, Financials, Industrials, Information, Technology, Materials, Health Care, and Telecommunication Services and Utilities. Although the high correlation among the stocks in the same sector would weaken the power of smart beta strategies, capturing that finding empirically still rpoves useful, so investors may be provided with some alternatives with respect to sector investment. The portfolio formation and rebalancing procedure of these smart beta sector indices are the same as those in Section 3.1. In Table 4, we report the holding period returns of different strategies in nine different SSE sectors.

Table 4: HPR of different strategies in different sectors

Consumer Staples	SSE 50	EW	Mean V	RP	FW	Min V
	180.09%	196.34%	229.64%	266.03%	363.55%	484.74%
Energy	Mean V	Min V	SSE 50	EW	RP	FW
	-39.45%	-12.03%	-10.22%	-10.10%	-5.51%	9.53%
Financials	Mean V	Min V	SSE 50	FW	RP	EW
	81.50%	111.93%	116.97%	138.87%	150.63%	150.91%
Industrials	SSE 50	FW	EW	RP	Mean V	Min V
	47.72%	50.27%	54.21%	61.67%	69.76%	84.17%
Information Technology	FW	SSE 50	EW	RP	Mean V	Min V
	156.14%	164.34%	182.31%	199.48%	200.01%	291.51%
Materials	Mean V	FW	EW	RP	SSE 50	Min V
	-40.97%	13.39%	21.53%	26.98%	39.91%	108.84%
Health Care	FW	EW	RP	SSE 50	Min V	Mean V
	192.30%	206.32%	225.04%	252.38%	323.64%	328.41%
Telecommunication Services	Min V	FW	RP	EW	SSE 50	Mean V
	58.85%	67.69%	70.20%	75.77%	96.91%	664.28%
Utilities	SSE 50	FW	EW	RP	Mean V	Min V
	58.77%	79.31%	89.47%	97.65%	98.60%	127.76%

In Table 4, we show that smart beta strategies do not outperform traditional cap-weighted indices all the time. For example, only in the Consumer Staples, Industrials, and Utilities sectors do all smart beta strategies obtain higher HPRs than SSE sector indices.

Different from the excellent performance in the SSE 50 stock universe, the HPRs of the mean variance portfolios in three sectors are the lowest. In contrast, the minimum variance portfolios have the best performance and the highest HPR in five sectors.

Table 5: Annualized volatilities of different strategies in different sectors

Consumer Staples	Min V	RP	EW	SSE 50	FW	Mean V
	24.98%	24.98%	25.64%	25.87%	26.13%	29.19%
Energy	Min V	FW	Mean V	RP	EW	SSE 50
	24.79%	26.09%	27.44%	28.30%	30.36%	31.31%
Financials	Min V	FW	Mean V	RP	EW	SSE 50
	21.75%	25.33%	25.94%	26.77%	27.84%	27.92%
Industrials	Min V	RP	SSE 50	EW	FW	Mean V
	28.27%	28.40%	28.66%	29.20%	29.83%	37.44%
Information Technology	Min V	RP	SSE 50	EW	FW	Mean V
	31.30%	32.60%	33.14%	33.41%	35.52%	38.07%
Materials	Min V	RP	SSE 50	EW	FW	Mean V
	30.18%	30.75%	31.36%	31.53%	32.00%	34.34%
Health Care	Min V	RP	SSE 50	EW	FW	Mean V
	26.72%	27.21%	27.44%	27.60%	28.34%	31.32%
Telecommunication Services	EW	RP	SSE 50	Min V	FW	Mean V
	30.99%	31.17%	32.17%	33.44%	35.11%	42.43%
Utilities	Min V	RP	EW	SSE 50	FW	Mean V
	21.59%	24.89%	25.69%	25.80%	25.84%	30.51%

In Table 5, we report the annualized volatilities. The minimum variance portfolios' volatilities are the lowest, except in the Telecommunication Services sector. Also, the mean variance strategy has the highest annualized volatilities in all sectors, except for the Energy and Financials sectors.

Table 6: Sharpe ratios of different strategies in different sectors

Consumer Staples	SSE 50	EW	Mean V	RP	FW	Min V
	0.482	0.511	0.527	0.621	0.715	0.850
Energy	Mean V	Min V	RP	EW	SSE 50	FW
	-0.214	-0.080	-0.006	-0.006	0.003	0.039
Financials	Mean V	SSE 50	Min V	FW	EW	RP
	0.275	0.354	0.370	0.409	0.418	0.423
Industrials	SSE 50	FW	EW	RP	Mean V	Min V
	0.189	0.199	0.208	0.226	0.267	0.282

Information Technology	FW	SSE 50	EW	Mean V	RP	Min V
	0.404	0.420	0.443	0.452	0.468	0.579
Materials	Mean V	FW	EW	RP	SSE 50	Min V
	-0.117	0.100	0.123	0.136	0.177	0.334
Health Care	FW	EW	RP	SSE 50	Mean V	Min V
	0.482	0.508	0.538	0.572	0.614	0.664
Telecommunication Services	Min V	RP	FW	EW	SSE 50	Mean V
	0.232	0.253	0.255	0.266	0.311	0.715
Utilities	SSE 50	FW	EW	Mean V	RP	Min V
	0.213	0.271	0.297	0.313	0.319	0.412

The Sharpe ratios of the defensive Consumer Staples and Health Care sectors are the largest (Table 6). Most strategies in the Energy sector have negative Sharpe ratios. Also, for six of the nine sectors, the minimum variance portfolios have the highest Sharpe ratios. If investors concentrate in a specific sector, then it is easier for them to earn higher risk-adjusted returns by investing with the minimum variance strategy. In our Appendix, we also report the tracking errors and information ratios of the different strategies in the different sectors.

4. Conclusion

As smart beta strategies in financial markets have rapidly developed, researchers have explored these strategies' effectiveness in U.S. and other developed markets. With this paper, we aim to empirically examine popular smart beta strategies in the Chinese A-share market, so we may further confirm the feasibility and potential implementation of smart beta strategies in this particular market. Taking the SSE 50 index and the SSE sector indices as our benchmarks, we demonstrate the superior performance of the five popular smart beta strategies. Specifically, all smart beta strategies outperform the SSE 50 index by an average of 2.57% per year, and the strategies improve the Sharpe ratio by 46.2%, on average.

Our findings add to the growing body of literature that explores smart beta strategies' effective implementation in different financial markets, and our findings offer insights for researchers as well as investors in the Chinese A-share market. We are optimistic about the feasibility and future development of smart beta strategies in the A-share market.

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Appendix:

Table A1: Tracking errors of different strategies in different sectors

Consumer Staples	EW	Min V	Mean V	RP	FW
	1.03%	1.82%	1.85%	1.92%	2.07%
Energy	EW	Mean V	Min V	FW	RP
	1.20%	1.74%	2.06%	2.32%	2.47%
Financials	EW	Mean V	Min V	FW	RP
	1.23%	1.64%	1.79%	1.87%	2.29%
Industrials	EW	Min V	FW	RP	Mean V
	1.72%	2.11%	2.12%	2.25%	2.37%
Information Technology	EW	Min V	FW	Mean V	RP
	1.47%	2.12%	2.21%	2.41%	2.45%
Materials	EW	Min V	Mean V	FW	RP
	1.50%	2.12%	2.17%	2.29%	2.39%
Health Care	EW	Min V	FW	Mean V	RP
	1.14%	1.81%	1.83%	1.98%	1.99%
Telecommunication Services	EW	RP	Min V	Mean V	FW
	1.88%	2.19%	2.41%	2.68%	2.85%
Utilities	EW	Min V	FW	RP	Mean V
	1.27%	1.65%	1.76%	1.92%	1.93%

Table A2: Information ratios of different strategies in different sectors

Consumer Staples	EW	Mean V	RP	FW	Min V
	0.61	1.57	1.59	3.00	4.80
Energy	Mean V	Min V	EW	RP	FW
	-3.44	-1.01	-0.23	-0.11	0.40
Financials	Mean V	Min V	FW	RP	EW
	-1.66	-1.02	0.26	0.64	1.42
Industrials	FW	EW	RP	Min V	Mean V
	0.26	0.40	0.46	1.22	1.94
Information Technology	FW	RP	EW	Mean V	Min V
	0.20	0.55	0.61	1.37	1.97
Materials	Mean V	EW	FW	RP	Min V
	-4.40	-1.11	-1.03	-0.58	2.13
Health Care	EW	FW	RP	Min V	Mean V
	-1.47	-1.11	-0.53	1.13	1.78
Telecommunication Services	RP	EW	Min V	FW	Mean V
	-0.97	-0.95	-0.94	-0.36	7.58
Utilities	FW	RP	EW	Min V	Mean V
	0.84	1.27	1.67	2.06	2.10