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A comparative analysis of alternative indexing strategies in an Emerging Equity Market

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ABSTRACT

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Objective: This study evaluates the performance of fundamentally weighted (FW) portfolios relative to the traditional capitalization-weighted (CW) portfolio in Pakistan's equity market and examines whether alternative weighting strategies generate superior risk-adjusted returns under varying market conditions.

Design/Methodology/Approach: Monthly secondary data from July 2000 to June 2024 were used to construct fundamentally weighted portfolios based on net income (NI), earnings before interest and taxes (EBIT), book value plus intangibles (BV+I), cash flows (CF), dividends (D), and a composite (COMP) index using both current and five-year moving average fundamentals. Portfolio performance was evaluated using descriptive statistics, Sharpe, Treynor, and Sortino ratios, alongside regression analysis employing multiple asset pricing models.

Findings: The test's results indicate that the complete sample period, the capitalization-weighted portfolio output performed all foundational weighted portfolios. Therefore, the composite foundational weighted index consistently generated at higher risk-adjusted returns during the periods of market volatility, specifically from July 2000 to June 2008 and July 2014 to June 2019. The tests output suggest that foundational weighting improves resilience in volatile market conditions by reducing the effect of market pricing.

Practical Implications: The results provide investors, portfolio managers, and policymakers with useful information that improves portfolio diversification and risk management by demonstrating that fundamentally weighted strategies can successfully replace capitalization weighting in uncertain economic times.

Originality/Value: This study extends the limited evidence on fundamental indexation in emerging markets by constructing multiple fundamentally weighted portfolios using firm-specific accounting measures and evaluating their performance over a 24-year period in Pakistan's equity market. The findings offer new evidence on the conditions under which fundamental weighting enhances portfolio efficiency and investment performance.

Keywords: Fundamentally-weighted (FW) index, Capitalization-weighted (CW) index, Mean-variance efficient portfolio

1| INTRODUCTION

Index-based investment management aims to replicate an index's benchmark performance, making the weighting method crucial to investment outcomes. Historically, CW indexes/portfolios that allocate weights based on market capitalization (MC) have served as the primary benchmarks. This passive investing strategy incurs no fees for trading, managing, or rebalancing, establishing it as the traditional method for constructing portfolios since the 1950s (Goltz & Le Sourd, 2011; Kumar & Tiwari, 2022). Based on Modern Portfolio Theory (MPT) or Mean-Variance Optimization, CW indexes/portfolios are argued to be the most mean-variance efficient (Arnott, 2005; Bodie et al., 2017). This underpins the weighting of major stock indices like the S&P 500, OMXS30, DAX, and MSCI. The justification for mean-variance efficiency is rooted in the Efficient Market Hypothesis (EMH), which posits that security prices reflect all relevant information and represent the most reliable estimates of a firm's value (Bodie et al., 2014). However, this perspective has been increasingly challenged in recent years (Abate et al., 2021; Arnott & Hsu, 2008; Balatti et al., 2017; Fillipozzi & Tomingas, 2017; Haugen & Baker, 1991; Markowitz, 2005; Hsieh, 2013; Kucuksahin & Coskun, 2020; Kumar & Tiwari, 2022).

The ‘price’ is an essential factor in traditional CW indexing methodology for weighting securities, but it is not necessarily the best estimator of their true intrinsic value. Although CW indexes have historically served as benchmarks for passive investments, they tend to allocate more weight to overpriced stocks and less to underpriced stocks, particularly when prices do not accurately reflect a company's fundamentals, especially in less efficient markets. This may lead to a CW bias, also known as ‘performance drag’ (Arnott et al., 2005; Arnott & Hsu, 2008; Fillipozzi & Tomingas, 2017; Haugen & Baker, 1991; Hsu, 2006; Naylor & Dai, 2016 and Siegal, 2006). This raises many questions about what causes this performance drag for academics and researchers. In this regard, Siegal (2006) explained this phenomenon in the Noise Market Hypothesis (NMH) that the prices of securities diverge from their true intrinsic value primarily due to speculative trading/bubbles or irrational behavior of investors in the stock market, which induces noise in stock prices which in turns affect both the weights and returns of a constructed CW index/portfolio, causing this drag. Consequently, the potential flaws in CW indexes/portfolios suggest that MC is a relatively volatile way to measure a company’s size. These shortcomings of the benchmark CW indexation highlight the need for researchers to explore alternative indexing methods to address the inherent biases of the traditional index. Therefore, alternative measures for building and weighting passive portfolios have been proposed.

Over the past 40 years, many academics, and research analysts have been investigating new investing paradigms in the equities market, with the earliest studies dating back several decades. In this regard, one of the newest developments in the realm of investment methods or international investment style is the “Smart-beta” strategy or “Factor-Investing” strategy. This idea of ‘Smart beta1’ or ‘Fundamental Weighting’ indexing was first pioneered by Arnott et al. (2005) to describe an investment strategy that combines the benefits of passive index investing with the potential for outperformance that comes with active management. The Smart beta strategy is an umbrella term for all portfolio strategies that avoid using "noisy" market prices to assign weights to stocks. Instead, they rely on 'accounting data,' which is presumed to be a more accurate estimator of a company's intrinsic value than stock prices, unburdened by the inherent flaw of mispricing (Arnott et al., 2005; Arnott et al., 2021; Treynor, 2005). Undoubtedly, the smart beta FW index/portfolio has demonstrated remarkable success, growth patterns, and global dominance in both developed, developing, and emerging markets. However, a slight divergence in the case of Pakistan’s equity market warrants additional consideration (Walkshaul & Lobe, 2010). Therefore, this study aims to compare the performances of alternative FW indexes/portfolios against the traditional CW index/portfolio in predicting stock returns by eradicating performance drag and providing a higher risk-return tradeoff.

2 | Literature Review

Alternative indexation frameworks based on accounting valuation focus on assigning weights based on ‘accounting’ information rather than price. This approach is not novel among investors; it has been antedated in many academic

[1] The term "smart" in smart beta refers to the fact that these strategies are designed to capture market inefficiencies and exploit specific factors or characteristics that are believed to drive returns, such as size, value, momentum, quality, or low volatility. These factors are chosen based on rigorous academic research that has demonstrated their historical outperformance over long periods.

studies for over a decade. The concept of utilizing accounting information in asset valuation was first introduced by Benjamin Graham, a renowned statistician and pioneer of security analysis on Wall Street. Later, Graham and Dodd's book 'Security Analysis', published in 1934, emphasized the use of metrics such as Sales, Dividends, and book values to determine whether individual stocks of firms are under or overvalued. This type of strategy is known as fundamental analysis, which helps investors find a stock's true intrinsic value, independent of noisy market prices.

Recently, there has been a renewed interest in selecting stocks based on income statements and balance sheet data due to the drift in stock prices after the announcement of the post-earnings, as reported by numerous research studies. These studies suggest that accounting ratios can help predict stock returns (Holthausen & Larcker, 1992; Pitroski, 2000). However, modern finance challenges this perspective, discouraging the use of past information for making profitable investment decisions. According to the EMH theory, prices follow a random walk, and all the relevant information is already incorporated. As a result, it is deemed impossible to generate anomalous returns using accounting data (Kendell, 1953). Similarly, the well-known CAPM model developed by Sharpe (1964) and Lintner (1965) creates a market portfolio that weights the securities according to their MC. This model is considered the most mean-variant efficient, as it creates an optimal portfolio that can yield high returns at a given level of risk (Bodie, Kane & Marcus, 2017). Consequently, holding a riskier portfolio is the only way an investor can potentially beat the benchmark CW index (Basu & Forbes, 2014).

In this regard, it is worth noting that Arnott et al. (2005) proposed a ground-breaking study introducing an indexing technique based on fundamental measures obtained from historical accounting data, which considerably outperforms the risk-adjusted CW market portfolio. The authors constructed a composite index, known as the "fundamental index", by combining four indicators: Book value, sales, cash flow, and dividends. It is also found that from 1964 to 2002, the fundamental index exhibited over 2% annual returns more than the equivalent CW index (S&P 500), while both exhibited similar levels of volatility. Treynor (2005) demonstrates that the noise in stock prices is equivalent to the return drag on a CW index. Siegel (2006) further argues that, because stock prices are prone to noise, CW indexes would perform worse than the alternative FW indexes as a portfolio construction technique. Later, Arnott et al. (2010) expanded their research to emerging markets by examining the debt market and asserted that FW indices outperform traditional ones. This trend was further explored by Walkshausl & Lobe (2010), who developed a global fundamental index and individual country indexes for 28 developed and 22 emerging markets (including Pakistan) and found no clear outperformance of country-specific indexes. However, their research confirmed that the global FW index outperformed the global CW index. Therefore, these findings underscore the need for additional investigation to explore the reasons behind the surprisingly divergent results as well as to assess the potential advantages of alternative FW indexation in Pakistan's equity market.

To date, there has been no comprehensive study conducted on FW indexation in the Pakistan stock market (PSX). However, subsequent research across various financial markets confirms that FW indexation performs better, particularly in emerging markets, where noise concentration is more pronounced (Abate et al., 2021; Bartelet, 2019; Casavecchia et al., 2022; Cohen et al., 2019; Hashimi, 2020; Kucuksahin & Coskun, 2020; Kumar & Tiwari, 2022; Naylor & Dai, 2016; Sukma & Namahoot, 2025). Hence, this study makes four critical contributions to the existing literature. Firstly, it assists financial investors in understanding alternative measures of indexing more comprehensively (Abadi & Silva, 2019; Arnott et al., 2010; Basu & Forbes, 2014; Ferreira & Krige, 2011; Kumar & Tiwari, 2022). Secondly, it contributes to the smart beta literature by considering alternative fundamental strategies based on the size of the firm in full (July 2000–June 2024) and sub-sample periods (July 2000- June 2008), (July 2008- June 2014), (July 2014- June 2019), (July 2019 - June 2024) considering both the pre-and post-crisis periods led by speculative bubbles. Thirdly, the study proposes modified smart beta indexes based on NI, EBIT, D, CF, and BV+I, which can help construct more efficient portfolios with superior risk-return trade-offs (Arnott et al., 2005; Naylor and Dai (2016). Lastly, the study offers invaluable insight to asset managers and fund managers into the risk-adjusted performance of FW indices during bubble periods of speculation, factoring in firm-specific characteristics like size, value, profitability, and investment.

3 | Methodology and Design

The study adopts the explanatory approach, using a deductive methodology to evaluate various financial theories, such as EMH, NMH, etc., by testing relevant hypotheses. The data is gathered from secondary sources, such as DataStream of Refinitiv, from the period of July 2000 and June 2024 to construct alternative indexes[2]. For this purpose, the following five key metrics were chosen: Net income available to stockholders (NI, wc01751), Earnings before interest and taxes (EBIT, wc18191), Total cash dividends (D, wc05376), Operating cash flows (CF, wc054860), Book value (BV, wc05486), Intangible assets (I), and the number of employees (wc07011). These were all in line with the study of Arnott et al. (2005), with some minor changes[3]. However, the variable labeled number of employees (wc07011) was removed from the analysis because the collected data were insufficient for additional research.

Index Construction Methodology

The performance of alternative indexes is analyzed through monthly portfolios as betas of portfolios are more stable over time due to their characteristic of lowest residual variance (Cochrane, 1991). The alternative indexes are constructed using a rigorous selection criterion of stocks (FTSE Russell, 2016[4] and Macharia, 2017). The process of constructing an index started with the universe of 1004 (Listed 556, Delisted 448). From this, data for 605 companies (listed and delisted) were available for common stocks. The dataset excluded Exchange-traded funds (ETFs), Closed-ended funds, Penny stocks, Preferred stocks, Petty stocks, Trust funds, Mutual funds, Growth funds, and Value funds. The next step is to clean the data in two stages before constructing the alternative indexes (Arnott et al., 2005; Kumar & Tiwari, 2022).

In the first stage, for the CW portfolios, the MC is considered as a benchmark to sort the data, and all the other variable data, such as Price (P), Market Value (MV), and Risk-Free Rate (RFR), are then selected based on this sorting. Then, stock returns are computed using this formula:

$$Returns(\,Monthly) = \frac{P_t - P_{t-1}}{P_{t-1}} \qquad \text{(i)}$$

Followed by cleaning the prices. In the second stage, each fundamental accounting measure is considered as a benchmark to sort the data, excluding all the missing and negative values, based on which all the other fundamental variables are then selected. Before constructing the FW portfolios, this process was repeated every year. For the construction of alternative FW indexes/portfolios, each fundamental measure is sorted from largest to smallest. Then, the Top 100 companies are selected for the fundamental index construction. In this case, weights are estimated by taking the fraction of each company's share by the sum of all companies' shares in that respective fundamental accounting measure. Thus, the Fundamental (metric) weight of each stock is calculated based on the application of the relevant formula:

$$W_{k,i,t} = max[\,0, F_{k,i,t}] / \sum^{N} i = 1\, max[\,0, F_{k,i,t}] \qquad \text{(ii)}$$

Where 'W' stands for the weight of security for fundamental metric (k) at time (t), $F_{k,i,t-1}$refer to the value of the metric (weight) of each stock at the fiscal year end (t-1), 'k' refers to the fundamental metric (for example, sales), and 'i' stands for the selected stock. The denominator represents the total fundamental size of the metric (for example, total sales) of "N" for all the companies combined. To avoid or minimize the look-ahead biasness, the weights of the last period (t-1) are matched with the current period stock returns (t). Hence, stock returns at time (t) are based on the

[2] Since the system was automated in the late 1990s, electronic data has been available since 1995; nonetheless, it is only since 2000 that more accurate, complete, and reliable data has become available. Moreover, since 90% of Pakistani companies submit their financial accounts by the end of June 30, the data was chosen from July 1, 2000 through June 30, 2024.

[3] See Appendix A, Table (1) for more details of the variables selected and used in this study.
[4]https://research.ftserussell.com/products/downloads/FTSE_Global_Financial_Metrics_Weighted_Index_Series_Ground_Rules.pdf

last period ended (t-1) weights of the considered variables. All the securities or stocks of companies are weighted according to the monthly values of metrics of Size. These weights were then multiplied by the individual stock price, and the cross-sectional sum of each fundamental accounting measure resulted in the value of an index. This process is repeated every year on July 31st for constructing FW indexes/portfolios, with rebalancing performed annually. For the construction of alternative FW indexation, a similar process is repeated, each fundamental measure is sorted from largest to smallest, and the Top 100 companies are selected for inclusion in the alternative indexes, which are compared against the traditional benchmark CW index[5]. In addition, this study also constructs the COMP alternative index/portfolio by averaging the weights of five fundamental metrics, namely net income, earnings before interest and taxes, dividends, book value plus intangibles, and cash flows, to gauge its performance in a broad perspective. The composite index offers traders and financial investors a simplified and comprehensive view of the stock market. The formula used is as follows,

$$[Weights\ of\ Net\ Income, EBIT, Dividends, (BV + Intangibles), Cash\ flows\ /\ 5] \qquad \text{(iii)}$$

To analyze the performance of constructed portfolios, various risk-adjusted measures are used. For instance, the Treynor, Sharpe, Information, and Sortino ratios are commonly used as downside risk-adjusted measures. In which the Sharpe ratio is measured as

$$\frac{R_p - R_f}{\sigma_p} \qquad \text{(iv)}$$

Where the excess returns are discounted against the standard deviation. It makes it easy to compare risk-adjusted performance between index portfolios. The Treynor Ratio is measured as

$$\frac{R_p - R_f}{b_p} \qquad \text{(v)}$$

To compute this ratio, the excess average stock return of the portfolio is required against the beta coefficient of the portfolio. The information ratio is measured as

$$E(R_{p,t} - R_{m,t}) / \sigma(R_{p,t} - R_{m,t}) \qquad \text{(vi)}$$

In which the average excess portfolio's returns over the CW market portfolio are discounted against the standard deviation of excess returns. The Sortino ratio is also measured as:

$$(R_{\ p} - R_{ft}) / \sigma_{s-d,p} \qquad \text{(vii)}$$

Where the excess returns of portfolios are discounted against the semi-deviation (using only negative returns) of portfolio "p". Besides this, the more robust risk-adjusted performance of various concentrated indexes/portfolios is also examined through firm-specific characteristics of econometric models such as CAPM, Fama, and French (three) factor model, and Fama and French (Five) factor models. The returns of the CW and FW indexes are then regressed, based on which beta coefficients and alphas are then determined by applying various asset pricing models to examine whether or not alternative indexes/portfolios are distinct investment styles.

CAPM (One-factor) model

It is used to assess the contribution of factors other than the market risk factor in explaining the performance of stock returns.

[5] The established KSE-100 index is used as a benchmark traditional CW index/portfolio for analysis and comparison with the alternative indexes/portfolios developed in this study.

$$R_{i,t} = \alpha_i + \beta rm + \varepsilon_{i,t} \qquad \text{(viii)}$$

Where, R_{it} is the monthly average excess returns of a constructed alternative FW index/portfolio at time t, α_i is the Jensen-alpha, which is used to evaluate the performance of a constructed portfolio, □□ is the market CW benchmark excess return, β_t shows the sensitivity to market risk.

Fama and French (three) factor model (1993)

Similarly, this study has also considered the Fama and French (F&F) three-factor model to measure the stock's risk-adjusted performance.

$$R_{i,t} = \alpha_i + \beta rm_t + s_i smb_t + h_i hml_t + \varepsilon_{i,t} \qquad \text{(ix)}$$

Where, R_{it} is the monthly average excess return of a constructed alternative FW index/portfolio, □□ is the excess return on benchmark (Kse-100 index) portfolio, and SMBt is the firm-specific size factor, i.e., small companies (bottom 20th percentile) minus big companies (top 20th percentile). HMLt is the firm-specific value factor, i.e., high-valued firms (top 20th percentile, B/M value stocks) minus low-valued firms (bottom 20th percentile, B/M value stocks). In the F&F three-factor model, SMBt is a 'size' factor that shows risk sensitivity in stock returns due to asset return over time. It represents the average monthly returns of the stocks that form the top 20th percentile by market capitalization, which are deducted from the average monthly returns of the stocks that form the bottom 20th percentile by market capitalization. HMLt is a book-to-market value showing a value factor. This factor can be obtained by subtracting the average monthly returns of stocks that form the bottom 20th percentile (measured through book-to-market ratio) from the average monthly return of stocks that form the top 20th percentile (measured through book-to-market ratio). These risk factors are also referred to as factor loadings, whereas the alphas of the portfolio show the risk-adjusted performance of the portfolios after accounting for all the factors.

Fama and French (five) factor model (2015)

In the F&F five-factor model, additional factors like RMWt represent the profitability factor that captures the excess return of highly profitable stocks over low profitable stocks over time, and CMAt represents the investment factor that captures the excess returns of conservative versus aggressive stocks as depicted in the equation.

$$R_{i,t} = \alpha_i + \beta rm_t + s_i smb_t + h_i hml_t + r_i rmw + c_i cma + \varepsilon_{i,t} \qquad \text{(x)}$$

In this regard, the profitability factor can be measured by using changes in operating profit (EBIT), and the investment factor is measured by changes in the book value of total assets. For the analysis, multiple sorting criteria are used to measure the factor loadings, such as SMBt, HMLt, RMWt, and CMAt (Zada et al., 2018). To provide deeper insight, multiple regression models are used along with the Generalized Method of Moments (GMM) and Wald test statistics to assess the predictability of estimated portfolio returns using various indexation approaches. Furthermore, the linearity assumption is examined to evaluate the mean-variance efficiency of all constructed (FW) indices, as this efficiency can only be established if the portfolio's higher betas can generate higher returns (Fongwa, 2015).

4 |Results and Analyses

We discuss the outcome and findings of returns obtained from the previously stated alternative indexation methodology in comparison with the benchmark CW market index returns, namely the KSE-100 index. The alternative (eleven) indexes are initially compared to the benchmark index before being assessed using a variety of risk-adjusted metrics and asset pricing models, including the CAPM, F&F3, and F&F5 models.

Figure 4. 1 Net-Income Index

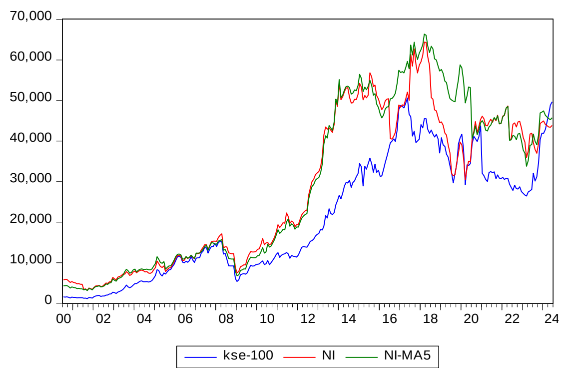


Figure 4. 2 EBIT Index

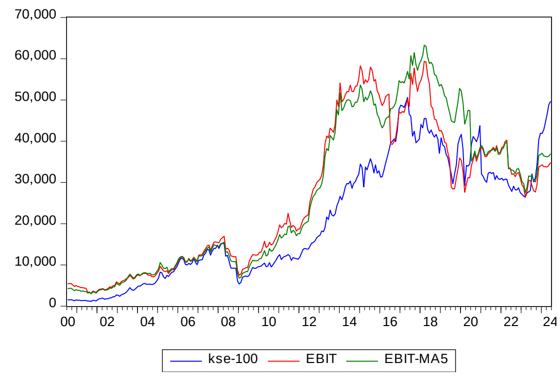


Figure 4. 3 Dividend Index

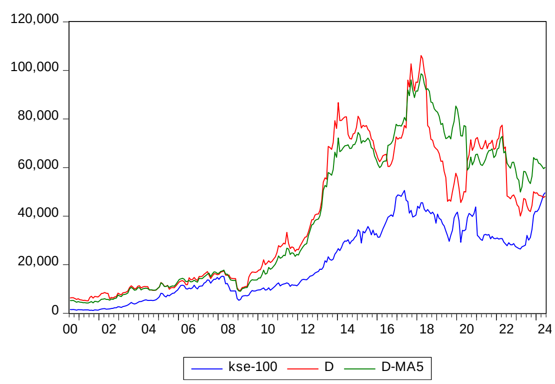


Figure 4. 4 Book Value + Intangibles Index

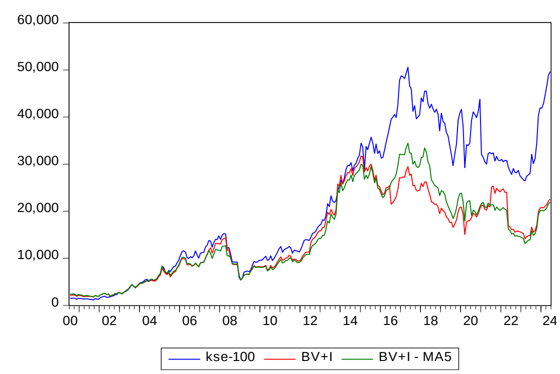


Figure 4. 5 Cash-flow Index

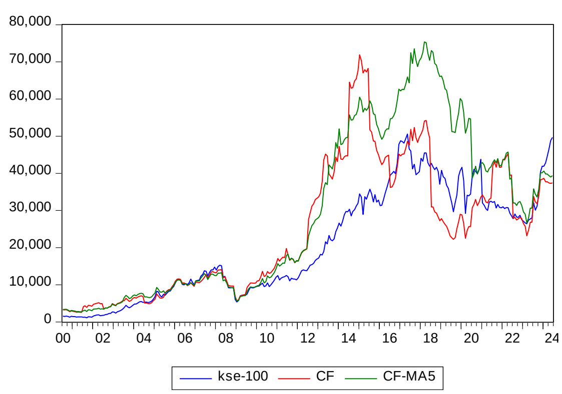
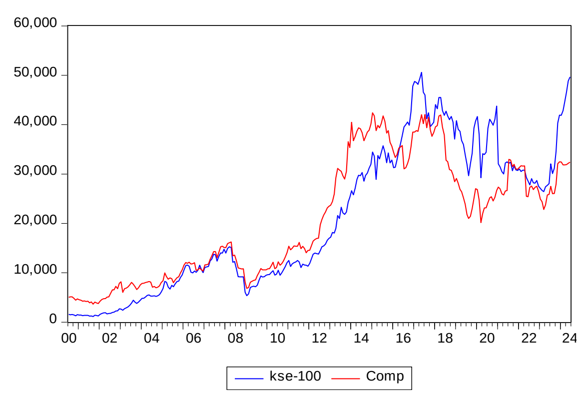


Figure 4. 6 Composite Index



The moving average indexes appear smoother than the most recent values of various alternative indexes, as seen in Figures 4.1- 4.6. This is primarily because moving averages smooth out sudden fluctuations in data that result from different seasonal and cyclical patterns and keep the weights of the portfolios at a constant level. Moreover, it appears that the COMP index values, which distribute weights according to the average of all the fundamental metrics used in this study, are smoother than the other possible index values since they eliminate the bias of individual indexes.

1.1 Comparison of Constructed Indexes with the Benchmark Index

Table 4.1 Correlation matrix of all indexes (latest values)-Full sample (July 2000- June 2024)

	KSE 100	NI	EBIT	BV+I	CF	D	COMP
KSE 100	1.00						
NI	0.93***	1.00					
EBIT	0.90***	0.98***	1.00				
BV+I	0.91***	0.96***	0.98***	1.00			
CF	0.84***	0.94***	0.96***	0.96***	1.00		
D	0.91***	0.98***	0.98***	0.95***	0.93***	1.00	
COMP	0.92***	0.99***	0.99***	0.99***	0.97***	0.96***	1.00

Table 4.2 Correlation matrix of all indexes (MA-5 year's values) - Full sample (July 2000- June 2024)

	KSE 100	NI	EBIT	BV+I	CF	D	COMP
KSE 100	1.00						
NI	0.96***	1.00					
EBIT	0.94***	0.99***	1.00				
BV+I	0.95***	0.97***	0.98***	1.00			
CF	0.94***	0.98***	0.99***	0.97***	1.00		
D	0.96***	0.98***	0.99***	0.96***	0.99***	1.00	
COMP	0.92***	0.95***	0.96***	0.98***	0.94***	0.93***	1.00

Note: shows the correlation matrix of all monthly indexes using moving average values with the p-values, where the single (*) means a 10% chance of rejecting the true null hypothesis that the mean rate of return of the portfolio return is zero. On the other hand (**) and (***) show 5% and 1% respectively.

Table 4.1 shows the correlation matrix between the benchmark index, namely the KSE 100 index, and alternative indexes, namely NI, EBIT, BV+I, CF, and D, using (latest) accounting metric values with the COMP index. At a significance level of 1%, the table shows that the benchmark index and the alternative FW indexes appear to be substantially highly correlated with each other. This indicates that the features or characteristics of the alternative FW portfolios based on the (latest) values make them appropriate stand-ins for the benchmark index. They would also almost completely correspond, which makes it logical considering how nearly identical the sample population is (Urnes & Haugland, 2018). On the other hand, Table 4.2 shows alternative indexes based on (moving average 5 years) values. Table 4.2 indicate that alternative FW indexes/portfolios appear to be smoother than those built with the latest values. This tends to happen because moving averages smooth out annual fluctuations, dilute speculative bubbles, and maintain a consistent weight for the portfolio.

Table 4.3 Descriptive statistics of (latest) index returns (Full sample July 2000- June 2024)

Variables	Rcw	Rni	Rebit	Rbvi	Rcf	Rd	Rcomp
Mean	0.015	0.011	0.010	0.010	0.012	0.009	0.009
Std. Dev.	0.255	0.401	0.308	0.269	0.580	0.342	0.238
Max	-0.343	-0.282	-0.276	-0.295	-0.374	-0.295	-0.260
Min	0.074	0.071	0.066	0.071	0.093	0.075	0.065
Skewness	-0.38	0.14	-0.27	-0.41	0.72	0.31	-0.39
Kurtosis	5.98	7.94	6.43	5.63	11.88	7.05	5.46
J-Bera	113.4	294.0	144.7	91.3	971.6	201.4	79.5
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4. 4 Descriptive statistics of (MA- 5-years) index returns (Full sample July 2000- June 2024)

Variable	Rcw	Rnima	Rebitma	Rbvima	Rcfma	Rdma	Rcomp
Mean	0.015	0.011	0.010	0.010	0.011	0.010	0.009
Std. Dev.	0.255	0.180	0.179	0.265	0.210	0.202	0.238
Max	-0.343	-0.283	-0.278	-0.254	-0.291	-0.259	-0.260
Min	0.074	0.061	0.059	0.068	0.065	0.058	0.065
Skewness	-0.38	-0.45	-0.48	-0.09	-0.39	0.01	-0.39
Kurtosis	5.98	6.11	6.25	4.83	6.43	5.73	5.46
J.Bera	113.4	125.4	137.9	40.7	148.5	89.3	79.5
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: Table 4.4 shows the values of mean, median, maximum, minimum, standard deviation, skewness, and kurtosis along with the Jarque-bera, its probability statistics, and the number of observations used in analysis.

The descriptive statistics for the monthly return series of a benchmark CW index and six fundamental indexes using (latest) values are displayed in Table 4.3. During the entire sample period of July 2000 to June 2024, the mean and standard deviation values of the alternative FW indexes demonstrate that none of the alternative FW indexes were able to generate better mean-variant efficient returns as compared to the benchmark CW index. These findings validate that the benchmark CW index outperformed all the constructed FW indexes during the full-sample period from July 2000 to June 2024. In addition, the skewness and kurtosis values seem to deviate from zero and three, respectively. Hence, we can conclude that the sample does not follow a normal distribution, as supported by the Jarque Bera statistics results. Similar results are also displayed in Table 4.4, which shows the descriptive statistics for the monthly return series of a benchmark CW index and six fundamental indexes using (moving average 5 years) values. During the entire sample period (July 2000 to June 2024), none of the alternative FW indexes were able to produce more mean-variant efficient returns than the benchmark CW index, according to the mean (average) return and standard deviation values of the alternative indexes. Additionally, both the benchmark index and the alternative indexes exhibit negative skewness and leptokurtosis, which is a distribution with heavy tails or outliers more prevalent in extreme shocks in Pakistan's stock market.

Table 4.5 Risk-Adjusted Measures of Alternative Indexes Full Sample (July 2000 - June 24)

	Rcomp	Rni	Rnima	Rebit	Rema	Rbvi	Rbvima	Rcf	Rcfma	Rd	Rdma	Rcw
A.ER	0.01%	0.27%	0.25%	0.16%	0.16%	0.20%	0.16%	0.34%	0.25%	0.14%	0.21%	0.80%
S.D	6.1%	7.1%	6.1%	6.7%	6.0%	7.2%	6.9%	9.3%	6.5%	7.5%	5.8%	7.2%
Beta	1.01	0.96	0.87	0.94	0.88	0.89	0.89	0.91	0.83	1.10	0.91	1.00
Sharpe	0.09%	3.74%	4.14%	2.35%	2.63%	2.74%	2.36%	3.69%	3.85%	1.83%	3.64%	11.04%
Treynor	0.01%	0.28%	0.29%	0.17%	0.18%	0.22%	0.18%	0.38%	0.30%	0.13%	0.23%	0.80%
Sortino	0.12%	5.33%	5.63%	3.20%	3.57%	3.63%	3.31%	5.21%	5.31%	2.71%	5.45%	15.06%
T-Test	0.00***	0.10*	0.06*	0.03**	0.22	0.02**	0.00***	0.36	0.17	0.11	0.17	0.00***

Note: The Avg (ER) represents the average monthly excess returns, SD represents the standard deviation, Sharpe represents the Sharpe ratio, Beta measures the sensitivity of the market risk, Treynor ratio shows the excess return per unit of systematic risk, and the Sortino ratio shows the excess return per unit of bad risk. The last row shows the T-statistics (p-value), where the single (*) means a 10% chance of rejecting the true null hypothesis that the mean rate of return of the portfolio return is zero. On the other hand (**) and (***) show 5% and 1% respectively.

According to the risk-adjusted metrics of alternative indexes in Table 4.5, the benchmark CW portfolio has the highest average excess return with a given level of risk in terms of standard deviation. It has the lowest downside risk during the entire sample period (July 2000–June 2024). Therefore, it has the highest Treynor, Sortino, and Sharpe ratios. On the other hand, alternative FW portfolios, such as Composite and EBIT, show the lowest standard deviation risk and are also statistically significant, at 1% and 5%, respectively. Furthermore, it is discovered that an alternative NI and BV+I portfolios are also statistically significant at the 10% and 5% level of significance, respectively. This leads to the conclusion that over the entire study period (July 2000–June 2024), the CW portfolio outperforms alternative constructed portfolios. Nevertheless, portfolio betas indicate that the D and COMP portfolios are more aggressive than the CW benchmark. However, the CW portfolio is the most efficient, followed by the NI, EBIT, BV+I, and COMP portfolios.

Table 4.6 Risk-Adjusted Measures of Alternative Indexes Sub-Sample (July 2000 - June 2008)

	Rcomp	Rni	Rnima	Rebit	Rema	Rbvi	Rbvima	Rcf	Rcfma	Rd	Rdma	Rcw
A.ER	1.37%	1.03%	0.97%	1.48%	1.24%	1.70%	1.17%	0.91%	0.87%	0.54%	0.78%	1.35%
S.D	6.4%	8.4%	6.8%	7.3%	6.4%	7.8%	8.0%	10.2%	6.8%	7.8%	6.2%	8.5%
Sharpe	21.4%	12.3%	14.3%	20.3%	19.2%	21.7%	14.6%	9.0%	12.9%	6.9%	12.6%	15.8%
Treynor	1.36%	1.07%	1.11%	1.58%	1.40%	1.91%	1.31%	1.00%	1.05%	0.50%	0.86%	1.35%
Sortino	29.8%	19.8%	21.1%	29.1%	27.5%	32.1%	23.8%	13.8%	18.5%	11.1%	19.6%	24.1%
T-Test	0.00***	0.10*	0.02**	0.05**	0.00**	0.10*	0.05**	0.30	0.15	0.05**	0.01**	0.00***

The risk-adjusted performance metrics of the alternative indexes during the Sub-Sample (July 2000 to June 2008) are displayed in Table 4.6, considering both the global financial crisis of 2008 and the dot-com bubble of 2000. During this subsample period, the alternative FW portfolio BV+I has the maximum average excess return of 1.70% with a given level of risk in terms of the standard deviation of 7.8% and the lowest downside risk of 5%. As a result, it has the highest Sharpe ratio of 21.7%, a Sortino ratio of 32.1%, and a Treynor ratio of 1.9%. However, the EBIT portfolio seems to be the second-best alternative portfolio, followed by Comp and NI, with slightly better average excess return and risk in terms of standard deviation, which were found to be statistically significant at 5%, 1%, and 10%, respectively.

Table 4. 7 Risk-Adjusted Measures of Alternative Indexes Sub-Sample (July 2008 - June 2014)

	Rcomp	Rni	Rnima	Rebit	Rema	Rbvi	Rbvima	Rcf	Rcfma	Rd	Rdma	Rcw
A.ER	0.76%	1.16%	1.25%	1.12%	1.15%	0.52%	0.58%	1.24%	1.39%	1.66%	1.30%	0.56%
S.D	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.09	0.07	0.08	0.07	0.07
Sharpe	10.9%	16.5%	17.5%	15.9%	16.4%	7.0%	8.2%	13.8%	18.6%	20.3%	19.3%	7.5%
Treynor	0.8%	1.2%	1.4%	1.2%	1.3%	0.6%	0.7%	1.4%	1.7%	1.5%	1.4%	0.6%
Sortino	16.6%	22.3%	27.2%	21.9%	25.5%	9.9%	11.8%	18.8%	29.6%	33.8%	32.6%	10.0%
T-Test	0.00***	0.10*	0.02**	0.05**	0.00**	0.10*	0.05**	0.30	0.15	0.05**	0.01**	0.00***

The alternative indexes' risk-adjusted performance measures for the Sub-Sample (July 2008–June 2014) are displayed in Table 4.7, taking into account the post-crisis or subsequent recovery period. The findings revealed that the EBIT portfolios are outperforming the benchmark portfolio, followed by the NI, Comp, and BV+I portfolios, even during the recovery or post-crisis sub-sample period.

Table 4.8 Risk-Adjusted Measures of Alternative Indexes Sub-Sample (July 2014 - June 2019)

	Rcomp	Rni	Rnima	Rebit	Rema	Rbvi	Rbvima	Rcf	Rcfma	Rd	Rdma	Rcw
A.ER	-1.4%	-1.1%	-0.7%	-1.1%	-0.7%	-1.3%	-1.0%	-1.3%	-0.3%	-1.1%	-0.5%	-0.3%
S.D	0.05	0.06	0.03	0.05	0.03	0.05	0.04	0.09	0.04	0.06	0.04	0.06
Sharpe	-0.31	-0.19	-0.22	-0.22	-0.22	-0.28	-0.23	-0.14	-0.09	-0.19	-0.14	-0.05
Treynor	-1.4%	-1.1%	-0.8%	-1.2%	-0.8%	-1.5%	-1.1%	-1.4%	-0.4%	-1.0%	-0.6%	-0.3%
Sortino	-30%	-21%	-15%	-22%	-16%	-25%	-21%	-20%	-7%	-23%	-13%	-5%
T-Test	0.06**	0.32	0.42	0.26	0.41	0.04**	0.07*	0.42	0.18	0.29	0.17	0.00**

Table 4.8 reveals that all the portfolios are performing poorly during the crisis period (July 2014 to June 2019). Even the benchmark portfolio produces negative excess returns at a particular risk level mainly because of the irrational behaviour of investors during that time, which had a significant impact on Pakistan's equity market (Liaqat et al., 2019; Shaikh et al., 2023).

Table 4. 9 Risk-Adjusted Measures of Alternative Indexes Sub-Sample (July 2019 - June 2024)

	Rcomp	Rni	Rnima	Rebit	Rema	Rbvi	Rbvima	Rcf	Rcfma	Rd	Rdma	Rcw
A.ER	-0.5%	-0.7%	-1.1%	-1.0%	-1.4%	-0.4%	-0.8%	0.0%	-1.5%	-1.1%	-1.3%	0.3%
SD	5.2%	6.1%	5.6%	5.9%	5.6%	7.4%	6.6%	8.3%	6.7%	7.6%	5.5%	6.4%
Beta	1.01	0.96	0.87	0.94	0.88	0.89	0.89	0.91	0.83	1.10	0.91	1.00
Sharpe	-10.5%	-10.9%	-20.2%	-16.9%	-24.4%	-5.9%	-11.6%	0.1%	-22.8%	-14.4%	-23.3%	5.1%
Treynor	-0.5%	-0.7%	-1.3%	-1.1%	-1.5%	-0.5%	-0.9%	0.0%	-1.8%	-1.0%	-1.4%	0.3%
Sortino	-11.8%	-13.4%	-25.1%	-20.2%	-30.9%	-8.0%	-15.8%	0.1%	-32.5%	-21.3%	-32.7%	6.1%
T-Test	0.03**	0.15	0.10*	0.04**	0.06*	0.24	0.07*	0.70	0.16	0.12	0.10*	0.0*

Table 4.9 demonstrates that during the pandemic (COVID-19) followed by the subsequent recovery period, the benchmark CW portfolio has the lowest downside risk and the highest average excess return with a given level of risk in terms of standard deviation. Due to this, it also shows the highest Treynor, Sortino, and Sharpe ratios during the sub-sample period (July 2019–June 2024). Despite the severe conditions, our market remained calm and confident, even though the impact of COVID-19 was more severe than in 2008, which completely upended world stock markets.

This section also examines firm-specific features of various econometric models, including the CAPM, Fama and French three-factor (FF3) model, and Fama and French five-factor (FF5) models, to present the results of the more robust risk-adjusted performance of various concentrated portfolios to examine whether or not alternative indexing strategies consistently predict higher excess returns better than benchmark market portfolio in a full and sub-sample period.

Table 4. 10 Full Sample Analysis (July 2000 to June 2024)

	Alpha	Beta	SMB	HML	RMW	CMA	R-Square
CAPM							
BV+I (Latest)	-0.004*	0.81***	-	-	-	-	0.67
BV+I (MA-5)	-0.005**	0.81***	-	-	-	-	0.72
Ebit (Latest)	-0.004	0.68***	-	-	-	-	0.54
Composite	-0.005**	0.65***	-	-	-	-	0.60
FF3							
BV+I (Latest)	-0.004**	0.81***	-0.02	0.01	-	-	0.67
BV+I (MA5)	-0.005**	0.80***	-0.00	0.02	-	-	0.72
Ebit (Latest)	-0.003	0.68***	0.03	-0.02	-	-	0.54
Composite	-0.005**	0.65***	-0.02	0.01	-	-	0.60
FF5							
BV+I (Latest)	-0.004	0.81***	-0.02	0.02	-0.09*	0.11	0.68
BV+I (MA5)	-0.004*	0.81***	-0.01	0.02	-0.06	0.08	0.72
Ebit (Latest)	-0.003	068***	0.03	-0.02	-0.12	-0.01	0.54
Composite	-0.005*	0.65***	-0.03	0.02	-0.09**	0.09	0.61

The table indicates the alphas and betas estimated through various regression models such as CAPM, FF3, and FF5 factor models. SMB, HML, RMW & CMA are the firm-specific characteristics, whereas the last column represents the R-square (R2) value. The alternate rows of each variable in different asset pricing models show the T-statistics (p-value), where the single (*) means a 10% chance of rejecting the true null hypothesis that the mean rate of return of the portfolio return is zero. On the other hand (**) and (***) show 5% and 1% respectively.

The full sample findings are displayed in Table 4.10, which reveals that the negative alphas were found to be different from zero and also statistically significant at the 10% and 5% levels, respectively. The findings regarding the better outcomes of alternative FW portfolios, including the Composite and BV+I (latest and MA 5 years), are therefore inconclusive for the full sample period (July 2000–June 2024). Consequently, the market is dominated by the benchmark CW index. Additionally, the alternative portfolios underperformed due to the presence of negative alphas. These findings are in line with Walkshausl and Lobe's (2010) investigation.

Table 4. 11 Sub-Sample Analysis: During Bubbles or Crisis (Jul 00- June 08)

GMM	Alpha	Beta	SMB	HML	RMW	CMA	R-Square

CAPM	BV+I (L)	-0.003	0.82***	-	-	-	-	0.72
	BV+I (MA5)	0.005	0.87***	-	-	-	-	0.78
	Comp	0.007**	0.69***	-	-	-	-	0.68
FF3	BV+I (L)	-00029	0.81***	0.162	0.016	-	-	0.72
	BV+I (MA5)	0.003	0.86***	0.114	0.017	-	-	0.79
	Comp	0.005*	0.68***	0.070	-0.033	-	-	0.69
FF5	BV+I (L)	-0.001	0.81***	0.172	-0.005	-0.020	-0.12	0.75
	BV+I (MA5)	0.003	0.86***	0.120	-0.009	0.040	-0.02	0.78
	Comp	0.006*	0.68***	0.079	-0.038	-0.020	-0.05	0.66

Table 4. 12 Sub-Sample Analysis: During Recovery or Post-Crisis (Jul 08- June 14)

	GMM	Alphas	Betas	SMB	HML	RMW	CMA	R-Square
CAPM	BV+I (L)	0.0004	0.86***	-	-	-	-	0.72
	BV+I(MA5)	0.0010	0.82***	-	-	-	-	0.75
	Comp	0.0029	0.780***	-	-	-	-	0.68
FF3	BV+I (L)	0.0020	0.86***	0.067	-0.060	-	-	0.72
	BV+I(MA5)	0.0020	0.82***	0.056	-0.057	-	-	0.76
	Comp	0.0052	0.78***	0.093	-0.086	-	-	0.69
FF5	BV+I (L)	0.0058	0.88***	0.088	0.011	-0.13	0.075	0.75
	BV+I(MA5)	0.0060	0.84***	0.077	0.030	-0.017	0.06	0.77
	Comp	0.0083	0.79***	0.112	-0.050	-0.058	0.095	0.66

Table 4. 13 Sub-Sample Analysis: During Recession or Economic downturn (Jul 14- June 19)

	GMM	Alphas	Betas	SMB	HML	RMW	CMA	R-Square
CAPM	BV+I (L)	-0.012**	0.69***	-	-	-	-	0.72
	BV+I(MA5)	-0.008**	0.66***	-	-	-	-	0.68

	Comp	-0.012**	0.59***	-	-	-	-	0.68
FF3	BV+I (L)	-0.0078**	0.64***	0.32*	-0.06	-	-	0.72
	BV+I(MA5)	-0.006**	0.67***	0.15*	-0.09	-	-	0.70
	Comp	-0.008**	0.52***	0.39**	-0.07	-	-	0.69
FF5	BV+I (L)	-0.003	0.64***	0.31**	-0.05	0.05	0.32**	0.75
	BV+I(MA5)	-0.004	0.66***	0.11	-0.07	0.03	0.44**	0.74
	Comp	-0.002	0.49***	0.28**	-0.02	-0.11	0.50**	0.66

Table 4. 14 Sub-Sample Analysis: During Post-Crisis or Covid-19 (Jul 19- June 24)

	GMM	Alphas	Betas	SMB	HML	RMW	CMA	R-square
CAPM	BV+I (L)	-0.007	0.86***	-	-	-	-	0.70
	BV+I(MA5)	-0.010**	0.78***	-	-	-	-	0.56
	EBIT (L)	-0.012**	0.63***	-	-	-	-	0.46
	Comp	-0.007*	0.44***	-	-	-	-	0.68
FF3	BV+I (L)	0.005	0.89***	0.49**	-0.06	-	-	0.70
	BV+I(MA5)	-0.005	0.79***	0.28	0.003	-	-	0.57
	EBIT (L)	-0.007*	0.63***	0.22	0.09	-	-	0.47
	Comp	-0.005*	0.46***	0.11	0.07	-	-	0.69
FF5	BV+I (L)	0.0012	0.89***	0.46*	-0.11	0.22	-0.03	0.72
	BV+I(MA5)	-0.006	0.79***	0.23	-0.07	0.24	-0.13	0.58
	EBIT (L)	-0.009	0.63***	0.22	0.10	-0.06	-0.13	0.47
	Comp	-0.003	0.44***	0.14	0.10	-0.34	0.08	0.66

The tables indicate the alphas and betas estimated through various regression models, including CAPM, FF3 & FF5 factor models. SMB, HML, RMW & CMA are the firm-specific characteristics, whereas the last column represents the R-square (R2) value. The alternate rows of each

variable in different asset pricing models show the T-statistics (p-value), where the single (*) means a 10% chance of rejecting the true null hypothesis that the mean rate of return of the portfolio return is zero. On the other hand, (**) and (***) show 5% and 1% respectively.

The estimation of the CAPM, FF3, and FF5 models over different sub-sample periods reveals significant insights into the performance of diverse investment portfolios. Table 4.11 presents the estimation results using time-series sub-sample data from July 2000 to June 2008 using the GMM estimation method. These models help in estimating the alpha and beta coefficients. Since then, various financial speculative bubbles have typically at the forefront of financial crises since their existence breeds macroeconomic and financial instability (Liaquat et al., 2019; Shaikh et al., 2023). The findings indicate that the Comp index/portfolio outperforms the benchmark CW index/portfolio in generating better excess returns, supported by the descriptive statistics as discussed earlier. Moreover, when considering the F&F3 and F&F5 factor models, it is also determined that the alphas have positive loadings and are statistically significant at 5% and 10%, respectively. This suggests that even in the presence of size, value, profitability, and investment determinants, the alternative Comp index/portfolio consistently performed better than the benchmark CW index throughout the speculative bubble period of 2000 to 2008. As the financial markets entered the recovery phase, Table 4.12 examines the period from July 2008 to June 2014. During this time, while the alphas maintained positive loadings, they were found to be insignificant at a 10% threshold. This suggests that even though the FW index/portfolio performed better during recessions or financial crises, the benchmark CW index/portfolio proved to be the most reliable portfolio during the recovery phase. Table 4.13 focuses on the findings from July 2014 to June 2019, a period marked by a significant crisis in the PSX. The market downturn was fuelled by investor overconfidence, panic selling, and economic instability caused by multiple speculative bubbles in the KSE-100 between June 2013 and March 2015. Consequently, alternative FW portfolios had significant negative alphas, which reflected their underperformance in line with the overall market meltdown. Lastly, the findings from July 2019 to June 2024 are presented in Table 4.14. Despite the worldwide effects of COVID-19, Pakistan's market held steady because of prompt government actions. These results were inconsistent, with the benchmark CW index beating alternative portfolios, even though the alternative BV+I, EBIT, and Comp indexes were considerable at 5% and 10% level of significance. These findings highlight the dynamic nature of financial markets and the fluctuating efficacy of investment strategies over several economic cycles. Hence, the benchmark CW index/portfolio's dominance in recovery periods contrasts with the higher performance of other alternative indexes during crises, highlighting the significance of adaptive investing strategies catered to current market conditions.

5 | Conclusion

This study discovered that the benchmark CW index/portfolio dominates the alternative FW indexes/portfolios in terms of risk-adjusted performance over the full-sample period from July 2000 to June 2024, based on both descriptive and risk-adjusted measures. However, the alternative COMP index/portfolio consistently and significantly outperforms the other alternative indexes/portfolios in terms of risk-adjusted performance only during periods of speculative bubbles from July 2000 to June 2008 and July 2014 to June 2019, which are marked by extraordinary financial disruptions or economic instability. These findings contrast with those of Walkshausl and Lobe (2010). Overall, we conclude that the alternative COMP index/portfolio provides superior risk-adjusted performance only during times of economic chaos. However, they cannot be suggested as a rational investing strategy under normal market conditions. This study can facilitate various investors and portfolio managers to better understand how various market situations affect portfolio performance while developing mean-variance efficient portfolios. For future areas of research, alternative FW index portfolios can be developed by examining other actively managed strategies like value, volatility momentum, etc. Moreover, alternative investing paradigms can also be explored, such as techniques based on artificial intelligence and machine learning, which employ big data analytics, algorithms, and computer advancements to instantly examine an enormous amount of market data to find better investment opportunities.

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