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ORIGINAL RESEARCH

Effect of Index Concentration on Index Volatility and Performance

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Abstract

The presented study investigated the effect of index concentration on component security and index variances to explore the possibility of concentration risk and its impact on index performance in different markets. The study also investigated the 1/n index with the market cap index to find possible concentration costs for the investors. We analyzed BRICSU (BRICS plus USA) by applying various tools for concentration measures and determining index volatility and returns with the help of the mean–variance model. We did a simple simulation to understand the sensitivity of relationships. The study found the impact of index concentration on index variance, component security covariance, and index performance varies with the market. It may be due to different levels of investor biases and the inclusion of multinational companies in the index. We show how excessive growth of a few companies does not increase risk in the index, even delivering information benefits to investors. The lower Sharpe ratio of the Equal weighted index confirms the nonexistence of any index concentration cost for investors. We concluded index concentration is a generic process in the competitive market condition.

Keywords Index concentration · Portfolio concentration · Volatility · Markowitz theory · Hirschman-Herfindahl index · Equal weighted portfolio

1 Introduction

Modern portfolio theory describes diversification as a tool for idiosyncratic risk management and reducing portfolio volatility. Considering this theory, several news articles have shown their concern about index concentration as a risk threat

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for investors due to the disproportionate growth rate of a few companies' market value in the index. Although, the Information advantage theory (Van Nieuwerburgh & Veldkamp, 2009) explains that investors invest their money based on the information in a few stocks and concentrate their portfolio compared to benchmarks portfolios (Ivković et al., 2008; Brands et al., 2005; Chen & Chen, 2017; Choi et al., 2017; Fulkerson & Riley, 2019; Hung et al., 2020; Fjesme, 2020). Stock market concentration is the extent to which a small number of disproportionately large companies control the performance of value-weighted stock market indices. In contrast, a market with low concentration or fragmentation would see many tiny businesses contesting for a comparatively small portion of the market (Tabner, 2007).

Various studies on stock market concentration explained its destructive effect on the economy due to the reduction of competition. These studies use stock market concentration as a tool of competition measurement (Triggs, 2021; Bae et al., 2021), but very few studies focused on interpreting its effect on stock market volatility(Chelley-steeley, 2008; Mazviona, 2014; Van Heerden & Saunderson, 2008). Tabner (2009) investigated changes in the concentration of the FTSE 100 Index of major UK companies between 1984 and 2004 and found little evidence that increased UK market concentration led to higher volatility in UK stock market returns. After three years, Chelley-Steeley, (2008) again studied the UK stock market and concluded that high concentration does not affect index volatility but increases individual stock volatility, offset by covariance. He observed that concentration and index volatility were negatively related but insignificant. Van Heerden and Saunderson (2008) studied the South African market and found a high concentration level, which increased portfolio risk resulting from increased covariance between the security. Sorensen et al. (2022) Investigate the 30-year history of the S&P 500 concentration cycle and conclude that regular comparisons of active skill investments and passive indexes are related more to index concentration behaviour and not skill volatility.

1.1 The Motivation for the Study

As per our knowledge, we did not find any study other than the UK based which directly examined the assumed index concentration risk. Based on one market study, we cannot deny index concentration risk. Different market sizes and characteristics can affect Chelley-Steeley (2008) results as literature shows small South African market shows the effect of index concentration on portfolio risk(Van Heerden & Saunderson, 2008). Moreover, examining the relationship between index concentration and performance becomes more significant in an era where index funds are getting popular, and researchers explored that the equal-weighted index outperforms the market-weighted index (Tabner, 2009; Amenc et al., 2016; Malladi & Fabozzi, 2017; Abadi & Silva, 2019) and look to use it for optimization of portfolio performance (Taljaard & Maré, 2021). Passive investors invest their money to perceived diversification in an index-based fund, but the index concentration can ruin their expectation to increase idiosyncratic risk. In a recent study, Sorensen et al. (2022) found a strong correlation between the monetary system and the concentration of benchmark indexes that promote the considerable performance advantage of stock price weighting.

1.2 The Objective of the Study

To clarify the contradiction, we first investigated the relationship between index concentration with index volatility and performance in different markets. Then study investigated the market cap-based index with an equal-weighted index to explore the possibility of concentration risk and its cost for investors(Mazviona, 2014). Ultimately, we examined whether a change in index concentration affects variance and covariance between constituent securities.

To consider the point mentioned above, we analyzed BRICS (one of the top emerging market groups) and the US market (commonly, we refer to this combination as BRICSU in this Study) to understand the relationship between index concentration with volatility and performance. The combination of BRICS and the USA allows us to examine concentration and volatility in different types of markets, which may affect their relationship as literature found emerging markets were high concentration than the developed market (Aggarawal et al., 1999; Roll, 1992). This study considers the combination of top 100 market valued registered companies indexes from every country except South Africa, where we have considered the top 40 companies index for analysis due to the unavailability of the top 100 index. We used IBrX 100 index, MOEXBMI index, NIFTY 100 index, CSI 100 index, JSE 40 index, and NASDAQ 100 index for Brazil, Russia, India, China, South Africa, and the United States, respectively.

We applied a range of concentration measures that have been used substantially in industrial economics to characterize market power (same as Chelley-steeley, 2008). The study uses GARCH (1,1) model to examine the relationship between concentration and volatility. We used Markovitz's theory (1952 & 1976) to calculate component security return, and Sharpe & Sortino ratios were used for risk-adjusted performance analysis. To check the sensitivity of the relationship, we did simple simulations that can observe the variance and performance under three different concentration levels by creating three synthesis indexes: high(HCSI), intermediate(ICSI), and low concentration(LCSI); along with these, we included an equal-weighted synthesis index(EWSI).

Analysis of BRICSU gives mixed results regarding index concentration. We found concentration recently increasing in NASDAQ 100, JSE 40, and NIFTY 100 index, whereas others showed a continuous decline. NIFTY 100 was the most diversified index, whereas JSE 40 was the most concentrated index. Except for fluctuation in stock market concentration over time, we found no direct link between stock market concentration and index variance, consistent with Chelley-steeley (2008) in all indexes except for NASDAQ 100 index, which we found to be highly positive. However, there was a moderate correlation between index variance and concentration. The study showed a mixed relationship between constituent securities variance and index concentration, whereas we did not find evidence where securities covariance offset component security variance effect.

Moreover, we found an increasing pattern in the sequence of EWSI, LCSI, ICSI, and HCSI in the maximum synthesis indexes in variance–covariance simulation. The variance difference between all synthetic indexes was meagre, so on this basis, the study cannot support the existence of concentration risk. High concentrated market cap-based index outperformed the equal-weighted index, which shows concentration is increasing due to excessive growth of a few companies and investor's biases (Van Nieuwerburgh & Veldkamp, 2009) without increasing the risk of the index. Even during the recession in 2008, we found that the market-cap index outperforms the equal-weighted index when investors believe diversification is best for risk minimization. The lower Sharpe ratio of the Equal weighted index confirms the nonexistence of any index concentration cost for investors. We believe this study will help investors in strategy formulation.

The remainder of this paper is set out as follows. Section 2 describes the indexes. Section 3 describes the data. Section 4 describes the methodology. Section 5 shows empirical results and discussion. Section 6 presented the conclusion.

2 Indexes

The top 100 registered firms indexes from every country were included in the study, except for South Africa. The top 40 companies index had been used to analyze South Africa due to the absence of the top 100 companies index. We did not want to drop South Africa from the study because it allows us to analyze this small market that was found highly concentrated in the literature. However, it is not comparable with others due to its uneven size. For Brazil, we chose the IBrX 100 index constructed on 2 January 1997, designed from the 100 most actively traded and best representative stocks of the Brazilian stock market by considering 1000 points on 28 December 1995 as a base. IBrX 100 index constituents rebalance quarterly in January, May, and September. MOEX Broad Market Index (MOEXBMI) represents Russia in our Study, first calculated in December 2011 with an initial value of 1000. The MOEX Broad Market index reconstitution takes effect on the 3rd Friday of March, June, September, and December based on ground rules published by the Moscow exchange.

NIFTY 100 index is an Indian index constructed from NIFTY 500. It was formally launched in December 2005 to consider January 2003 as a base year on a base value of 1000 to measure large market capitalization companies. Computation of NIFTY 100 is based on the free-float market capitalization method wherein the index level reflects the total free-float market value. NIFTY 100 Index is semi-annually rebalanced based on rules published by NSE. We computed the CSI 100 Index launched in May 2006 with a base value of 1000 points in December 2005, which is the composition of the largest 100 and most influencing securities from the Shanghai and Shenzhen 300 index to reflect the overall performance of the securities of a group of large capitalized listed companies. The securities in the sample space are ranked according to the average daily market value of the past year from high to low and are adjusted every six months, and the implementation time of the sample adjustment is June and December of each year. South Africa is the smallest member of BRICS, for we consider the FTSE/JSE Top 40

(JSE 40) Index to consist of the largest 40 companies based on the investable market value of the FTSE/JSE All-Share Index. The FTSE/JSE Africa Index was launched in June 2002 with a base value of 10,300.31 to represent South African companies' performance. This index is reviewed quarterly every March, June, September, and December, whereas constituent changes occur on the third Friday of the review month. We consider NASDAQ 100 (launched on 31 January 1985) a developed market representative, the composition of the 100 largest US and international non-financial companies listed on the NASDAQ Stock Market based on market capitalization. Index composition is reviewed annually in December and becomes effective after trading on the third Friday of December. Reconstitution of the indexes is not the same for all indexes, so we incorporated these changes annually every 31 December for all indexes.

3 Data

Based on the list of companies available on Bloomberg as of 31st December of each year, we prepared a constituent securities list for all indexes. From that basis, we have taken the quarterly market value of each constituent security from Bloomberg for 2006–2020. Instead of dropping any country index, we analyzed maximum available data for those indexes like we found CSI 100 data from 2012 and MOEXBMI 100 data from 2014 onwards. We have taken constituent securities last 520 days' closing price from 31st December for each year to performance evaluation and a ten-year US Treasury bill as a risk-free rate.

4 Methodology

We have found two sorts of concentration measures from the literature: absolute measures and inequality measures (Tabner, 2007). Absolute measures of concentration consider both the number of distinct categories of units in a sample and the dispersal of relative weights between these various categories. However, inequality measures disregard the absolute number of companies from the sample. We connected one estimation apparatus from both strategies. We have applied the HHI and Gini indices as absolute and inequality measures, respectively. For variance analysis, we used GARCH (1,1) model. We also included variance–covariance methodology in our study to see whether index concentration affects constituent security variance and covariance, whereas to examine performance, we applied Sharpe and Sortino ratio. And finally, we did a simple simulation to explore the possibility of concentration cost and sensitivity of the relationship.

4.1 Concentration Analysis

4.1.1 Gini Index

we examine concentration from the Gini coefficient, which measures the area between the 45-degree line and the concave Lorenz curve, where values vary between 0 and 1. It can be calculated according to the following formula:

$$G = \frac{1}{2n^2\overline{y}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| y_i - y_j \right| \tag{1}$$

where G is the Gini coefficient, n is the total number of index constituents, y is the average value of the observed market value, y_i and y_j are market values of constituents i and j (Litchfield, 1999). The zero Gini coefficient shows well diversification, whereas one represents high concentration. In contrast, the value of one means index is highly concentrated, and one constituent owns a 100% index share.

4.1.2 HHI Index

we estimated concentration by focusing on the dispersion of the firm with the help of the Hirschman-Herfindahl index (Hirschman, A. O., 1980; Weinstock, D. S., 1982), commonly known as the H index.

$$H_n = \sum_{n=1}^{n} \left(\omega_i\right)^2 \tag{2}$$

where (ω_i)^2 are squared firm weighting of security i. The H index takes account of all focuses on the concentration point because it is the entirety of the squared weights of all securities within the index. In this manner, in case the total index value is characterized as the sum of the market value of individual security. The share of the whole index involved by one security is that securities' market value divided by the entire index value. If n securities have market values xi (i = 1,……,n), and the total value of the index is characterized as x, then:

$$x = \sum_{n=1}^{n} \left(x_i\right) \tag{3}$$

whereas the weight of constituent security is

$$\omega_i = \frac{x_i}{x}$$

Clarke (1993) found the reciprocal of H is known as the numerical equivalent of H because 1/H equals the number of companies in an equally weighted portfolio that would be needed to create the same value for H in the concentrated portfolio. The h ratio considers all 100 firms for calculating concentration, which can lie between 0.01 and 1. For equal weights value, it is 0.01 and increases with concentration.

4.2 Variance Analysis

4.2.1 GARCH (1,1)

we applied GARCH (1,1) model as the equation below to use daily, weekly, and monthly index logarithmic returns from 2011 to 2020 to avoid the global recession effect. We followed Chelley-steeley's (2008) GARCH model and included a dummy variable in which we assigned the value one to the top three years based on the higher H ratio and zero otherwise. A positive value of the dummy coefficient would suggest higher volatility during high concentration, and a negative would reflect the opposite.

$$R_t = \propto_0 + u_t \tag{4}$$

$$h_t = \beta_0 + \delta_0 D_t + \beta_1 u_{t-1}^2 + \beta_2 h_{t-1} \tag{5}$$

$$\beta_0 > 0, (ut)| - N(0, h)$$

where, h_t is conditional variance, u_t are residuals, and R_t is the logarithmic index return, whereas $\propto, \beta, \delta$ are all coefficients. In this study on the bases of H index we assigned one during 2011,2018, and 2020 in JSE 40 index,2014,2018 and 2019 in MOEXBMI index,2012,2019, and 2020 in NASDAQ 100 index,2011,2012, and 2013 in IBrX 100 index, 2012,2013, and 2014 in CSI 100 index and 2011,2019, and 2020 in NIFTY 100 index. However, it does not show the causal relationship between volatility and concentration, which means only the index had high volatility when the concentration was high and vice versa.

4.2.2 Variance and Covariance

We followed modern portfolio theory for variance analysis, according to which Markowitz (1952) determined the variance of the portfolio from covariance and weighted variance of the component securities, as shown below.

$$\sigma^2(I) = \sum_{i=1}^{100} x_i^2 \sigma_i^2 + \sum_{i=1}^{100} \sum_{\substack{i=1 \\ i \neq j}}^{100} x_i x_j \sigma_{ij} \tag{6}$$

where, x_i and x_j are the weights attached to each security within the index, σ_i^2 the variance of the component security, σ_{ij} are covariance between security i and j, and $\sigma^2(I)$ is the variance of the index. Every index has 100 variances and 9,900 covariance terms except the JSE top 40 index, which has 40 variances, and 1560 covariance terms scaled by their squared weight and covariance from the weight of stock i and j. The equation shows index variance will increase if either covariances or variance of component security increases, although the weighting structure change can create an illusion of its effect. Index variance may be reduced by increasing the weight of securities with lower covariances, while index volatility may be decreased by increasing securities' weight with lower variances. If companies that have a higher weighting also have higher variances or covariances, the effect of lowering the weighted covariances or variances may be offset. Also, if the concentration in the index is increasing due to multinational companies, it can reduce index variance due to international diversification(Davies et al., 2001).

4.3 Performance Analysis

We calculated the index return with the help of Markovitz's mean–variance theory (Eq. 7), while for performance analysis, we had used Sharpe(Sharpe, W. F., 1994; Lo, A. W., 2002)and Sortino ratio(Sortino, F. A., & Price, L. N., 1994) from the equation mentioned below.

$$R(I) = R_1X_1 + R_2X_2 + R_3X_3 + \ldots\ldots\ldots\ldots\ldots\ldots + R_nXn \tag{7}$$

$$\text{Sharpe Ratio} = \left(R_i - R_f\right)/\sigma_i \tag{8}$$

$$\text{Sortino Ratio} = \left(R_i - R_f\right)/\text{downside risk} \tag{9}$$

R(I) is index return, Rn is the return of constituent security n, and Xn is the weight of security n, whereas σ_i is the standard deviation of the index, R_i is index return, and R_f is the risk-free rate. In this study with performance analysis, we compared the market cap-based and equal-weighted indexes and took analysis in depth.

4.4 Simulation Analysis

We did a simple simulation study like Chelley-steeley (2008) to examine volatility sensitivity at different concentration levels. We used the 100×100 variance–covariance matrix and imposed squared weight on each diagonal variance element. In contrast, the imposed product of two weights is off-diagonal covariance elements, as shown below. We classified our study into three [low(LCSI), intermediate(ICSI), and high(HCSI)] levels and assigned three different weight structures based on the H ratio.

$$\begin{pmatrix} X_{1C}^2\sigma_1^2 & X_{1C}X_{2C}\sigma_{12} & X_{1C}X_{3C}\sigma_{13} & \cdots & X_{1C}X_{100,C}\sigma_{1,100} \\ X_{2C}X_{1C}\sigma_{21} & X_{2C}^2\sigma_2^2 & X_{1C}X_{3C}\sigma_{13} & \cdots & X_{2C}X_{100,C}\sigma_{2,100} \\ X_{3C}X_{1C}\sigma_{31} & X_{3C}X_{2C}\sigma_{32} & X_{3C}^2\sigma_3^2 & \cdots & X_{3C}X_{100,C}\sigma_{3,100} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ X_{100,C}X_{1C}\sigma_{100,1} & X_{100,C}X2_C\sigma_{100,2} & X_{100,C}X2_C\sigma_{100,2} & X_{100,C}X2_C\sigma_{100,2} & X_{100,C}X2_C\sigma_{100,2} \end{pmatrix} c = 1, 2, 3$$

From the matrix, we calculated index variance as Eq. (10), where σ^2_{it} is the estimated security variance for security *i* for sub-period *t*, Var(I_t) is index variance, σ_{ijt}

is the covariance of security between security i and j at time t, X_{ic} and X_{jc} are the weights of security.

$$\mathrm{Var}\left(I_t\right) = \sum_{i=1}^{100} X_{ic}^2\sigma_{it}^2 \sum_{\substack{i=1\\ j\neq 1}}^{100} X_{ic}X_{jc}\sigma_{ijt} \tag{10}$$

$$i = 1\ldots\ldots\ldots 100 \quad j = 1\ldots\ldots\ldots\ldots 100 \quad i \neq jc = 1, 2, 3$$

We consider the actual weight of the particular index based on the H index concentration ratio to decide which year reflects low, intermediate, and high weight structure. We consider a year with a high concentration ratio for high, low concentration ratio for a low, and near average concentration ratio for an intermediate weight structure for the study.

5 Empirical Results and Discussion

5.1 Concentration

The Gini coefficient was highest for MOEXBMI excluding JSE 40 with an average of 0.83995, followed by IBrX 100, NASDAQ 100, NIFTY 100, and lowest for CSI 100 index has an average of 0.56122. The Gini index value is more than 0.60 in the maximum index, indicating the concentration, whereas NIFTY 100 and CSI 100 show comparative diversification. Recently NASDAQ 100 concentration increased rapidly, and CSI 100 showed a declining pattern that reached even lesser than NIFTY 100 (Table 1).

IBrX 100 has a higher average than the NASDAQ 100 average, while the NIFTY 100 index was more diversified than the Nasdaq 100 average but was more concentrated than the CSI 100. JSE 40 concentration peaked in 2020 with a maximum coefficient of 0.86941 from the lowest 0.8243 value in 2006. MOEBXMI reached its lowest point in 2020 and the highest in 2019.CSI 100 Index had its highest ratio in 2012 and declined to the lowest in 2020. IBrX 100 index maximum concentration 0.7680 was in 2007, whereas the lowest was 0.6312 in 2020. With an upward trend, the NASDAQ 100 concentration ratio reached its highest point in 2020.

H ratio replicates the finding of the Gini index with marginal change in which MOEXBMI has the highest average in all Indexes excluding JSE 40, followed by IBrX 100, NASDAQ 100, and CSI 100, respectively (Table 2). In contrast, the H ratio shows NIFTY 100 most diversified index, instead of CSI 100. In the initial year, the H ratio of NIFTY 100 was high, but from 2007 it started declining until 2016 except for marginal up movements in 2011 and 2013, after moving upward and reaching its highest value in the immediate last decade ending in 2020. Although NIFTY 100 shows a declining trend for more than half a period, even then, it is consistently above its average of 0.02686. Until 2016, NASDAQ 100 marginally varied except for the 2012 jump, and after started an upward trend which reached an all-time peak in 2020. JSE 40 is the only index that shows a different path for the H

Table 1 Gini Coefficient

Year	JSE 40	MOEXBMI	IBrX 100	CSI 100	NIFTY 100	NASDAQ 100
2006	0.82430		0.65324		0.63349	0.62752
2007	0.84172		0.76800		0.64696	0.64664
2008	0.84238		0.73339		0.63462	0.67938
2009	0.84554		0.71507		0.58421	0.64727
2010	0.84309		0.71571		0.56475	0.63024
2011	0.83719		0.70772		0.59914	0.65096
2012	0.82725		0.70239	0.64071	0.54714	0.66126
2013	0.83866		0.70719	0.61525	0.56011	0.63521
2014	0.82564	0.79949	0.68642	0.59569	0.53173	0.61540
2015	0.82960	0.78332	0.69269	0.51488	0.52876	0.64128
2016	0.83692	0.77818	0.69257	0.52000	0.49360	0.62455
2017	0.83718	0.76774	0.66737	0.53007	0.48255	0.64456
2018	0.85320	0.81070	0.68126	0.53365	0.51623	0.65350
2019	0.84711	0.81121	0.63543	0.50370	0.54761	0.67453
2020	0.86941	0.76392	0.63125	0.47010	0.54743	0.70762
Mean	0.83995	0.78779	0.69265	0.54712	0.56122	0.64933
High	0.86941	0.81121	0.76800	0.64071	0.64696	0.70762
Low	0.82430	0.76392	0.63125	0.47010	0.48255	0.61540

Table 2 Hirschman-Herfindahl index

Year	JSE 40	MOEXBMI	IBrX 100	CSI 100	NIFTY 100	NASDAQ 100
2006	0.07633		0.04340		0.03207	0.04175
2007	0.10100		0.07073		0.03351	0.04530
2008	0.11654		0.05938		0.03338	0.04262
2009	0.12489		0.05605		0.02849	0.04320
2010	0.11595		0.05817		0.02578	0.03995
2011	0.08986		0.04937		0.02766	0.04567
2012	0.08441		0.05005	0.04353	0.02432	0.04979
2013	0.08563		0.04773	0.04062	0.02647	0.03855
2014	0.07137	0.05657	0.04195	0.03454	0.02344	0.04029
2015	0.08764	0.05157	0.04524	0.02731	0.02298	0.04316
2016	0.08748	0.05398	0.04218	0.02754	0.02039	0.04057
2017	0.08788	0.05467	0.04287	0.02733	0.02095	0.04552
2018	0.10195	0.06177	0.04479	0.02831	0.02520	0.04886
2019	0.08580	0.06441	0.03762	0.02509	0.02806	0.05535
2020	0.10698	0.05159	0.03595	0.02205	0.03020	0.06226
Mean	0.09492	0.05637	0.04836	0.03070	0.02686	0.04552
High	0.12489	0.06441	0.07073	0.04353	0.03351	0.06226
Low	0.07137	0.05157	0.03595	0.02205	0.02039	0.03855

ratio from the concentration ratio in which it got the highest point in 2009 and lowest point in 2014. otherwise, CSI 100, MOEXBMI, and IBrX 100 H ratios show the same decline pattern.

We also calculated the top 5 markets valued constituent securities concentration ratio to sum their weight, calculated from the last quarter's market value for each index. In which the JSE 40 index had the highest average concentration ratio. However, we cannot compare JSE 40 with other indexes due to the uneven number of companies. So MOEXBMI is a highly concentrated index with a maximum average, and NIFTY 100 was the most diversified index in the sample with an average of 27.30%. When we did a difference analysis with the top 10 constituent securities concentration ratio, we found that weight addition from the following five security decreases with time for each index except IBrX 100, in which contribution of the next five security increased from 16.48% to 18.46% from 2006 to 2020. JSE 40 weight contribution of the following five stocks in the top 10 was 17.67% in 2006, which decreased to 13.79% in 2020, although the maximum ten concentration ratio increased with time. NASDAQ 100 followed the same behavior where the contribution of the next five stocks in the top 10 was 16.74% in 2006, which decreased to 11.66% in 2020. The weight contribution of the following five companies in MOEXBMI also reduced from 19.88 in 2014 to 18.96% in 2020, which means the top 5 concentrations in JSE 100, NASDAQ 100, and MOXBMI increase disproportionately with time. The weight contribution of the next five companies in CSI 100 decreased from 16.14% in 2012 to 12.86% in 2020, the same as in NIFTY 100, in which the next five stocks' weight contribution in 2006 was 17.16% which declined to 13.33% in 2020, although the top ten concentration ratio of the index decreased with time. Both methodologies are shown almost similar analyses with small contradictions. However, with the Concentration ratio, we found more consistency with the HHI index, so we have taken it as the base for further analysis.

5.2 Variance Analysis

Table 3 contains the coefficient and p-value obtained from GARCH (1,1) model in which the NIFTY 100 δ coefficient is positive and significant in daily and monthly frequency but insignificant in the weekly frequency. It was negative and significant in IBrX 100 for the weekly frequencies at a 10% level of significance. However, CSI 100 and MOEXBMI were positive and significant daily, while NASDAQ was not significant. JSE 40 δ coefficient was significant and positive with daily and weekly frequency and insignificant on the monthly frequency. We found all statistically significant δ coefficients near zero, which indicated index concentration and index volatility are independent of each other. β_1 and β_2 both were significant in the maximum scenario except for JSE 40 and NASDAQ 100 monthly data, whereas β_2 was insignificant in CSI 100 and MOEXBMI monthly frequency separately. $\propto$ also has a different outcome with different frequencies and indexes in which CSI 100 was insignificant for monthly and weekly frequency and IBrX 100 for all frequencies. In contrast, MOEXBMI and NIFTY 100 were insignificant for monthly frequency. However, except for JSE 40 and NASDAQ 100, and MOEXBMI monthly

Table 3 GARCH (1, 1)Volatility Estimates

Index	Frequency	α_0	B_0	B_1	B_2	δ_0
	Daily	0.0005	0.0000	0.0790	0.9153	0.0000
		(2.26)**	(4.26)***	(16.76)***	(202.55)***	(2.83)***
CSI 100	Weekly	0.0010	0.0000	0.1252	0.8275	0.0000
		(0.78)	(2.54)**	(3.93)***	(20.94)***	(1.30)
	Monthly	0.002	0.002	0.4876	0.0091	0.0013
		(0.52)	(3.22)***	(2.63)***	(0.087)	(1.24)
	Daily	0.0004	0.0000	0.0885	0.8594	0.0000
		(1.84)*	(6.18)***	(11.36)***	(61.61)***	(-2.69)***
IBrX 100	Weekly	0.0018	0.0002	0.1577	0.6846	-0.0001
		(1.45)	(2.71)***	(5.12)***	(9.75)***	(-1.78)*
	Monthly	0.0055	0.0002	-0.941	1.0680	-0.0001
		(1.11)	(41.80)***	(-22.92)***	(6399.559)***	(-16.15)***
	Daily	0.0004	0.0000	0.0839	0.8754	0.0000
		(2.64)***	(4.67)***	(8.52)***	(55.32)***	(4.27)***
JSE 40	Weekly	0.0018	0.0001	0.1146	0.7031	0.0001
		(2.11)**	(2.80)***	(4.46)***	(9.72)***	(3.37)***
	Monthly	0.0077	0.006	0.2648	0.0864	0.0007
		(2.69)***	(1.39)	(1.64)	(0.20)	(1.28)
	Daily	0.0010	0.0000	0.1502	0.8034	0.0000
		(5.63)***	(8.21)***	(11.53)***	(49.55)***	(1.44)
NASDAQ 100	Weekly	0.0045	0.0001	0.2692	0.6583	0.0000
		(5.23)***	(2.81)***	(4.53)***	(10.22)***	(0.50)
	Monthly	0.0140	0.003	0.2036	0.6010	0.0003
		(3.64)***	(0.84)	(1.29)	(1.67)*	(0.53)
	Daily	0.0006	0.0000	0.0829	0.8887	0.0000
		(3.64)***	(4.47)***	(10.53)***	(70.22)***	(3.03)***
NIFTY 100	Weekly	0.0025	0.0001	0.1535	0.7111	0.0000
		(2.76)***	(2.19)**	(3.58)***	(7.92)***	(1.57)
	Monthly	0.00084	0.0002	-0.0751	0.9666	0.0005
		(1.81)*	(2.03)**	(-2.76)***	(25.90)***	(3.40)***
	Daily	0.0005	0.0000	0.0708	0.8992	0.0000
		(2.65)***	(5.47)***	(11.08)***	(106.23)***	(7.83)***
MOEXBMI	Weekly	0.0022	0.0001	0.1266	0.7480	0.0000
		(2.05)**	(3.33)***	(5.60)***	(13.18)***	(-1.014)
	Monthly	0.0079	0.0012	0.3103	0.1330	-0.0001
		(1.85)*	(1.67)*	(2.06)**	(0.35)	(-0.3291)

Table contains coefficient and t value in parentheses

***, **, * denotes level of significance at a 1%,5%,10% respectively data, β_0 was significant in the maximum situation. A high significant coefficient of GARCH(1,1) implies persistent volatility clustering in the maximum scenario.

Table 4 contains index variance information in which the NIFTY 100 index has the second-highest index average variance after IBrX 100, while the H ratio for the NIFTY 100 index was the lowest (Table 2). However, MOEXBMI had the highest h value, excluding JSE 40, and showed the lowest average variance, whereas IBrX 100 had a high H index and a high variance. CSI 100 and JSE 40 had equal average variance, JSE 40 had the highest h ratio, and CSI 100 had the second-lowest h ratio. In contrast, NASDAQ 100 had both the H ratio and index variance as third-highest. However, we found a moderate correlation between all indexes' H ratios and index variance. The NIFTY 100 index and JSE 40 index had a positive correlation, whereas others had negative values except for the NASDAQ 100 index, which had the highest positive correlation.

Table 4 reflects the 2008 downfall effect in every index where variance fluctuated at a high rate. When we examined index valuation, we found rapid fluctuation in total index value from 2007 to 2010, indicating massive withdrawal and money deposits in the index (K. H. Bae & Zhang, 2015). To avoid this effect and get a clear picture, we did a comparative analysis from 2011. we found a moderate positive correlation between concentration and index variance in the NIFTY 100(0.561), JSE 40(0.570), and whereas high positive correlation in NASDAQ 100(0.867) indexes. In contrast, there was a moderate negative correlation in MOEXBMI (−0.694), IBrX 100(−0.672), and a weak negative correlation in CSI 100(-0.346) index. Although analysis shows moderate correlation from trend

Table 4 Index Variance (Annualized variance)

Year	IBrX 100	MOEXBMI	NIFTY 100	CSI 100	JSE 40	NASDAQ 100
2006	0.00859		0.00941		0.00734	0.00356
2007	0.01155		0.01245		0.00956	0.00518
2008	0.03085		0.02388		0.02052	0.01856
2009	0.03169		0.02829		0.01994	0.02296
2010	0.01059		0.01153		0.01117	0.00963
2011	0.00745		0.00517		0.00618	0.00821
2012	0.00707		0.00503	0.00453	0.00485	0.00696
2013	0.00566		0.00405	0.00481	0.00341	0.00315
2014	0.00752	0.00635	0.00408	0.00687	0.00362	0.00319
2015	0.00942	0.00761	0.00347	0.01676	0.00387	0.00473
2016	0.01407	0.00511	0.00418	0.01561	0.00654	0.00534
2017	0.01064	0.00336	0.00289	0.00375	0.00436	0.00345
2018	0.00880	0.00404	0.00217	0.00460	0.00328	0.00568
2019	0.00788	0.00349	0.00307	0.00693	0.00331	0.00737
2020	0.02325	0.00655	0.00934	0.00712	0.01037	0.01542
Mean	0.01300	0.00521	0.00860	0.00789	0.00789	0.00823
High	0.03169	0.00760	0.02828	0.01675	0.02052	0.02295
Low	0.00565	0.00335	0.00217	0.00375	0.00328	0.00314

analysis, we did not find a direct link between index variance and concentration, same as Chelley-steeley (2008), excluding NASDAQ 100, where we found an increasing pattern in both h ratios and index variance from 2017 to 2020 when concentration peaked.

Further, we examined the average component security variance with the HHI index. We found a high correlation between average component security variances and H index in NIFTY 100, NASDAQ 100, and JSE 40 of 0.779, 0.861, and 0.827, respectively. CSI 100, MOEXBMI, and IBrx 100 have 0.344, 0.460, and 0.618, respectively, negative correlations between the H index and average component securities variance. We calculated the average variances and covariance of constituent securities presented in Tables 5 and 6, respectively, to get insights into the relationship between constituent securities covariance and concentration. We found high average covariance in the JSE 40 index, followed by IBrX 100 index, NIFTY 100 index, CSI 100 index, NASDAQ 100 index, and MOEXBMI index, respectively. Correlation between covariance and HHI index shows a similar picture as we found between concentration and Index variance moderate in all cases except NASDAQ 100. Analysis of 9,900 securities variance and covariance of IBrX 100 index, MOEXBMI index, and CSI 100 index showed an increased component securities volatility. And NASDAQ 100 index, NIFTY 100 index, and JSE 40 showed the opposite relationship as covariance increased with the H ratio, resulting in increased volatility of indexes. We noticed a synchronized change in constituent security variance with an index concentration in a positive and negative direction, which might affect index performance.

We also checked Chelley-Steeley's (2008) argument on weather covariance offset component securities variance and found the opposite result in NASDAQ 100,

Table 5 Component securities average variances ($\sigma^2 * 1000$)

YEAR	IBrX 100	MOEXBMI	NIFTY 100	CSI 100	JSE 40	NASDAQ 100
2006	0.007966		0.007418		0.032188	0.004508
2007	0.014254		0.009958		0.05038	0.006446
2008	0.029482		0.014545		0.141042	0.013061
2009	0.027891		0.014623		0.160273	0.016015
2010	0.010948		0.006592		0.073081	0.006909
2011	0.007015		0.004569		0.029779	0.006242
2012	0.00776		0.00359	0.002491	0.024204	0.006821
2013	0.007035		0.00378	0.002686	0.018997	0.004927
2014	0.007503	0.007814	0.003571	0.004038	0.017122	0.004734
2015	0.009257	0.009495	0.003004	0.00765	0.023216	0.005434
2016	0.01512	0.008368	0.00276	0.006502	0.041316	0.005059
2017	0.011159	0.006202	0.002365	0.002155	0.033209	0.003783
2018	0.01029	0.007446	0.002674	0.003078	0.03689	0.005722
2019	0.008582	0.007887	0.003284	0.003478	0.027922	0.007725
2020	0.015302	0.009449	0.006845	0.003588	0.060053	0.015432
Mean	0.012638	0.008094	0.005972	0.003963	0.051311	0.007521

Table 6 Component securities Average Covariance (σ^2 * 10,000)

YEAR	IBrX 100	MOEXBMI	NIFTY 100	CSI 100	JSE 40	NASDAQ 100
2006	0.003146		0.003441		0.00600591	0.00123353
2007	0.004068		0.004545		0.00748088	0.00180076
2008	0.011088		0.008898		0.01475929	0.00684849
2009	0.011409		0.010645		0.01329827	0.00847499
2010	0.003725		0.004315		0.00818259	0.00354655
2011	0.002667		0.001869		0.00494978	0.00300978
2012	0.002542		0.001852	0.0017	0.00385549	0.00249298
2013	0.001932		0.001459	0.001803	0.00263222	0.00105378
2014	0.002676	0.002241	0.001477	0.002567	0.00291272	0.00107817
2015	0.003357	0.002682	0.00126	0.006347	0.00291613	0.00166312
2016	0.005014	0.001737	0.001551	0.005935	0.00484374	0.00191672
2017	0.003869	0.001115	0.001054	0.001404	0.00301145	0.00121695
2018	0.003151	0.001337	0.000756	0.001702	0.00176448	0.00202794
2019	0.002823	0.001093	0.001087	0.002613	0.00217078	0.00261852
2020	0.008586	0.002232	0.003434	0.002685	0.0077626	0.00550598
Mean	0.00467	0.001777	0.003176	0.002973	0.00576975	0.00296588

NIFTY 100, and JSE 40. As we show, covariance did not offset component security variance as it was moving in the same upward direction along with concentration and component security variance. In contrast, IBrX 100, MOEXBMI, and CSI 100 movement was in the same order but showed downside movement and did not offset the falling effect of component securities variance.

5.3 Portfolio Return Analysis

The previous study only focussed on variance analysis, but our research found that component securities do not offset index variance, which may affect portfolio performance. Table 7 contains the market-weighted index return, which we calculated using the last 520 days' daily return from 31st December for every year. Comparatively least concentrated NIFTY 100 average return is the highest, followed by NASDAQ 100, MOEXBMI, CSI 100, and IBrX 100, respectively, while during the 2008 recession, NASDAQ 100 suffered the highest loss.

JSE 40 shows a positive return in 2008 and has a 5.349% average return across the years. 2020 was affected by covid 19, in which duration we saw a positive jump in NASDAQ, CSI 100, and NIFTY 100 index from 7.18%,2.53%, 4.37 to 19.68%,16.36%, and 8.58%, respectively, while IBrX 100 and MOEXBMI suffer from downfall as same as experienced by JSE 40. However, in the Sharpe ratio, NASDAQ 100 has the highest average, followed by the sequencing of MOEXBMI, NIFTY 100, CSI 100, and IBrX 100. JSE 100 has an average ratio of 0.3534. From the Sortino ratio, we found the same pattern: IBrX 100 had the lowest ratio, whereas NASDAQ 100 had the highest ratio. The value of the Sortino

Table 7 Market weighted index annualized return

Year	JSE 40	CSI 100	IBrX 100	MOEXBMI	NIFTY 100	NASDOQ 100
2006	0.1574		0.1532		0.1728	0.0458
2007	0.1239		0.1522		0.2312	0.0680
2008	0.0034		−0.0355		−0.0346	−0.0586
2009	−0.0136		0.0074		−0.0201	0.0039
2010	0.0809		0.0940		0.1973	0.1332
2011	0.0398		−0.0291		−0.0064	0.0435
2012	0.0585	−0.0213	−0.0002		0.0038	0.0462
2013	0.0963	−0.0020	0.0063		0.0703	0.1085
2014	0.0639	0.0853	−0.0201	0.0050	0.0817	0.1155
2015	0.0464	0.1385	−0.0277	0.0433	0.0730	0.0689
2016	0.0182	−0.0118	0.0593	0.1283	0.0122	0.0530
2017	0.0575	0.0676	0.1404	0.0709	0.0875	0.0893
2018	0.0034	0.0196	0.0851	0.0267	0.0756	0.0676
2019	−0.0081	0.0253	0.1013	0.0824	0.0437	0.0718
2020	0.0745	0.1636	0.0768	0.0786	0.0858	0.1968
Mean	0.0535	0.0517	0.0509	0.0622	0.0716	0.0702

ratio is more than the Sharpe ratio, which is obvious due to its characteristic difference. We included an equal-weighted index in the analysis to explore any cost arising due to index concentration. An equal-weighted portfolio averagely underperforms the market-cap-weighted portfolio. It has a lower Sharpe and Sortino ratio (presented in Tables 8 and 9) which indicates market concentration does not add any cost for investors.

Investors believe diversification is a way to reduce risk and portfolio optimization. However, it was interesting that the market cap index during the 2008 Global recession outperformed the equal-weighted portfolio, although it had a negative but better Sharpe value. When we analyze the index individually, NASDAQ 100 and NIFTY 100 market cap indices outperform in the whole period except in 2014 for NASDAQ 100 index and in 2010 for the NIFTY 100 index, whereas others also show the almost same patterns. IBrX 100 and JSE 40 market cap indices outperform 10 out of 15 and 13 out of 15 years, respectively. However, CSI 100 and MOEXBMI analyses were done only in 2012–20,2014–20, respectively, showing the outperformance of the market cap index over the equal-weighted index. During high concentration, as defined in the variance section, the comparison result was the same as the average result, where the equal-weighted index underperformed the market-weighted index except for one or two years in IBrX 100, JSE 40, and CSI 100 index. Although we found a slight low variance in the equal-weighted index but on this basis, we cannot support concentration risk theory as we show market cap risk-adjusted performance is better than the equal-weighted index.

Table 8 Sharpe Ratio

Year	JSE 40	CSI 100	IBrX 100	MOEXBMI	NIFTY 100	NASDOQ 100
Market cap index sharpe ratio						
2006	1.3074		1.1638		1.3141	0.5145
2007	0.7854		0.9786		1.6502	0.7347
2008	−0.2654		−0.4377		−0.4919	−0.5412
2009	−0.3403		−0.1518		−0.3241	−0.0740
2010	0.4609		0.6012		1.5373	1.2036
2011	0.1272		−0.6824		−0.5043	0.3130
2012	0.5132	−0.6549	−0.2729		−0.2680	0.3726
2013	1.2960	−0.3246	−0.1890		0.7808	1.6639
2014	0.6574	0.7351	−0.5124	−0.2422	0.8992	1.7759
2015	0.3711	0.8900	−0.5260	0.2287	0.8428	0.7808
2016	−0.0193	−0.2526	0.3331	1.5191	−0.1180	0.5183
2017	0.5566	0.7637	1.1597	0.8641	1.2402	1.2630
2018	−0.3978	−0.0966	0.6286	0.0076	1.0606	0.6955
2019	−0.3381	0.1684	1.0135	1.2024	0.5854	0.6599
2020	0.5870	1.7591	0.4046	0.7848	0.7315	1.4631
Mean	0.3534	0.3319	0.2341	0.6235	0.5957	0.7562
Equal weighted index sharpe ratio						
2006	0.16337		1.07781		0.61602	−0.16914
2007	−0.06132		0.54803		0.94659	−0.24550
2008	−0.58300		−0.97545		−0.78402	−1.03817
2009	−0.33316		−0.24834		−0.43632	−0.28391
2010	0.02508		1.27165		2.10498	0.98480
2011	−0.16659		−0.67928		−0.96771	−0.04049
2012	0.07617	−0.87714	−0.62969		−0.39380	−0.09726
2013	0.22710	−0.13809	−0.35297		0.55392	1.39789
2014	−0.03679	0.86494	−1.06497	−1.02245	0.64358	1.47735
2015	−0.07483	1.08342	−1.17701	0.13552	0.85022	0.26180
2016	−0.25812	−0.08270	0.02770	2.42578	−0.12819	0.04414
2017	−0.15532	0.25442	1.33746	1.49582	1.06855	0.66575
2018	−0.44232	−0.37138	0.58677	−0.72241	0.27659	0.12674
2019	−0.14436	0.01907	1.10421	0.16989	−0.31202	0.36894
2020	−0.01028	1.51278	0.43991	0.88254	0.45293	0.93635
Mean	−0.11829	0.25170	0.08439	0.48067	0.29942	0.29262

5.4 Simulation

5.4.1 Variance Analysis by Weight Simulation

We examined volatility sensitivity in different concentration levels and found a shallow effect of change in concentration on index volatility. Table 10 presents the

Table 9 Sortino Ratio

Year	JSE 40	NIFTY 100	CSI 100	IBrX 100	MOEXBMI	NASDAQ 100
2006	1.7307	1.5721		1.4635		−0.0985
2007	0.9691	2.0165		1.2811		0.284
2008	−0.387	−0.6988		−0.6064		−1.0661
2009	−0.4925	−0.4907		−0.2489		−0.3262
2010	0.6348	2.2336		0.8037		1.3402
2011	0.1482	−0.8322		−0.9784		0.1583
2012	0.6751	−0.4364	−0.9981	−0.4395		0.3472
2013	1.6891	1.0288	−0.5687	−0.3229		2.1032
2014	0.829	1.1925	1.0368	−0.8281	−0.3822	2.0893
2015	0.4194	1.0269	0.9381	−0.836	0.2723	0.8558
2016	−0.0148	−0.196	−0.4008	0.449	2.0612	0.5476
2017	0.719	1.469	0.9057	1.5647	1.1003	1.4972
2018	−0.6256	1.2955	−0.2129	0.7517	−0.02	0.6849
2019	−0.4284	0.3754	−0.1172	1.1296	1.2068	0.6945
2020	0.6565	0.864	2.1527	0.4627	0.7908	1.8429
Mean	0.43485	0.69468	0.30395	0.24306	0.71846	0.73028
Equal weighted Index Sortino ratio						
2006	1.6646	0.6421		1.1143		−0.355
2007	0.7669	1.0632		0.6061		−0.4611
2008	−1.0749	−1.0948		−1.3422		−1.4979
2009	−0.5295	−0.6508		−0.4195		−0.4485
2010	0.8245	2.0616		1.6231		1.1714
2011	0.2883	−1.3666		−1.0055		−0.1132
2012	0.9044	−0.606	−1.3492	−0.8095		−0.1509
2013	1.3464	0.6958	−0.3304	−0.6741		1.8528
2014	0.5943	0.8049	1.143	−1.6537	−1.4583	1.8685
2015	0.3679	1.0007	1.056	−1.8603	0.0271	0.2742
2016	−0.2929	−0.2145	−0.242	−0.024	3.1126	−0.0374
2017	0.1232	1.1658	0.2196	1.6958	1.7039	0.8004
2018	−0.6772	0.2672	−0.6886	0.6111	−0.9688	0.0965
2019	−0.501	−0.8953	−0.3312	1.1606	−0.3721	0.204
2020	0.1067	0.4862	1.6822	0.48	0.7563	1.1658
Mean	0.26079	0.22396	0.12881	−0.03319	0.40009	0.29131

variance of each H index in all scenarios, which shows index variance is less sensitive to change in concentration as you can see uniformity between low and high variance. NIFTY 100 all synthesis index showed high variance in 2008,2009 and 2010 as global crisis effect and decreased until 2019 and again jumped in 2020 due. The variance difference between all synthetic indexes was meagre. Still, we notice an increasing pattern from low to high, whereas the equal-weighted index has a lower variance than other synthesis indexes. In the JSE 40 index, we found a slight change

Table 10 Variance of synthesis indexes (Annualized variance)

INDEX	NIFTY 100 Index					CSI 100 Index				
Synthesis Index	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI
2006	0.0093	0.0099	0.0110	0.0094	0.0017					
2007	0.0101	0.0135	0.0116	0.0111	0.0015					
2008	0.0217	0.0243	0.0239	0.0232	0.0022					
2009	0.0311	0.0330	0.0290	0.0278	−0.0021					
2010	0.0117	0.0132	0.0135	0.0061	0.0018					
2011	0.0057	0.0061	0.0075	0.0055	0.0018					
2012	0.0058	0.0060	0.0064	0.0053	0.0006	0.0067	0.0070	0.0045	0.0074	−0.0022
2013	0.0048	0.0041	0.0049	0.0053	0.0001	0.0076	0.0069	0.0072	0.0071	−0.0005
2014	0.0054	0.0055	0.0059	0.0053	0.0004	0.0085	0.0078	0.0082	0.0066	−0.0002
2015	0.0047	0.0044	0.0054	0.0046	0.0007	0.0183	0.0165	0.0181	0.0194	−0.0003
2016	0.0042	0.0049	0.0045	0.0047	0.0003	0.0171	0.0186	0.0174	0.0195	0.0004
2017	0.0034	0.0035	0.0047	0.0034	0.0013	0.0047	0.0048	0.0052	0.0050	0.0006
2018	0.0032	0.0029	0.0035	0.0029	0.0003	0.0054	0.0046	0.0066	0.0048	0.0012
2019	0.0049	0.0040	0.0056	0.0040	0.0008	0.0082	0.0070	0.0090	0.0074	0.0009
2020	0.0093	0.0093	0.0091	0.0092	−0.0002	0.0071	0.0077	0.0089	0.0076	0.0018
Mean	0.0090	0.0096	0.0098	0.0085	0.0008	0.0093	0.0090	0.0095	0.0094	0.0002
INDEX	MOEXBMI Index					NASDAQ 100 Index				
Synthesis Index	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI
2006						0.0040	0.0041	0.0033	0.0040	−0.0007
2007						0.0051	0.0050	0.0060	0.0051	0.0009
2008						0.0200	0.0235	0.0283	0.0211	0.0083
2009						0.0224	0.0255	0.0263	0.0248	0.0039

Table 10 (continued)

INDEX	MOEXBMI Index					NASDAQ 100 Index				
Synthesis Index	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI
2010						0.0095	0.0111	0.0110	0.0096	0.0015
2011						0.0096	0.0104	0.0094	0.0083	−0.0002
2012						0.0089	0.0079	0.0095	0.0034	0.0006
2013						0.0031	0.0039	0.0044	0.0034	0.0013
2014	0.0066	0.0070	0.0065	0.0056	−0.0001	0.0036	0.0037	0.0038	0.0032	0.0003
2015	0.0076	0.0078	0.0082	0.0056	0.0006	0.0044	0.0047	0.0047	0.0042	0.0003
2016	0.0046	0.0051	0.0053	0.0023	0.0007	0.0052	0.0055	0.0055	0.0053	0.0003
2017	0.0036	0.0035	0.0039	0.0017	0.0003	0.0038	0.0041	0.0040	0.0033	0.0002
2018	0.0038	0.0037	0.0041	0.0024	0.0003	0.0042	0.0055	0.0059	0.0045	0.0017
2019	0.0031	0.0030	0.0035	0.0016	0.0004	0.0078	0.0072	0.0089	0.0060	0.0011
2020	0.0063	0.0058	0.0065	0.0037	0.0002	0.0140	0.0130	0.0154	0.0137	0.0014
Mean	0.0049	0.0050	0.0052	0.0032	0.0004	0.0080	0.0087	0.0094	0.0076	0.0014
INDEX	IBrX 100 index					JSE 40 index				
Synthesis Index	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI
2006	0.0086	0.0091	0.0096	0.0065	0.0009	0.0073	0.0077	0.0058	0.0057	−0.0016
2007	0.0108	0.0115	0.0115	0.0083	0.0008	0.0078	0.0087	0.0077	0.0070	0.0000
2008	0.0317	0.0319	0.0352	0.0256	0.0035	0.0150	0.0131	0.0136	0.0116	−0.0015
2009	0.0303	0.0352	0.0347	0.0239	0.0044	0.0181	0.0149	0.0165	0.0125	−0.0017
2010	0.0094	0.0098	0.0112	0.0069	0.0019	0.0105	0.0090	0.0086	0.0057	−0.0019
2011	0.0069	0.0073	0.0076	0.0069	0.0007	0.0052	0.0046	0.0057	0.0042	0.0006
2012	0.0074	0.0071	0.0079	0.0046	0.0005	0.0041	0.0038	0.0048	0.0034	0.0007
2013	0.0051	0.0057	0.0053	0.0046	0.0002	0.0044	0.0034	0.0038	0.0034	−0.0005

Table 10 (continued)

INDEX	IBrX 100 index					JSE 40 index				
Synthesis Index	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI	LCSI	ICSI	HCSI	EWSI	HCSI- LCSI
2014	0.0073	0.0076	0.0073	0.0058	0.0000	0.0041	0.0041	0.0039	0.0037	−0.0002
2015	0.0085	0.0080	0.0080	0.0071	−0.0005	0.0058	0.0046	0.0042	0.0044	−0.0016
2016	0.0109	0.0144	0.0127	0.0085	0.0018	0.0047	0.0056	0.0067	0.0056	0.0020
2017	0.0105	0.0109	0.0105	0.0076	0.0000	0.0037	0.0030	0.0050	0.0034	0.0012
2018	0.0076	0.0087	0.0087	0.0065	0.0011	0.0039	0.0035	0.0025	0.0036	−0.0014
2019	0.0073	0.0075	0.0080	0.0060	0.0007	0.0034	0.0034	0.0033	0.0038	−0.0001
2020	0.0233	0.0227	0.0237	0.0243	0.0005	0.0104	0.0097	0.0102	0.0127	−0.0001
Mean	0.0116	0.0125	0.0127	0.0092	0.0011	0.0070	0.0064	0.0066	0.0056	−0.0004

in negative variance from the high weight while equal weight showed the same behavior as NIFTY 100, whereas all its synthesis index reflected the 2008 recession and 2019 covid effect. NASDAQ 100 synthesis indexes also show the same pattern as NIFTY 100 but had higher variance during the Global crisis effect period in 2008, 2009, and 2010. In contrast, it has a higher value during the covid effect period in 2020. Whereas CSI 100, MOEXMBI, and IBrX 100 index show a thin line between synthesis index variances.

We noticed the same effect from the average variance of all synthetic indexes calculated from all periods. We verified this by calculating the correlation coefficient between LCSI and HCSI, and the value was close to one for all indexes indicating a high correlation between indexes' variances.

5.4.2 Simulated Study of Sharpe Ratio

We did a simple simulation study like variance analysis to examine the sensitivity of the relationship between index concentration and index return. Table 11 contains the Sharpe ratio for all syntheses and an equal-weighted index reflecting a mixed relationship. JSE 40, CSI 100, and NIFTY 100 average Sharpe ratio were higher in LCSI than HSCI for the whole period, while MOEXBMI and NASDAQ 100 showed the opposite result. IBrX 100 results varied when we took the immediate decade average, which indicated that the index performed better in LCSI. In contrast, the whole period average showed that the index outperformed HCSI, whereas both averages indicated the same interpretation for other indexes. However, it was interesting that HCSI performed better in recent years than in NASDAQ 100, where from 2017 onward, HCSI outperformed LCSI and MOEXBMI followed the same, while IBrX 100 HCSI exceeded LCSI from 2014 onward except in the year 2019. Although, on average, we found that NIFTY 100 LCSI performed better, recently, HCSI outperformed the LCSI from 2017 to 2019. Equal index underperforms all market synthesis indexes except for NIFTY 100 HCSI and LCSI. Surprisingly, in NASDAQ 100, HCSI underperformed the EWSI from 2006 to 2014 except in 2007 and 2012, and in NIFTY 100 from 2010 to 2020 except in 2016 and 2017. Before that, HCSI outperformed LCSI except in the initial year of 2006. MOEXBMI, IBrX 100, CSI 100, and JSE 40 HCSI beat the EWSI at maximum time. However, it was interesting that the high concentration index performed better in recent years, although the Equal index underperforms all synthesis indexes in all markets except the NIFTY 100 high and low synthesis index. We found index return was sensitive to changes in index concentration, and the direction of change was different from market to market-based on the relationship between concentration and covariance.

6 Conclusion

The stock market concentration ratio of BRICSU showed a high concentration fluctuating over time. Some indexes showed an upward trend, like NASDAQ 100 and JSE 40, whereas some showed continued downside movement, like CSI 100 and IBrX 100, but all indexes always had a high Gini ratio. We found NIFTY 100 most

Table 11 Sharpe Ratio of Synthesis Indexes

	JSE 40 index				CSI 100				IBrX 100			
Year	LCSI	ICSI	HSCI	EWSI	LCSI	ICSI	HSCI	EWSI	LCSI	ICSI	HSCI	EWSI
2006	1.2381	1.2603	1.1940	0.1634					1.2513	1.1155	1.1668	1.0778
2007	0.8560	1.4577	1.0799	−0.0613					0.6772	0.8719	0.9786	0.5480
2008	−0.8081	−0.4868	−0.8209	−0.5830					−0.5919	−0.4844	−0.4658	−0.9755
2009	−0.3088	−0.2253	−0.3403	−0.3332					−0.1304	−0.1471	−0.1514	−0.2483
2010	0.6513	0.4679	0.5096	0.0251					0.8476	0.8267	0.5519	1.2716
2011	0.3725	0.1272	0.5058	−0.1666					−0.5040	−0.5409	−0.7079	−0.6793
2012	0.3715	0.4066	0.7626	0.0762	−0.5373	−0.4302	−0.6549	−0.8771	−0.3075	−0.2992	−0.3990	−0.6297
2013	1.3897	0.4630	0.8138	0.2271	0.2799	−0.1442	0.2887	−0.1381	−0.0192	−0.1890	−0.0668	−0.3530
2014	0.6574	−0.5790	0.1461	−0.0368	0.8575	0.9200	0.8702	0.8649	−0.6272	−0.4042	−0.2204	−1.0650
2015	−0.0067	0.1351	−0.6204	−0.0748	0.8189	0.9022	0.8248	1.0834	−0.5505	−0.5088	−0.4032	−1.1770
2016	−0.1559	−0.3175	−0.1952	−0.2581	−0.2108	−0.1789	−0.2086	−0.0827	0.2247	0.2897	0.2333	0.0277
2017	0.3131	0.5145	−0.0217	−0.1553	0.8748	0.8580	0.8261	0.2544	1.1806	1.1456	1.2062	1.3375
2018	−0.1279	−0.3545	0.1626	−0.4423	0.3330	−0.0966	0.3015	−0.3714	0.5187	0.6815	0.6731	0.5868
2019	−0.2328	0.6794	−0.2609	−0.1444	0.2418	0.1132	0.2300	0.0191	1.0660	1.0862	0.8996	1.1042
2020	0.4639	0.6346	0.2489	−0.0103	2.3121	1.7957	2.0649	1.5128	0.4046	0.3957	0.4268	0.4399
Mean	0.3115	0.2789	0.2109	−0.1183	0.5522	0.4155	0.5047	0.2517	0.2293	0.2560	0.2481	0.0844
	MOEXBMI Index				NIFTY 100 Index				NASDAQ 100 Index			
Year	LCSI	ICSI	HSCI	EWSI	LCSI	ICSI	HSCI	EWSI	LCSI	ICSI	HSCI	EWSI
2006					0.4910	0.8338	0.6139	0.6160	0.1152	−0.0578	−0.3586	−0.1691
2007					0.8663	1.0300	1.6577	0.9466	−0.0667	−0.3096	−0.0112	−0.2455
2008					−0.7716	−0.7097	−0.4919	−0.7840	−0.9086	−0.9417	−1.0834	−1.0382
2009					−0.4878	−0.3984	−0.4022	−0.4363	−0.3206	−0.2986	−0.3465	−0.2839

Table 11 (continued)

	MOEXBMI Index				NIFTY 100 Index				NASDAQ 100 Index			
Year	LCSI	ICSI	HSCI	EWSI	LCSI	ICSI	HSCI	EWSI	LCSI	ICSI	HSCI	EWSI
2010					1.8373	1.4363	1.3748	2.1050	0.7390	0.8217	0.7156	0.9848
2011					−0.7867	−0.8518	−0.9822	−0.9677	0.0060	−0.1300	−0.0626	−0.0405
2012					−0.2784	−0.3165	−0.5376	−0.3938	−0.0243	0.1496	0.2542	−0.0973
2013					0.6807	0.7808	0.2990	0.5539	1.5676	1.2891	1.0451	1.3979
2014	−0.3498	−0.2422	−0.3266	−1.0224	0.6474	0.4882	0.3962	0.6436	1.2795	1.2208	1.3452	1.4773
2015	0.2287	0.1950	0.2187	0.1355	0.9286	0.8079	0.3120	0.8502	0.4234	0.3905	0.3514	0.2618
2016	1.4426	1.4273	1.3035	2.4258	−0.1180	−0.0209	−0.1127	−0.1282	0.3060	0.0859	0.1336	0.0441
2017	0.6637	0.4756	0.8454	1.4958	0.8531	1.0331	1.2340	1.0685	0.7700	1.1776	1.2164	0.6658
2018	−0.1689	−0.1218	−0.1357	−0.7224	0.0740	0.2402	0.2077	0.2766	0.0111	0.1478	0.1424	0.1267
2019	1.1413	1.2794	1.2024	0.1699	−0.4891	−0.2881	−0.3909	−0.3120	0.2776	0.6396	0.7888	0.3689
2020	0.8624	0.8595	0.9386	0.8825	0.4286	0.5096	0.1659	0.4529	0.8244	0.9541	1.4631	0.9363
Mean	0.5457	0.5533	0.5781	0.4807	0.2584	0.3049	0.2229	0.2994	0.3333	0.3426	0.3729	0.2926

diversified and JSE 40 most concentrated index from the h ratio. The GARCH analysis result shows index concentration and volatility are independent of each other. Whereas variance–covariance analysis clarified the impact of index concentration on index volatility is mild and differs from market to market. We noticed a synchronized change in constituent security variance with an index concentration in a positive and negative direction, which might affect index performance. We also checked Chelley-Steeley's (2008) argument on whether covariance offset component securities variance and found that covariance did not offset component security variance as it was moving in the same direction along with concentration and component security variance. We have not found any relation between concentration and index performance. Comparative analysis between market cap and the equal-weighted index did not show any Concentration cost for investors as we found a lower Sharpe ratio for an equal-weighted index. Sensitivity analysis reveals index variance is less sensitive to change in index concentration, whereas Sharpe ratio sensitivity depends upon index concentration and covariance relationship.

Although, the study did not find any direct effect of index concentration on index variance, component security variance, and performance. It shows how excessive growth of a few companies does not increase risk in the index, even after delivering information benefits to investors. In contrast, the NIFTY 100 index has the lowest concentration but the highest variance. The impact of concentration on index variance, component security covariance, and index performance depends upon the individual index. It may be due to different levels of investors' biases(Van Nieuwerburgh & Veldkamp, 2009) and the inclusion of multinational companies (Davies et al., 2001) in the index, as we show in the case of NASDAQ 100 has the highest Sharpe and high H ratio. Index concentration is a generic process in the competitive market condition where few beat competition from resource and technological up-gradation like the FANNG in the US market (B. H. Taljaard & Maré, 2021). investors should take it as the generic nature of the markets despite considering index concentration a risk. We hope this paper will help investors in investment related decision. We hope this study thrown some light on contradiction related index concentration risk and will help investors in investment decision.

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