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August 2024 Buy-Sell Guide India's Nifty Top 29 Stocks

Hrishikesh D. Vinod*

Abstract

We study recent monthly data to help long-term investors buy or sell from the top 29 Nifty Fifty Stock Index components. The recommendations are based on six stock-picking algorithms and their average ranks. Since the version of the "omega" stock-picking algorithm in the literature uses weights that distort the actual gain-to-pain ratio faced by investors, we use modified weights. We use data for 29 stocks using the recent 345 months (28.75 years) of monthly closing prices ending in August 2024. Our buy-sell recommendations also use newer "pandemic proof" out-of-sample portfolio performance comparisons from the R package 'generalCorr.' We report twelve sets of ranks for both out-of-sample and in-sample versions of the six algorithms. Averaging the six out-of-sample ranks yields the top and bottom k stocks. For example, k = 2 suggests buying BAJFINANCE and LT while selling BRITANNIA and MARUTI.

Keywords: Stock-Picking, Portfolio Choice, Deciles, Pandemic-Proofing, Omega Gain to Pain Ratio, Stochastic Dominancea

Introduction

Investing in the stock market is vital in directing national resources to the most productive applications. The stock-picking activity of the financial services sector annually commands billions of dollars in fees. Misallocation of resources creates waste and other losses to the economy. This paper offers investors public domain stock-picking tools to reduce such losses using free, open-source software by R Core Team (2023). This paper uses tools mentioned in my open-access paper, Vinod (2024a).

Bombay Stock Exchange (BSE), established in 1875, is the oldest in Asia and is located on Dalal Street in downtown Mumbai, India. We use pretty long price data for 28.75 years, ending in August 2024. If Rs.1 is invested in buying a stock priced at P_t at time t, if the price (adjusted for dividends) at time $t + 1$ is higher, the net return $r_t = [(P_{t+1} - P_t)/P_t]$ will exceed the initial investment of Rs.1. Since the net return is negative when losses are incurred; one defines gross return as $(1+r_t) = 1+(P_{t+1} - P_t)/P_t = P_{t+1}/P_t$. The gross return is always positive since prices are positive.

Continuously compounded return is the exponential return, $\exp(r_t)$, which is always positive. The series expansion of $\exp(r_t)$ is $(1+r_t+r_t^2/2!+..)$. Assuming higher-order terms in the expansion can be ignored, $(|r_t| < 1)$, one can write $\exp(r_t) = 1 + r_t$. It is customary to equate the exponential return to the gross return and write $r_t = \log(P_{t+1}/P_t) = \log P_{t+1} - \log P_t$. Many published papers use the *first difference* of logs of prices evaluated at time t+1 as a return from investment. Since the return data do not always satisfy $(|r_t| < 1)$ for some time periods, let us define $r_t = [(P_t - P_{t-1})/P_{t-1}]$ for our monthly returns from 29 components of the Nifty Fifty index.

Let $f(r)$ denote the probability distribution function of returns (r) from investing in one of the 29 stocks, and $F(r)$ denote the (cumulative) distribution function of returns. Denote the expected value (mean) of $f(r)$ by μ and standard deviation by σ. The Sharpe Ratio, Sharpe (1966), is named after a Nobel-winning economist. It represents a risk-adjusted average return from investment X, defined as:

$$SR(r_X) = \mu(r_X)/\sigma(r_X), \quad (1)$$

where, the denominator makes risk adjustment. Typical SR ranks investment opportunities based on data on market returns represented by the probability distribution $f(r)$ mentioned before.

Although SR of (1) can also be used for ranking gambles, this paper uses it for stock-picking. Gambling is a zero-sum or negative-sum game. By contrast, buying (selling)

* Professor of Economics, Fordham University, Bronx, New York City, United States. Email: vinod@fordham.edu

a share of companies contributing to socially desirable (unneeded) goods and services often yields positive μ and a larger *SR*.

Aumann and Serrano (2008) propose an 'index of riskiness' of an investment as if it is a gamble. They conjure imaginary gambling situations to assess their riskiness using an axiomatic framework and economic decision-making context. They reject the reciprocal of *SR* of (1) as a measure of riskiness because it fails the monotonicity property based on first-order stochastic dominance. Aumann and Serrano (2008) focus too much on the attributes of the stock buyer measured by a buyer's risk-averse utility function. These authors refer to constant absolute risk-averse "CARA person" (page 816).

Cheridito and Kromer (2013) study mathematical formulas defining 45 performance measures similar to the reward-risk ratio (1). Among the 45 are tweaks on Sharpe Ratios and ratios involving the value at risk (VaR). They evaluate the following four properties.

- *(M) Monotonicity* means that more is better than less. This is a common-sense minimal requirement. All performance measures should satisfy it. Vinod (2024a) shows that the Sharpe Ratio satisfies monotonicity.
- *(Q) Quasi-Concavity:* Describes uncertainty aversion linked to economists' utility and decision theories. It is not relevant if we include investors who allocate a (small) proportion of investor funds as if they are risk-loving. We need not accept this criterion for our purposes.
- *(S) Scale Invariance* or $SR(X) = SR(\lambda X)$: The invariance requirement is inappropriate for modern investing, where some technologies need very large (or small) scale, and transaction costs are low for large transactions.
- *(D) Distribution-Based:* All six stock-picking algorithms in this paper are distribution-based.

Cheridito and Kromer (2013) evaluations are not necessarily for stock market investment but include the ranking of gambles where the "probability measure" (as in the measure theory of statistics) may be unknown. By contrast, our probability measure is well approximated by $f(r)$, and its riskiness is well represented by its dispersion.

We argue that property (Q) is linked to utility theory can be ignored when allocating resources. After all, economists have long avoided interpersonal utility comparisons. An individual investor's utility experience is personal, rarely identical across individuals and exhibits marked change for the same individual over time and space. Psychologists have documented that utility from profits and losses is asymmetric and sensitive to profit and loss sizes. It is futile to assess whether someone is a "CARA person" before deciding which decision theory applies to him. In summary, care is needed before applying the M, Q, S and D criteria for stock-picking purposes.

Let us turn to the 29 stocks from the BSE Nifty index. We begin with Table 2 for the first fifteen companies (ordered alphabetically by their ticker symbols). Table 3 has the remaining fourteen company names. The tables report ticker symbols and a (case-sensitive) single-character name to identify the stock for later use in graphics and tables.

Fig. 1 is inspired by Markowitz's efficient frontier model, without the straight line representing a risk-free rate. The figure has the mean return on the vertical axis and the standard deviation of returns measuring the volatility (risk) for that stock on the horizontal axis. We depict 29 single-character symbols in Fig. 1 for each Nifty index component sticker.

The basic idea behind Fig. 1 is that we imagine grouping stocks into a certain number (=6) of unequal-width ranges of standard deviation class intervals. Our 29 stocks are implicitly assigned to these six σ intervals. Now, the stock yielding the highest average return for each level of risk (measured by the midpoints of the sd class interval) dominates all those below it in Fig. 1. The six stocks are in Table 1, where we report the x-coordinate under the column title "sd," and the y-coordinate under the column title "mean." The dominating stocks from Nifty are graphically identified as (s, n, g, q, e, a). See the last column entitled "abb" of Table 1. The upward trend of the efficiency frontier is seen from the monotonically increasing mean returns in Table 1.

Table 1: Stocks on the Markowitz Efficiency Frontier Dominate Others in the Same Risk Class Measured by "SD"

Stock Ticker	*SD*	*Mean*	*Sharpe Ratio*	*abb.*
NESTLEIND	0.0561	0.0083	0.1479	s
ITC	0.0803	0.0187	0.2326	n
BRITANNIA	0.0826	0.0224	0.2705	g

Stock Ticker	*SD*	*Mean*	*Sharpe Ratio*	*abb.*
LTIM	0.0931	0.0295	0.3167	q
BAJFINANCE	0.1252	0.0375	0.2999	e
ADANIENT	0.74	0.076	0.1026	a

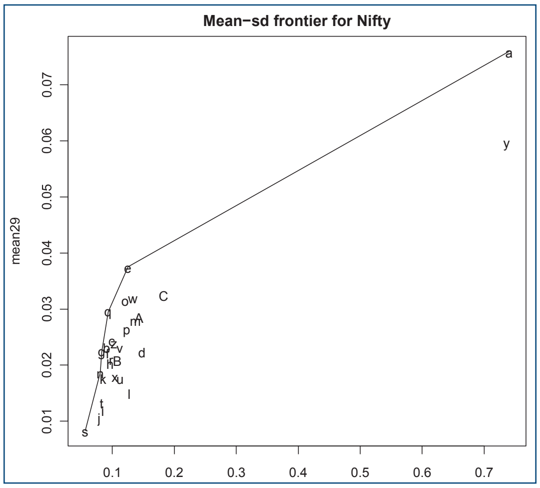

Fig. 1: Mean-Standard Deviation Efficiency Frontier for Nifty29 Stocks

Table 2: Ticker Symbols, Company Name and Abbreviations with 1 Character *(Part 1)*

Sr. No.	*Ticker*	*Company Name*	*abb*
1	ADANIENT.NS	Adani Enterprises Ltd	a
2	APOLLOHOSP.NS	Apollo Hospitals Enterprise Ltd	b
3	BAJAJ-AUTO.NS	Bajaj Auto Ltd	c
4	BAJAJFINSV.NS	Bajaj Finserv Ltd.	d
5	BAJFINANCE.NS	Bajaj Finance Ltd	e
6	BHARTIARTL.NS	Bharti Airtel Ltd	f
7	BRITANNIA.NS	Britannia Industries Ltd	g
8	CIPLA.NS	Cipla Ltd	h
9	COALINDIA.NS	Coal India Ltd	i
10	HDFCLIFE.NS	HDFC Life Insurance Company Ltd	j
11	HEROMOTOCO.NS	Hero MotoCorp Ltd	k
12	HINDALCO.NS	Hindalco Industries Ltd	l
13	INDUSINDBK.NS	IndusInd Bank Ltd	m
14	ITC.NS	ITC Ltd	n
15	KOTAKBANK.NS	Kotak Mahindra Bank Ltd	o

Descriptive Statistics for the Nifty Stock Returns

This section reports some basic information about our data using standard descriptive stats. We report 'min' for the smallest return, Q1 for the first quartile, where 25% of data are below Q1 and 75% above Q1. 'Median' and 'mean' are self-explanatory. Q3 is for the third quartile (75% below and 25% above), and 'max' denotes the largest return.

In finance, two additional descriptive stats are referenced. The $SR = \mu/\sigma$ defined before and the 'expected gain to expected pain ratio.' The latter is called 'omega' (Ω) in Keating and Shadwick (2002), or "KS02" hereafter. While we include *SR* and Ω among descriptive statistics associated with each stock, we also include them among our six stock-picking algorithms.

Table 3: Ticker Symbols, Company Name and Abbreviation with Only One Character *(Part 2)*

Sr. No.	*Ticker*	*Company Name*	*abb*
16	LT.NS	Larsen & Toubro Ltd	p
17	LTIM.NS	LTIMindtree Ltd	q
18	MARUTI.NS	Maruti Suzuki India Ltd	r
19	NESTLEIND.NS	Nestle India Ltd	s
20	NTPC.NS	NTPC Ltd	t
21	ONGC.NS	Oil and Natural Gas Corp. Ltd	u
22	RELIANCE.NS	Reliance Industries Ltd	v
23	SHRIRAMFIN.NS	Shriram Finance Ltd	w
24	TATACONSUM.NS	Tata Consumer Products Ltd	x
25	TATASTEEL.NS	Tata Steel Ltd	y
26	TCS.NS	Tata Consultancy Services Ltd	z
27	TITAN.NS	Titan Company Ltd	A
28	ULTRACEMCO.NS	UltraTech Cement Ltd	B
29	WIPRO.NS	Wipro Ltd	C

Sharpe Ratios for Risk-Adjusted Stock Returns

SR of (1) is a popular stock-picking tool. Many researchers have studied it and suggested modifications. *SR* treats a symmetric measure σ as an approximation to the risk. It treats volatility on the profit and loss side as equally undesirable. Volatility on the loss side is undesirable but desirable on the profit side. An adjusted version, $SR_{dsd} = \mu/DSD$, replaces the $\sqrt{\sigma}$ in the original denominator by downside standard deviation ($DSD = DSV$) from the square root of DSV, the downside variance. Let n^b denote the number of observations below the mean. Downside variance in Vinod and Reagle (2005) (page 111, eq. (5.2.2)) is computed as

$$DSV = [\Sigma_t w_t (r_t - r^{-})^2]/n^b, \qquad (2)$$

where $w_t = 0$ when $r_t > r^{-}$, and $w_t = 1$, otherwise. The summation is over n^b returns involving possible losses. The adjusted version

$$SR_{dsd} = \mu/\text{DSV}^{0.5}, \qquad (3)$$

is not difficult to compute.

Page 114 of Vinod and Reagle (2005) was perhaps the first to identify an often ignored serious problem with Sharpe Ratios. Now, we show how SR gives wrong rankings when risk-adjusting any stocks with negative average returns. We explain the wrong ranking using an example of two stocks, p and q, with Sharpe ratios, $SR_p = \mu_p/\sigma_p$ and $SR_q = \mu_q/\sigma_q$. Now assume that both have a negative average loss of 100, or $\mu_p = \mu_q = -100$. Next, assume that stock p is twice as volatile (risky) as stock q, or $\sigma_p = 10$ and $\sigma_q = 5$. We expect that money-losing and more risky stock p is worse than q. Note that $SR_p = -100/10 = -10$ is larger than $SR_q = -100/5 = -20$. The ranking by SR says q is worse than p, which is against common sense.

Page 114 of Vinod and Reagle (2005) also explains how to use suitably large "add factors" to get the SR to yield the correct ranking. Fortunately, columns entitled 'Mean' in Tables 4 and 5 (of descriptive stats reported later) show that all 29 stocks have positive average returns. Thus, we do not need any 'add factor' adjustment in our context. Note that the "short ticker" column contains self-explanatory abbreviations of the ticker symbols listed in Tables 2 and 3.

Note that our $SR = \mu/\sigma$ assumes that the researcher has true unknown values of μ and σ, rather than their sample estimates ignoring estimation errors. A "Double Sharpe Ratio" divides the sample estimate $\hat{sr}$ by its standard error (SE), the standard deviation of the sampling distribution. The division penalizes stocks with higher estimation risk. A double SR, which penalizes for estimation risk represented by a bootstrap standard error, is discussed on page 227 of Vinod and Reagle (2005). We denote it as SR with subscript 'se' as:

$$SR_{se} = sr/\hat{SE}(sr), \qquad (4)$$

The online appendix provides software for computing SR_{dsd} of (3) using downside standard deviation in the denominator. Next, the appendix software computes a large number J of SR^j_{dsd} based on bootstrap replicates. Then, the code computes $SE(sr)$ in the denominator of (4), which becomes the standard deviation of J bootstrap values SR^j_{dsd}.

Recall that the risk (horizontal axis) versus return (vertical axis) scatterplot of Fig. 1 suggests that stocks listed in Table 1 graphically dominate others. The respective Sharpe ratios of these stocks are also listed in that table. Note that the Sharpe ratio is a direct measure of risk-adjusted return, bypassing the grouping of stock returns into standard deviation (sd) intervals.

Markowitz's theory supports a stock-picking algorithm based on the original Sharpe Ratio (SR). It is one of the six algorithms listed later in a separate section. Our computations use the original SR rather than more sophisticated SR_{dsd} or SR_{se}.

Computation of "Omega" for Stock Returns

KS02 authors name a "cumulative probability weighted" gain-loss ratio "omega" (Ω) and claim that it is a "universal" performance measure. Vinod (2024a) explains (a) the logic behind the cumbersome weighting scheme in KS02, and (b) that such weighting is not really needed to achieve the intent of Bernardo and Ledoit (2000).

Recall that we regard omega as one of many stock-picking algorithms. This subsection suggests a direct computation of omega as an aggregate gain to aggregate loss ratio without using $F(r)$ and $(1 - F(r))$ weights. We divide the vector of returns r_t into positive (r_t^+) and negative (r_t^-) parts (also made positive) and define as:

$$\Omega_{sum} = \frac{\Sigma_t(r_t^+)}{\Sigma_t|(r_t^-)|}, \qquad (5)$$

where, the subscript 'sum' refers to summations in the formula. The numerator and denominator are both positive. For example, the stock A with returns r^A_t = (–3, –1, 2, 5) has $\Omega_{sum} = ((2 + 5)/(3 + 1)) = 7/4$. The stock B with returns r^B_t = (–4, 1, 2, 4) has the same $\Omega_{sum} = 7/4$. The computation of Ω_{sum} is seen to be easy and intuitive.

Table 4: **Table of Basic Descriptive Stats Including Sharpe and Ω_{sum}, Non-Missing Sample Size in the Last Column *(Part 1)***

Short Ticker	Min	Q1	Median	Mean	Q3	Max	SD	Sharpe	Ω_s	Non mis
ADANI	-4.87	-0.06	0.02	0.08	0.12	10.28	0.74	0.10	36.4	266
APOLL	-0.34	-0.03	0.01	0.02	0.07	0.34	0.09	0.26	12.2	266
BJAUT	-0.46	-0.03	0.02	0.02	0.08	0.61	0.10	0.25	12.9	266
BJFSV	-0.91	-0.04	0.02	0.02	0.09	0.67	0.15	0.15	15.4	264
BJFIN	-0.50	-0.03	0.03	0.04	0.10	0.53	0.13	0.30	17.3	266
BHART	-0.30	-0.04	0.02	0.02	0.07	0.37	0.09	0.24	12.7	266
BRITA	-0.19	-0.03	0.02	0.02	0.07	0.33	0.08	0.27	14.9	343
CIPLA	-0.23	-0.04	0.01	0.02	0.07	0.47	0.10	0.21	16.2	344
COALI	-0.19	-0.04	0.01	0.01	0.07	0.31	0.08	0.14	6.5	165
HDFCL	-0.19	-0.05	0.01	0.01	0.07	0.21	0.08	0.14	3.1	81
HEROM	-0.20	-0.04	0.01	0.02	0.08	0.36	0.09	0.21	11.4	266
HINDA	-0.39	-0.07	0.01	0.02	0.10	0.57	0.13	0.12	19.6	344
INDUS	-0.68	-0.04	0.02	0.03	0.08	0.75	0.14	0.20	16.5	266
ITC	-0.23	-0.03	0.02	0.02	0.07	0.31	0.08	0.23	13.9	344
KOTAK	-0.39	-0.03	0.03	0.03	0.08	0.76	0.12	0.26	16.0	277

Table 5: **Table of Basic Descriptive Stats Including Sharpe and Ω_{sum}, Non-Missing Sample Size in the Last Column *(Part 2)***

Short Ticker	Min	Q1	Median	Mean	Q3	Max	SD	Sharpe	Ω_s	Non miss
LT	-0.56	-0.03	0.02	0.03	0.09	0.67	0.12	0.21	14.6	266
LTIM	-0.25	-0.03	0.03	0.03	0.10	0.23	0.09	0.32	5.2	97
MARUT	-0.32	-0.03	0.02	0.02	0.08	0.39	0.10	0.21	12.2	253
NESTL	-0.52	-0.01	0.00	0.01	0.04	0.18	0.06	0.15	5.5	264
NTPC	-0.31	-0.04	0.00	0.01	0.07	0.38	0.08	0.16	8.9	237
ONGC	-0.34	-0.05	0.01	0.02	0.07	0.54	0.11	0.16	17.2	344
RELIA	-0.56	-0.04	0.01	0.02	0.08	1.01	0.11	0.21	17.2	344
SHRIR	-0.45	-0.04	0.02	0.03	0.10	0.90	0.13	0.24	17.1	266
TATAC	-0.31	-0.05	0.01	0.02	0.08	0.45	0.10	0.17	17.0	344
TATAS	-0.93	-0.07	0.01	0.06	0.10	13.29	0.74	0.08	35.8	344
TCS	-0.21	-0.02	0.01	0.02	0.07	1.06	0.10	0.23	11.5	264
TITAN	-0.39	-0.05	0.02	0.03	0.09	1.12	0.14	0.20	22.3	344
ULTRA	-0.73	-0.04	0.02	0.02	0.08	0.43	0.11	0.20	13.1	264
WIPRO	-0.69	-0.04	0.01	0.03	0.08	1.57	0.18	0.18	23.3	344

Table 6: **Descriptive Stats Ranks (1=Most Desirable) for Stocks. Avg=Average of Ranks in the row. The Smallest SD is Most Desirable with Rank=1. Part 1**

Short Ticker	Min	Q1	Median	Mean	Q3	Max	SD	Sharpe	Ω_s	Non mis	Avg
ADANI	29	27	12	1	1	2	29	28	1	16.0	14.44
APOLL	13	6	16	13	23	23	8	5	22	16.0	14.33
BJAUT	19	5	5	11	13	12	13	6	19	16.0	11.44
BJFSV	27	15	9	15	8	11	26	23	14	22.5	16.44
BJFIN	20	3	2	3	6	15	21	2	6	16.0	8.67

Short Ticker	Min	Q1	Median	Mean	Q3	Max	SD	Sharpe	Ω_s	Non mis	Avg
BHART	9	13	4	16	21	21	9	7	20	16.0	13.33
BRITA	2	11	14	17	26	24	5	3	15	10.0	13.00
CIPLA	6	22	18	20	19	16	11	13	12	5.0	15.22
COALI	3	21	27	27	27	26	6	25	26	27.0	20.89
HDFCL	1	23	21	28	20	28	2	26	29	29.0	19.78
HEROM	4	18	24	23	18	22	7	14	24	16.0	17.11
HINDA	15	28	26	25	4	13	22	27	5	5.0	18.33
INDUS	24	19	15	9	11	9	24	16	11	16.0	15.33
ITC	7	9	13	21	28	25	3	10	17	5.0	14.78
KOTAK	16	7	3	6	10	8	19	4	13	11.0	9.56

Table 7: Descriptive Stats Ranks (1=most desirable) for Stocks. Avg=Average of Ranks in the Row. The Smallest SD is Most Desirable with Rank=1 *(Part 2)*

Short Ticker	Min	Q1	Median	Mean	Q3	Max	SD	Sharpe	Ω_s	Non mis	Avg
LT	22	10	11	10	9	10	20	12	16	16.0	13.33
LTIM	8	4	1	7	2	27	10	1	28	28.0	9.78
MARUT	12	8	7	19	17	19	12	11	21	25.0	14.00
NESTL	21	1	29	29	29	29	1	24	27	22.5	21.11
NTPC	11	12	28	26	22	20	4	21	25	26.0	18.78
ONGC	14	26	20	24	25	14	18	22	7	5.0	18.89
RELIA	23	16	19	14	12	6	17	15	8	5.0	14.44
SHRIR	18	14	8	5	3	7	23	8	9	16.0	10.56
TATAC	10	25	25	22	15	17	15	20	10	5.0	17.67
TATAS	28	29	23	2	5	1	28	29	2	5.0	16.33
TCS	5	2	22	12	24	5	14	9	23	22.5	12.89
TITAN	17	24	10	8	7	4	25	17	4	5.0	12.89
ULTRA	26	17	6	18	16	18	16	18	18	22.5	17.00
WIPRO	25	20	17	4	14	3	27	19	3	5.0	14.67

Unbiased Out-of-Sample Calculations

Most authors define their out-of-sample from the last few periods of the data. Since any such out-of-sample time series is sensitive to the peculiar characteristics of the last few periods, their calculations can be biased. For example, if the out-of-sample (oos) series coincides with the 2020 pandemic, the calculations will have a pessimistic bias.

Vinod (2023) suggests removing the bias by "pandemic proofing" the calculations on (40% here) randomly chosen 'oos' data. Each j-th choice yields a ranking of stocks. Repeating the ranking J (=50, say) times, we compute their mean μ and standard deviation σ for the i-th stock-picking algorithm. We have $i = 1, \ldots, 6$ here. Assuming no transaction costs, Vinod (2023) computes a zero-cost arbitrage, executing the following trades. One short-sells (selling without first possessing) certain dollars worth of the worst stock in Nifty and buys the appropriate fraction of the best stock as determined by each method.

Our unbiased 'oos' strategy here does not seek a zero-cost arbitrage. Instead, we just compute distinct stock rankings by each method in-sample and randomly choose 40% observations for each j-th 'oos' realisation. Finally, the average of ranks over $j = 1, \ldots, J$ random choices determine the 'oos' stock choice by that method.

Ranking 29 Stocks by Six Algorithms

We split our report into three tables, ranking the 29 Nifty stocks by two versions of six stock-picking algorithms.

Each table has ten stocks at a time in alphabetical order of their ticker symbols. Tables 9 to 11 report two versions of the ranks produced by each algorithm for (a) **in-sample** ranks and (b) unbiased **out-of-sample** ranks.

- *Sharpe-in/out:* An earlier section mentions the Sharpe ratio as a stock picking algorithm.
- *Omega-in/out:* Our computation is described earlier and in equation (5) for Ω_{sum}.
- *Decile-in/out:* It is generally agreed that the stock whose probability distribution of returns is more to the right-hand side is more desirable.

One way to do this is to compare their deciles. The R package 'generalCorr,' offers a convenient function called decileVote(.). The R command ?generalCorr::decileVote provides details.

- *Descr-in/out:* We compare the traditional descriptive stats of each stock's data. Most stats are in the "the larger, the better" category and get (+1) as weight. The sd (standard deviation) represents risk and gets (–1) weight. This algorithm uses a weighted summary of these stats for stock-picking. It excludes the Sharpe Ratio and Omega (items 1 and 2 in this list) to avoid double counting.
- *Momen-in/out:* Moment values: The first four moments of a probability distribution provide information about centering, variability, skewness and kurtosis. Our weights incorporate the prior knowledge that low variability and low kurtosis are desirable, while larger mean and skewness are desirable. A weighted summary is implemented in the R package 'generalCorr,' function called momentVote(.). The R command ?generalCorr::momentVote provides details about optional weights.
- *Exact-in/out:* This algorithm refers to the exact stochastic dominance mentioned in the next section. The stochastic dominance (SD) of the first four orders is summarised in the R package 'generalCorr.' See the R function called exactSd(). The theoretical details are available in Vinod (2024b), where iterated integrals of cumulative distribution functions are used. See the following subsection for a summary of general ideas behind the theory of stochastic dominance.

Ranking Stocks by Exact Stochastic Dominance

We apply some tools described in Vinod (2024b) to the portfolio selection problem for the Nifty29 dataset used here. We use exact computation of stochastic dominance using an imaginary stock (x.ref) as worse than the worst-performing stock in Nifty29. Thus, all 29 stocks in our data always dominate (x.ref) throughout the period with varying dominance amounts.

The exact stochastic dominance computation invented by Vinod (2024b) measures the dominance of each one of the 29 Nifty stocks over the (x.ref) imaginary stock. The 29 dominating amounts are comparable to each other and allow the ranking of the 29 stocks. The computation of dominating quantities depends on the order k of stochastic dominance (SDk).

The first-order computation of the dominating amount depends on the exact area between two empirical cumulative distribution functions (ECDFs). It is customary to use iterated integrals for higher-order computation of dominating areas since Levy (1973). The R package 'generalCorr' computes dominating areas for SD1 to SD4 and summarises their rankings.

Let us begin the discussion of our results with a table summarising our analysis from a practical viewpoint. Table 8 considers only the top and bottom two stocks for buying and selling, respectively. It spells out the algorithm names used as criteria for choosing stocks.

In more detailed tables, we have to use abridged row names to fit in with reasonable table widths. The bottom row of Table 8 is named AvOOS. It averages the ranks using out-of-sample versions of all six criteria. Thus, our study recommends BJFIN and LT for buying and BRITA and MARUT for selling.

Table 8: Abridged Ticker Symbols of the Top Two Stocks for Buying and the Bottom Two for Selling by Each of Our Six Algorithms. Row Names are Algorithm Names. Column names are Ranks

Criterion	*1*	*2*	*28*	*29*
Sharpe-in	LTIM	ITC	SHRIR	TCS
Sharpe-out	BJFIN	INDUS	MARUT	NTPC
Omega-in	BJFIN	SHRIR	BJAUT	APOLL

Criterion	*1*	*2*	*28*	*29*
Omega-out	BJFIN	INDUS	LT	MARUT
Decile-in	LTIM	INDUS	BHART	TITAN
Decile-out	BJFIN	HDFCL	INDUS	KOTAK
Descr-in	BJFIN	BJAUT	LTIM	KOTAK
Descr-out	HDFCL	SHRIR	BJFSV	KOTAK
Momen-in	SHRIR	INDUS	TCS	LT
Momen-out	SHRIR	ADANI	LT	BRITA
Exact-in	LTIM	BJAUT	HEROM	BHART
Exact-out	LTIM	BJFIN	HEROM	INDUS
AvgRank	BJFIN	BJAUT	INDUS	MARUT
AvOOS	BJFIN	LT	BRITA	MARUT

Tables 9 to 11 headings refer to the lowercase versions of the short ticker symbols mentioned earlier. The bodies of the tables contain the ranks of stock tickers named in the column heading. The stocks ranked with low numbers (e.g., 1 to 8) are worth buying according to the algorithm implied by the row name. On the other hand, stocks ranked with high numbers (e.g., 22 to 29) are worth selling. Interestingly, stocks recommended for buying using in-sample data do not generally agree with the unbiased out-of-sample averages, even for the same algorithm. This is not unexpected because each algorithm has a distinct criterion.

Table 9: All Criteria Summary Ranks of Nifty29 Stocks for In-Sample and Average Over Randomised Out-of-Sample Returns (Avo) *(Part 1)*

	Adani	*Apoll*	*Bjaut*	*Bjfsv*	*Bjfin*	*Bhart*	*Brita*	*Cipla*	*Coali*	*Hdfcl*
Shi	28.0	5.0	6.0	23.0	2.0	7.0	3.0	13.0	25.0	26.0
Sho	29.0	16.0	18.0	4.0	1.0	22.0	3.0	19.0	7.0	2.0
Omi	5.0	9.0	8.0	23.0	1.0	12.0	7.0	19.0	27.0	28.0
Omo	26.0	20.0	15.0	5.0	1.0	24.0	7.0	23.0	12.0	4.0
Dci	12.5	14.5	4.0	6.0	2.0	8.0	16.0	23.0	29.0	27.0
Dco	11.0	27.0	13.0	3.0	1.0	18.0	7.0	24.5	14.5	10.0
Dsi	14.4	14.6	11.1	15.9	10.0	13.3	14.1	16.0	19.6	17.6
Dso	15.1	16.4	16.6	8.1	7.7	17.3	11.7	17.0	13.4	10.4
Moi	4.0	14.0	12.0	15.0	5.0	18.0	16.0	17.0	27.0	29.0
Moo	10.0	19.0	13.0	4.0	3.0	28.0	9.0	17.0	18.0	21.0
Exi	14.0	11.0	10.0	16.0	13.0	9.0	21.0	25.0	3.0	2.0
Exo	15.0	7.5	16.0	5.0	11.0	18.0	21.0	25.0	2.5	2.5
avg	16.0	12.0	10.0	6.0	1.0	18.0	7.0	25.0	19.0	14.0
Avo	20.0	19.0	14.0	2.0	1.0	25.0	8.0	24.0	11.0	5.0

The three tables, 9 to 11, represent the main finding of our study of monthly data spanning over 28 years. The tables report alphabetically arranged ticker symbols in the column headings. Each table has ten stocks out of the 29 stocks of the Nifty. The bodies of the tables report rank by each of the twelve methods for six algorithms in two versions. For example, the first column, Table 9, has ranks of the Adani stock by the twelve methods. The first four ranks (28, 29, 5 and 26) have no repetitions. The twelve methods rarely agree. If we respect the independent logic of all twelve algorithms, the average rank reported in the last two rows may be thought of as a gist from the twelve ranks along the first twelve rows.

Table 10: All Criteria Summary Ranks of Nifty29 Stocks for In-Sample and Average Over Randomised Out-of-Sample Returns (Avo) *(Part 2)*

	Herom	*Hinda*	*Indus*	*Itc*	*Kotak*	*Lt*	*Ltim*	*Marut*	*Nestl*	*Ntpc*
Shi	14.0	27.0	16.0	10.0	4.0	12.0	1.0	11.0	24.0	21.0
Sho	12.0	26.0	10.0	11.0	5.0	13.0	17.0	8.0	20.0	9.0
Omi	21.0	29.0	16.0	14.0	4.0	13.0	3.0	18.0	22.0	25.0
Omo	19.0	28.0	10.0	13.0	2.0	8.0	21.0	9.0	22.0	11.0
Dci	22.0	21.0	10.5	17.0	3.0	5.0	1.0	12.5	18.0	26.0

	Herom	Hinda	Indus	Itc	Kotak	Lt	Ltim	Marut	Nestl	Ntpc
Dco	19.0	24.5	8.0	14.5	9.0	2.0	12.0	5.0	20.0	6.0
Dsi	16.6	19.0	15.9	15.1	9.9	13.1	8.4	13.4	19.9	17.6
Dso	16.1	20.4	12.9	14.7	9.4	12.9	15.1	14.3	17.0	12.6
Moi	25.0	23.0	10.0	24.0	3.0	9.0	13.0	20.0	28.0	26.0
Moo	25.5	20.0	6.0	23.0	2.0	8.0	27.0	15.0	29.0	11.0
Exi	8.0	29.0	15.0	26.0	18.0	12.0	1.0	6.0	17.0	5.0
Exo	9.5	27.0	9.5	24.0	19.0	17.0	1.0	7.5	6.0	4.0
avg	22.0	28.0	8.5	21.0	3.0	5.0	4.0	8.5	26.0	13.0
Avo	18.0	27.0	7.0	16.0	4.0	10.0	15.0	9.0	22.0	6.0

The buy or sell recommendations from our study need some slicing and dicing of the three tables 9 to 11. Accordingly, Table 12 reports abridged (case-sensitive single-character) names of the top eight stocks for buying (ranked 1 to 8) and the bottom eight for selling (ranked 22 to 29) by each of our six algorithms. Algorithm names are listed in a separate section. The algorithm names also appear as row names in Tables 9 to 11. To save table space, we must abridge the row names to only three characters. Column names are lowercase versions of the stock ticker symbols. We are reporting 12 rows, two for each of the six criteria (in-sample and out-of-sample). The 13-th row, named 'avg' (Avg Rank), refers to the average rank from all 12 criteria listed above. The last 14-th row Avo is the average rank of six out-of-sample versions for six algorithms used as criteria for choosing stocks.

Table 11: All Criteria Summary Rank of Nifty29 Stocks and Avo, part 3

	Ongc	Relia	Shrir	Tatac	Tatas	Tcs	Titan	Ultra	Wipro
Shi	22.0	15.0	8.0	20.0	29.0	9.0	17.0	18.0	19.0
Sho	28.0	15.0	6.0	25.0	27.0	23.0	24.0	14.0	21.0
Omi	26.0	15.0	10.0	24.0	2.0	6.0	17.0	20.0	11.0
Omo	29.0	18.0	6.0	27.0	3.0	14.0	25.0	16.0	17.0
Dci	28.0	24.0	7.0	25.0	19.5	14.5	9.0	10.5	19.5
Dco	29.0	21.0	4.0	26.0	17.0	23.0	22.0	16.0	28.0
Dsi	20.1	15.3	11.1	18.4	16.6	12.0	13.6	16.7	15.7
Dso	21.7	14.3	11.4	20.7	15.4	16.4	19.9	16.1	19.7
Moi	21.0	11.0	1.0	22.0	6.0	8.0	7.0	19.0	2.0
Moo	24.0	16.0	1.0	25.5	5.0	12.0	22.0	14.0	7.0
Exi	28.0	24.0	7.0	27.0	20.0	4.0	23.0	19.0	22.0
Exo	29.0	23.0	13.0	28.0	20.0	12.0	26.0	14.0	22.0
avg	29.0	23.0	2.0	27.0	15.0	11.0	24.0	17.0	20.0
Avo	29.0	21.0	3.0	28.0	12.0	17.0	26.0	13.0	23.0

Table 12: One Character Name of the Top and Bottom Eight Stocks for Buying and Selling by each of Our Six Algorithms. Algorithm Names from Earlier Tables are Abridged to Only Three Characters (Suffix I= In-Sample, O= Out-of-Sample). Column Names are the Ranks by the Criterion Named Along the Row.

algo	1	2	3	4	5	6	7	8	22	23	24	25	26	27	28	29
Shi	q	n	r	p	h	k	v	m	y	g	o	b	c	f	w	z
Sho	e	m	n	k	p	B	v	b	a	g	d	o	w	i	r	t
Omi	e	w	C	f	p	n	v	m	l	q	o	a	z	g	c	b
Omo	e	m	t	i	n	z	c	B	u	y	j	d	w	g	p	r

algo	1	2	3	4	5	6	7	8	22	23	24	25	26	27	28	29
Dci	q	m	B	a	r	b	z	g	i	o	c	p	d	w	f	A
Dco	e	j	a	q	c	i	n	B	u	d	w	r	t	g	m	o
Dsi	e	c	w	z	p	f	r	A	t	x	l	i	s	u	q	o
Dso	j	w	g	t	m	p	i	r	C	A	l	x	u	e	d	o
Moi	w	m	v	c	q	b	d	g	j	o	a	e	y	A	z	p
Moo	w	a	t	z	c	B	r	v	s	e	d	y	m	C	p	g
Exi	q	c	b	p	e	a	m	d	l	i	z	t	r	w	k	f
Exo	q	e	z	w	B	a	c	p	u	t	d	s	b	r	k	m
avg	e	c	z	b	t	j	y	a	u	o	q	p	d	g	m	r
avo	e	p	i	y	B	c	q	n	u	w	o	j	t	m	g	r

Final Remarks

We study the probability distribution of monthly stock returns *f*(*r*) and various stock-picking tools. We review Cheridito and Kromer's M, Q, S and D properties. We also introduce new weights for the Omega ratio to address the distortions in the gain-to-pain ratio faced by investors.

This paper focuses on six stock-picking algorithms for long-term investment in the Nifty29 stocks. Our omega (gain-to-pain ratio) and exact stochastic dominance implementations are somewhat novel. We use monthly return data for the recent 28+ years to find that each algorithm leads to a distinct ranking. We report the ranks by each criterion, implying that rank 1 is the top stock worthy of buying, and rank 29 is the bottom stock worthy of selling. As we change the time periods (e.g., quarters, months, weeks, hours, etc.) included in the selected Nifty29 datasets, the entire analysis will change and our data-driven buy-sell recommendations are also expected to change.

For our example of monthly returns, Table 12 lists the top *eight* onecharacter abbreviations of ticker symbols to buy or sell. Table 8 lists the top *two* ticker symbols for stocks to buy and sell.

Our research shows that the ultimate choice of stock tickers to buy or sell in suitable quantities within one's own budget is possible for anyone. Long-term investors need price data for long time intervals. It helps to compare many stock-picking algorithms along the lines shown here using a clear statement of the algorithms. The in-sample and unbiased out-of-sample ranks rarely coincide, even for the same algorithm. Averaging the ranks over six criteria using in-sample and an average of 50 randomised out-of-sample results suggests a choice of Bajaj Finance and Larsen and Turbo for possible buying. The least desirable average ranks indicate that long-term investors should consider selling shares in Britannia and Maruti Suzuki India.

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