Top-bottom investing skill and the fund alpha in Indian mutual fund industry: an empirical investigation

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Abstract

Purpose – Mutual funds are the second most preferred investment option in India and have garnered considerable research interest. The focus of Indian studies thus far has been restricted to the bottom-up approach of investing which rewards a fund manager for picking winner stocks and generates superior returns. While changing portfolio allocation as per varying macro-trends has been instrumental in generating superior returns, it has not been given the desired attention. This study addresses this important research gap.

Design/methodology/approach – The authors analyze the industry selection ability of the fund manager on a robust sample by decomposing alpha into alpha due to industry selection and alpha attributable to stock selection. Alpha estimates are computed on a robust sample of 34 open-ended Indian equity mutual funds for a 10-year duration 2011–2020 using three base models of asset pricing – single-factor, four-factor and five-factor alpha under panel data methodology.

Findings – The study leads us to four major findings. One, industry selection explains more than two-fifth of the alpha both in cross-section and time series of returns; two, industry selection exhibits persistence for more than four quarters across asset pricing model; third, younger funds have level playing when alpha from picking right industries is concerned; four, broad industry allocation continues to explain superior returns as sector allocation undergoes consolidation during ongoing COVID-19 pandemic and funds increase exposure to defensive stocks, consistent with folio allocations as per macroeconomic conditions.

Research limitations/implications – The authors find strong evidence of persistence in the case of alpha attributable to the industry selection component, and the findings are consistent with the persistence results reported in the empirical literature. While some funds excel in stock-picking skills and others excel in picking the right industries, both skills together make for winner funds that attract larger investor flows as investors chase superior performance. The authors also find no evidence of diseconomies of scale in the case of industry allocation alpha generated by the fund managers.

Practical implications – The results suggest a fresh approach for investors while making mutual fund investment decisions; the investors can achieve superior returns by assessing industry selection skills as it tends to provide a more holistic picture concerning a perennial question – why some funds outperform and continue to contribute to investor's wealth?

Social implications – Mutual funds have become a favored investment option for Indian investors more so as a disciplined investment option owing to dismal financial literacy rates. The study throws light on a relatively unaddressed dimension of choosing winner funds. The significance of right sector allocation assumed even more significance with the onset of the pandemic which lends further credence to the findings of the study.

JEL Classification — C23, G12, G23

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Originality/value – Research has been conducted on secondary data extracted from a well-cited database for Indian mutual funds. Empirical analysis and conclusion drawn are based on authentic statistical analysis and adds to the existing literature.

Keywords Industry selection, Alpha, Asset pricing, Persistence

Paper type Research paper

Top-bottom
investing skill
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alpha

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1. Introduction

Over the last decade, the mutual fund business in India has grown at a breakneck pace. Assets under management (AUM) in the industry surged by 41% year on year to Rs 31.4 trillion in F.Y. 2021. Over the last five years, the industry's AUM has expanded at a compound annual growth rate (CAGR) of 20.6 percent, while equity-oriented AUM has grown at a rate of 25%. Investors are increasingly recognizing the value of mutual funds in attaining both long- and short-term financial goals. This is reflected in the growth in the number of investor accounts from 4.03 crore in 2014 to 10.26 crore in June 2021, according to the Association of Mutual Funds in India's (AMFI) database.

The phenomenal growth of mutual funds is a result of investor awareness programs and the groundwork laid by distributors, investment advisors and mutual funds in educating and shepherding investors through their investing odyssey. Investor preference, assisted by the growing distribution network is shifting away from real estate and gold towards financial products, especially in the last year and a half. Despite its rapid growth, India's penetration rates are appallingly low when compared to other developed economies. A reference to two ratios: mutual fund assets under management AUM to GDP at 15%, compared to a global average of 75%, and equity asset to market capitalization ratio at 5%, compared to a global average of 30% shed light on the enormous potential that remains untapped. Similar trends are evident in the asset mix; the number of investor accounts held is skewed towards equity-oriented funds. While AUM in smart beta funds has surpassed \$1.2 trillion globally, according to the March 2021 ETFGI Smart Beta Industry Landscape report, the AUM in Indian index funds (umbrella category to which smart beta funds belong) accounts for the smallest share of investors' wallets at around 0.7%, ACE Mutual Fund database, month ending July 2021.

With the growing popularity of mutual funds as an investment vehicle, investors are perpetually on the lookout for funds that deliver outstanding performance. This has also attracted academia's and researchers' interest in examining the fund manager's ability. The range and depth of research devoted to assessing a fund manager's potential to generate higher returns are immense. The fund manager's performance has been reviewed at both the fund and security levels. At the fund level, performance has been compared to established benchmarks (Jensen, 1968; Carhart, 1997; Fama and French, 2013; Wermers, 2000), among others, while at the security level, excess returns have been compared to stock-specific benchmarks (Grinblatt and Titman, 1989; Daniel *et al.*, 1997; Wermers, 2000). Both techniques – fund level and security level – are contingent on the fund manager's ability to identify outperforming stocks.

The skill to generate superior returns can be traced back to factors way beyond picking the right stocks. A fund manager might generate superior returns based on his ability to study trends in the economy and shift portfolio towards industries expected to perform better in certain macroeconomic conditions. There are essentially two approaches to investing – bottom-up and top-bottom (EIC technique). The famed stock-picking ability relates to the former approach, while picking the right industries relates to the latter. The capital market's rally over the last year and a half has been fueled by momentum in specific sectors of the economy, highlighting the importance of the fund manager's sectoral allocation decision. The ability to choose-pick outperforming industries has not been given due attention in mutual

studies in the Indian context. Our study addresses this research gap by exploring manager's skills in conducting broader industry allocations. We utilize panel data analysis on a strongly balanced panel of 34 large-cap equity open-ended mutual funds with growth orientation and investigate the extent to which industry allocations drive superior performance compared to the decision on picking winner stocks within the broad sector allocations. We address three critical research questions:

- RQ1.* Contribution of industry allocation towards superior fund performance. To calculate alpha, we utilize three asset pricing models for alpha controlling for SMB, HML, WML, Industry MoM risk exposures – single-factor (CAPM), Carhart four-factor and five-factor model (with the addition of industry momentum).
- RQ2.* Whether alpha generated by industry allocation holds the test of persistence? To answer this, we test for persistence in returns up to eight quarters (2 years).
- RQ3.* Whether alpha attributable to broad industry allocation decision suffers from diseconomies of scale?

These questions have been well-researched and addressed in developed markets ([Jiang et al., 2007](#); [Kacperczyk et al., 2005](#); [Busse and Tong, 2012](#); [Tchamyou and Asongu, 2018](#)). However, the evidence is sparse in emerging markets like India. Mutual fund studies in India have largely focused on fund performance concerning stock selection and market timing skills ([Deb et al., 2007](#); [Dhar and Mandal, 2014](#); [Agarwal and Pradhan, 2018, 2019](#)). Our study, to the best of our information, is the first-ever study focused on assessing the industry selection decision of fund managers.

Our study covering more than a decade leads us to valuable inferences. First, we discover that industry selection makes a considerable contribution; at least one-fifth of the alpha generated by funds is attributable to broad sector allocation skill, which also demonstrates persistence, with the mean contribution remaining consistent over time. Second, when compared to industry allocation, fund style (stock selection as defined by SMB, HML and WML factors) explains only around a fifth to a half of the fund's superior performance. Third, younger funds compete on an equal footing when it comes to alpha generated by industry selection.

The remainder of the paper is structured as follows: [Section 2](#) summarizes the existing literature, [Section 3](#) discusses the dataset and methodology and [Section 4](#) presents the empirical findings. [Section 5](#) of the study concludes with a discussion on the future scope.

2. Review of the literature

The evaluation of a fund manager's performance has long been a focus of research in the mutual fund industry. There is a substantial body of the literature on the several variables addressed and the findings of investigations. These studies have also provided investors with a route to follow in their never-ending quest for the best funds. [Jensen \(1968\)](#) and [Fama \(1970\)](#), for example, focused their early research on estimating the value added in terms of extra returns generated by active fund management. The usefulness of active fund management has been questioned on several fronts, from excess returns to return persistence, and proof of outperformance has even been dropped in closing statements ([Malkeil, 1995](#)). Fund alpha generated by active fund management was determined to be the most significant indicator of managerial competence by [Sharpe-Lintner \(1964\)](#), [Carhart \(1997\)](#) and [Fama and French \(1999, 2013\)](#). The alpha measure was used by [Kosowski et al.](#) to explore and reach a conclusion on the presence of managerial talent, and how it varies across different types of funds. Active fund management's ability to maintain expertise or consistency in superior returns brought a new dimension to performance evaluation studies. Numerous

studies have established that performance is highly unpredictable (Elton *et al.*, 1996; Zheng, 1999; Bollen and Busse, 2001). The persistence of the overall fund management (stock selection and market timing) has then been studied at length by various researchers. Grinblatt and Titman (1993), Hendricks *et al.* (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Malkiel (1995) and Elton *et al.* (1996), among others, concluded that superior performance persists for a quarter or at maximum two; however, poor performance persists for a longer period. The persistence of poor performance has been highly attributed to expenses, age of the fund and diseconomies of scale. Cremers and Petajisto (2009) found that a fund's divergence from its benchmark is adequate proof of superior performance, while Cohen *et al.* (2010) and Jiang *et al.* (2007) ascribed superior performance to the portfolio's overweighted and underweighted stocks.

Market timing is the second most researched measure of skill in the fund management literature; Treynor and Mazuy (1966) and Henriksson and Merton (1981) measures have been cited well in all market timing literature. Market timing skill essentially relates to the ability to shift between stocks and idle reserves of cash in AUM. Diseconomies of scale, deterioration in excess returns with the increasing fund size have been common experiences of large funds. Berk and Green (2004) conducted a study with the initial hypothesis that large fund flows into outperforming funds ultimately leads to deterioration in alpha generated by the fund. The negative relation between fund performance and increasing fund size has been attributed to an increase in transaction costs and inclusion of overvalued stocks in the portfolio, consistent with findings of Chen *et al.* (2004). Contrary to these findings, a study conducted by Elton *et al.* (2012), analyzed fund performance at different-size breakpoints and found weak to no evidence of negative relation between outperformance and increasing fund size. Baker and Nofshinger (2010) looked at stock ability by constructing a trading skill measure based on the outperformance of stocks acquired and sold close to the earnings release. According to the findings, recent buys by funds outperform recent selling in the weeks leading up to results announcements. According to Kacperczyk *et al.* (2014), a fund manager's skill is based on his or her ability to time the market in difficult times and pick superior stocks in good times.

The potential of industry selection skill and its contribution to the overall alpha has been undervalued in research investigations. The majority of mutual fund research has examined the role of size, value and momentum aspects in performance indicators linked to empirical asset pricing studies (both at the company and industry level). Recent studies include those by Kacperczyk *et al.* (2005) and Avramov and Wermers (2006). Kacperczyk *et al.* (2005) investigate the role of broad portfolio allocations based on industry. As a result of these studies, a consensus emerged that funds focusing on a few outperforming industries generate greater returns than funds diversified across several industries. Avramov and Wermers (2006) discover that optimally chosen funds are capable of timing the market and rebalancing portfolio industries in response to economic cycle variation. These funds demonstrate consistency in shifting their portfolios away from cyclical to defensive stocks during economic downturns. Cremers and Petajisto (2009) demonstrate that fund manager skill reveals itself in portfolios that deviate significantly from passive index benchmarks, and that there is a significant positive correlation between these portfolio deviations and superior fund performance. Brinson *et al.* (1986) examined fund managers' allocation decisions across asset classes, namely cash, equities and debt, and concluded that allocation decisions between asset classes account for more than 90% of the variation in overall fund return. According to Amihud and Goyenko (2012), excessive or insufficient allocation to specific industries explains why a portfolio deviates from its benchmark or has a lower regression model *R*-Squared.

Busse and Tong (2012) examined the fund alpha attributable to industry allocations in portfolios and concluded that the extent to which a fund outperforms on a relative basis is significantly dependent not on the performance of passive indices but on the performance of the industries to which the portfolio's stocks belong.

3. Data and methodology

3.1 Data

We work on a database of 34 open-ended equity mutual fund schemes investing in large-cap securities and having growth orientation. The data are obtained on monthly frequency from the ACE MF database [1] of mutual fund holdings for a period of 10 years from (January 2011 to July 2020). Both existing, as well as schemes launched after January 2011 have been included in the dataset. Passively managed, sector mutual funds are excluded as the industry allocation decision is substantially constrained in passive funds. For cross-referencing, open-access databases such as value research and the AMFI website were used.

3.2 Methodology

We get sector-specific allocations for each scheme monthly from January 2011 to July 2020. The portfolio weights evolve during the month in the same way as they would in a buy-and-hold portfolio. These are used to compute industry allocation-driven returns, which are calculated by multiplying sector weights by the returns delivered by each industry during that month. The procedure for calculating industry allocation-led returns is similar to that employed by Wermers (2000) and Busse and Tong (2000, 2012). Given the variations in market structure, data availability and fund size, the measure of alpha decomposition has been modified to include a proxy for industry returns rather than the value weights generated by previous studies. The returns calculated using proxy indices are then multiplied by industry allocation weights calculated using portfolio data retrieved from the ACE Mutual Fund Database. The return series generated by this approach may differ from actual returns as they do not account for transaction fees, expenses and other intra-portfolio adjustments. We ensure that our sample includes at least 85–90% industry allocation representation for all periods observed. A ten-year time frame from January 2011 to July 2020 across all schemes in the study provides us with a robust database of over 114 monthly observations per variable for each scheme category. This results in a total observation set of more than a lakh observations (149,000 datasets approx.).

3.3 Research questions

3.3.1 What constitutes fund alpha or superior performance? As we proceed with the article, we evaluate monthly fund returns following Busse and Tong (2012), utilizing three well-known asset pricing models – single-factor model (also known as Capital Asset Pricing Model (CAPM)), which utilizes the excess of market returns factor; Carhart four-factor model, which incorporates size (small minus big), value (high minus low) and momentum (up minus down) factors in addition to the market factor (Carhart, 1997) and a five-factor model, which incorporates an additional factor of Industry Momentum (Moskowitz and Grinblatt, 1999).

$$r_{p,t} = \alpha_p + \sum_{k=1}^n \beta_{p,r_{j,t}} + \epsilon_{p,t} \quad (1)$$

where $r_{p,t}$ is the excess portfolio returns ($R_{p,t} - R_{f,t}$) at time t and $r_{j,t}$ is the return of factors $k = 1$ to n , where n is 5 dependant on the factor model utilized. We employ monthly survivorship bias free data derived from Fama French and momentum factors: data library for the Indian market, IIM Ahmedabad, to calculate market proxy, SMB, HML and WMD factors, and risk-free return (to calculate excess returns). The industry momentum component is calculated using the industry bins established during the computation of the sector-wise return; we use Moskowitz and Grinblatt's (1999) and Busse and Tong's (2012) methodologies. Industry momentum factors are derived by dividing the number of industries with a positive twelve-month performance by the number of industries with negative twelve-month performance. The median third quartile and median first quartile values are used to

define high and low industry returns, respectively. The intercept α_p is a standard measure of funds used in mutual fund studies to represent the fund manager's ability to generate superior risk-adjusted returns. Our method is comparable to that of [Ferson and Schadt \(1996\)](#), who employ monthly frequency data and longer estimation intervals.

Alpha, a typical measure of fund management skill is calculated as the sum of two distinct components: broader industry selection and stock-picking. The ability of a fund manager to achieve superior performance (excess returns) based on the understanding of economic trends and shifting portfolios towards industries projected to outperform in varying macro conditions is referred to as industry selection skill. While stock-picking skill refers to a fund manager's ability to pick stocks that are likely to outperform within the larger umbrella of sector allocations.

Industry returns $R_{pi,t}$ are computed for each scheme under the study corresponding to the time series of portfolio excess returns. The sector-wise allocation data retrieved from the ACE Mutual Fund database is used to calculate industry weights. The returns generated by a specific industry for a given period are then mapped to industry weights. We use monthly BSE industry indices returns as a proxy for returns given by specific industries. For example, S&P BSE Bankex returns were used as a proxy for banking sector returns. Each portfolio's industry return value is calculated by multiplying industry return with the portfolio's sector-wise allocation weight. This procedure yields a time series of returns that are attributable directly to the industry allocations decision.

Excess of portfolio returns attributable only to industry allocation is regressed against factors (market, SMB, HML, UMD, Ind Mom) dependant on the asset pricing model. The regression equation for the same is as stated below:

$$r_{pi,t} = \alpha_{pi} + \beta_{Mkt} \text{ExMkt}_t + \beta_{SMB} \text{SMB}_t + \beta_{HML} \text{HML}_t + \beta_{UMD} \text{UMD}_t + \epsilon_{p,t} \quad (2)$$

where $r_{pi,t}$ is the excess of portfolio industry returns over and above risk-free asset returns $r_{f,t}$ that is $r_{pi,t} = (R_{pi,t} - R_{f,t})$. α_{pi} is the intercept which measures portfolio alpha attributable only industry selection skill of fund managers. Changing industry allocation dependant on varying economic conditions in a way captures the essence of market timing. Standard market timing estimates Treynor and Mazuy model (1966). [Henriksson and Merton \(1981\)](#) measure market timing skill based on fund manager decision of shifting portfolio allocation between idle cash reserves to the equity asset class; industry selection skill focuses on fund movement across industries. We compute the market timer's alpha based on industry selection skills and the results are discussed in [Section 4](#).

Stock selection skill, measured by α_{ps} is defined in our study as the difference between total fund alpha α_p and the industry alpha α_{pi} , computed in [equation \(2\)](#). Stock selection skill is the ability of fund managers to pick outperforming stocks within the broader sector allocations.

Regression [equations \(1\) and \(2\)](#) are estimated for each year under the sample period. The overall and year wise estimates for α_p , α_{ps} and α_{pi} are shared in [Tables 4 and 5](#), respectively.

3.3.2 Does industry selection skill contribute to overall fund alpha? We begin to examine the relative contribution of industry selection skill to the overall alpha generated by the fund over the sample period. To do this, we compute the fraction of alpha attributable to the industry selection skill of the fund manager; the results are presented in panel I of [Table 5](#). For a comparative analysis, we also compute the fraction of alpha attributable only to the fund style selection. We extract data of benchmark performance in form of monthly returns generated by the respective benchmarks over the sample period. For example, monthly return from NIFTY 50 TRI is used as the benchmark for fund style. Decision on a characteristic benchmark to be used is taken based on the percentage match of the portfolio with the respective fund portfolio holdings. We ensure at least 85–90% match in the portfolio

(based on stock and sector-wise contribution) as the criteria for benchmark selection. This time series of style returns $r_{\text{benchmark},t}$ represents the returns generated and attributable to only fund style selection and removes the stock selection effect. Much similar to the regression equation (2), we use excess returns of fund style as the explained variable and run single-factor, four-factor and five-factor models to compute alpha attributable only to fund style selection. The next step is to compute the fraction of overall alpha contributed by style selection.

$$r_{\text{pstyle},t} = \alpha_p + \sum_{k=1}^n \beta_{\text{benchmark}_k} r_{k,t} + \epsilon_{p,t} \quad (3)$$

where $r_{\text{pstyle},t} = R_{\text{pbenchmark},t} - R_{f,t}$. The alpha attributable to fund style is computed as a fraction of the $\alpha_{\text{benchmark}}$ in Equation (3) to α_p , the overall fund alpha computed in Equation (1). The results are shown in panel II.

3.3.3 Industry selection and persistence. We analyze the persistence of fund alpha related to industry selection skills in this section. Numerous mutual fund studies have examined persistence in overall skill, concluding with strong evidence of persistence in superior performance over yearly intervals (Grinblatt and Titman, 1993; Hendricks *et al.*, 1993; Brown and Goetzmann, 1995; Malkiel, 1995; Elton *et al.*, 1996; Carhart, 1997) and Bollen and Busse (2001) and Busse and Tong (2012) in four-factor alpha over a shorter interval. Historically, mutual fund research has discovered greater persistence in underperformance than in outperformance. We investigate the persistence of alpha attributable to industry selection ability over an eight quarter or two-year timeframe post ranking. Each quarter alpha attributable to overall skill, industry skill and stock selection skill are regressed on its past performance. We utilize regression equations as stated under:

$$\alpha_{p,t} = a + \gamma \alpha_{p,t-1} + \epsilon_{p,t} \quad (4)$$

where $\alpha_{p,t}$ is the overall alpha of the fund from Equation (1) and l ranges from one to eight quarters.

$$\alpha_{pi,t} = \alpha_{pi} + \gamma \alpha_{pi,t-1} + \epsilon_{pi,t} \quad (5)$$

where $\alpha_{pi,t}$ is the overall alpha attributable to industry selection skill from Equation (1) and t ranges from one to eight quarters.

Stock selection skill, α_{ps} is the difference between Equation (1) and (2), the panel regression with past stock selection alpha as explanatory factor follows the model below:

$$\alpha_{ps,t} = \alpha_{ps} + \gamma \alpha_{ps,t-1} + \epsilon_{ps,t} \quad (6)$$

3.3.4 Does the age of the fund matter? To investigate the role played by fund age (a measure of existence and experience in the market), we sort the funds into deciles basis fund age values with deciles 2, 5 and 9 representing interim deciles funds sorted on fund age. Consistent with Chen *et al.* (2004) and Busse and Tong (2012), we investigate both decomposed components of alpha: industry selection skill and stock selection skill. The relationship between alpha and fund turnover is also examined with the Karl-Pearson correlation coefficient between the alpha values as per three base models and the turnover ratio.

4. Empirical findings

4.1 Our sample

The summary of the sample set used in the study is depicted in Figure 1. We disregard schemes in which no data for all variables is available for two consecutive years. The average number of stocks in each portfolio has remained close to the median of the entire sample over

Figure 1.
Summary statistics

Source(s): ACE MF database. Sector-wise holdings, median assets are in Rupee crores (CR.)

the years, while the median asset value has increased more than 1.5 times, commensurate with the growth in the mutual fund industry's AUM in the equity segment. In addition, we see that the number of industries per portfolio has stayed consistent with the sample's overall median value of 21 across years and schemes. Each fund in our sample invests in a median of at least 36 stocks across a minimum of 20 industries. Thus, on average, funds own approximately 1–1.5% of companies within the industries in which they invest, or 36/20 stocks per industry out of 236 stocks in the BSE. At any point in time, the schemes in the sample own at least 90% of the industries covered by the BSE Largecap index, the closest proxy for the sample in consideration (see Figure 1).

Table 1 presents the descriptive statistics of our sample over the 10-year duration (2011–2020). As is evident from the table, mean industry returns are very close to the mean portfolio returns of 0.5974. Industry returns are arrived at based on sector-wise portfolio weights mapped with returns offered by the respective industry. The mean fund age is 10 years approximately, consistent with the sample period of the study. When classified into cyclical and defensive stocks, broader industry allocations reflect the dominance of pro-cyclical stocks (maximum statistic of 94%), this is consistent with the underlying theme of equity funds

	N	Minimum	Maximum	Mean	Std. Deviation
Industry returns	3,390	−24.0000	19.0000	0.5448	4.4320
Fund returns	3,390	−27.0000	21.8310	0.5974	4.8365
Sharpe ratio	3,390	−8.0000	5.0000	0.0257	1.0439
Treynor ratio	3,390	−73.0000	39.0000	−0.4369	7.7183
Single-factor return (CAPM)	3,390	−22.9299	19.2576	1.0423	5.7259
Expense ratio	3,390	0.0000	3.0000	2.6773	0.7730
Turnover ratio	3,378	0.0000	550.9000	12.1057	39.3906
Fund age	3,390	−0.0278	26.8000	10.0128	6.5065
Monthly corpus	3,388	0.0000	25025.0000	2,426.5035	4,630.5497
Cash, equivalent	3,390	−164.0000	2,118.0000	87.3271	223.3224
Cyclical stock (%)	3,390	3.0000	94.0000	55.8442	16.0227
Defensive stock (%)	3,390	4.0000	74.0000	31.2032	13.1048

Table 1.
Descriptive statistics

aiming to offer superior returns based on fund managers' skill. The mean monthly corpus held under the portfolio is 2,426 crores, standard deviation, however, is very high, the statistic being 4,630 crores, and this also aligns with the highest median corpus value (646 crores) in Figure 1. We deliberate on the role played by fund size in empirical analysis Section 4.6.

In Table 2, we utilize a battery of tests to determine the stationarity of our sample's panel data. Given the fact that panel data contains time series and cross-sectional characteristics, tests for the presence of a unit root are undertaken in many dimensions. Under the cross-section independence framework, we generally utilize two types of tests: first, tests that verify for the presence of a unit root for each series in the panel [Im, Pesaran (IPS, 1997) and Shin W-Stat (2003), ADF Fisher(p) test, ADF Choi (2001)], PP-Fisher and PP Choi tests. The second type examines the panel for the presence of a common root by systematically testing the unit root on smaller fractions of the original data set (Levin *et al.*, 2002, Breitung and Das, 2005). These tests remove a significant disadvantage associated with less restrictive alternative hypotheses and discrimination between stationary and nonstationary series associated with homogenous unit root tests. We used both types of tests, including trend and constant; the results are reported in Table 2. All the tests utilized test the null hypothesis tests of nonstationary portfolio log returns. The p -values are significant at the 5% level, as denoted by ** hence, we fail to accept the null hypothesis of the presence of a unit root in panel data.

4.2 Do industry returns explain fund alpha?

Table 3 presents the results of panel regression analysis conducted on a strongly balanced panel of portfolio returns generated by respective schemes over the sample period. Returns attributable to industry (R_{pi}) allocation are taken as an explanatory variable, and portfolio returns (R_p) is explained variable for all schemes under the sample period. We utilize sector allocations as portfolio weights and returns delivered by the respective industry for a given period are mapped to portfolio weights. Across all the years under the sample period, the R -squared value is more than 60% (maximum statistic 96.43%), and the coefficient is significant at a 5% confidence level (p -value being zero). Hausman specification test (Hausman and Taylor, 1981) is conducted to arrive at the appropriate method for panel data analysis, and the results are shared in Table 3. The null of random effects is rejected as the

Cross-sectional independence		
Heterogenous unit root	Statistic	Prob
Im, Pesaran and Shin W -stat	-21.2501	1.64E-100
ADF-Fisher chi-square	445.1742	2.23E-89
ADF-choi Z -stat	-17.9729	1.59E-72
PP-Fisher chi-square	143.5676	7.82E-26
PP-choi Z -stat	-9.4263	2.12E-21
$H_0 = \text{Unit root (Individual unit root process)}$		
Homogenous unit root	Statistic	Prob
Levin, Lin and Chu t -stat	-32.8143	1.84E-236
Breitung t -stat	-4.8712	5.55E-07
$H_0 = \text{Unit root (Common unit root process)}$		
Cross-sectional dependence		
Cross section augmented IPS	-9.0754	0.0000
$H_0 = \text{Unit root}$		

Table 2.
Test of stationarity

Time Period	β_{pi}	$p > [Z]$	Std. Error	R^2	Wald – X^2	ρ
2019–20	1.0214	0	0.0087	0.9643	13712.58	0
2018	1.0492	0	0.0159	0.9238	4,342.88	0
2017	0.9837	0	0.0199	0.867	2,453.43	0.0628
2016	1.0209	0	0.0112	0.959	8,371.24	0
2015	1.1991	0	0.0316	0.8004	1,435.47	0
2014	0.8692	0	0.0199	0.8422	1916.99	0.00558
2013	1.0408	0	0.0187	0.8966	3,105.77	0
2012	0.9956	0	0.0209	0.8632	2,279.29	0.0094
2011	1.1194	0	0.0469	0.6136	568.55	0
			Chi-sq. Stat	Chi-sq. d.f	Prob	Result
Hausman specification test		79.94877837	1	3.84E–19	Reject H ₀	
Note(s): H ₀ : Period Random effects						
Source(s): The Author(s)						

Table 3.
Industry returns as
explanatory variable

p -value is significant at the 5% level. We, therefore, use a fixed-effects model, and the relevance of the model is reinstated with the rho statistic being close to 0 across all the years. This initial regression analysis builds confidence in our hypothesis of the broader allocation decision of fund managers being highly significant in generating superior returns.

4.3 Overall alpha, stock selection alpha and industry alpha

The results of the Hausman test specify random effects to be the appropriate method for estimating mean values of overall skill, industry selection and stock selection skill under three different models; the results are shared in Table 4. The p -value of more than 0.05 across all models fails to reject the null of non-systematic differences in the coefficients. It is noteworthy that mean estimates of industry allocation skills remain positive in the case of all three base models. Most of the overall skills at individual fund level estimates are not significantly different from zero as estimates have been calculated on basis of monthly time series of returns. Between funds, return estimates, however, are significantly different from zero. Our return values are gross of expenses, transaction costs. Given the short monthly time series of returns associated with estimation, returns are directionally consistent with estimates of Busse and Tong (2012). The expense ratio averages approximately 2.45% (higher than the average of 1.1% reported by Elton *et al.* (1996) and Wermers (2000) average of 0.75% per year in their mutual fund sample). Netting returns from expense and transaction costs estimates will lead to returns consistent with negative net returns reported in the earlier literature (Elton *et al.*, 1996). Though industry skill estimates are positive across all regression models, and stock selection skill estimates report some negative values, our main aim of the study is to examine the relative contribution of broader industry selection skills of fund managers in overall fund alpha. As is evident from the initial analysis, industry selection contributes at least 30% to the overall alpha generated by the fund across all models of estimation. We analyze the relative contribution of industry selection skill to the total alpha in greater detail in the next section on empirical analysis.

4.4 Does industry skill contribute to overall alpha?

Consistent with the findings of Chan *et al.* (2002) and Busse and Tong (2012), we find style selection to be a significant contributor to the overall alpha generated by the fund. The results are reported in panel II, Table 5; style selection drives on an average more than 50% of the

Table 4.
Factor model estimates
based on monthly
returns

Skill type	A	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β_{INDMoM}	R^2	ρ
<i>I. Capital asset pricing model</i>								
α_p	0.04541 (0.06)	0.89156					0.8149	0.0160
α_{pi}	0.01631 (−1.63)	0.81077					0.8239	0.0160
α_{ps}	0.02910							
<i>II. Four-factor model</i>								
α_p	−0.03615 (−1.08)	0.89050	0.09280	0.03873	0.01957		0.8226	0.0167
α_{pi}	0.05582 (1.95)	0.75334	0.05948	0.07663	−0.0334		0.8400	0.0175
α_{ps}	−0.09197							
<i>III. Five-factor model</i>								
α_p	−1.19544 (−12.8)	0.95339	0.11344	0.05976	0.02344	0.08062	0.8336	0.0175
	0.39981 (−2.3)	0.76535	0.06342	0.08065	−0.0327	0.01539	0.8427	0.0176
α_{ps}	−1.39625							
Source(s): The Author(s). <i>T</i> -Statistic for skill estimates (total alpha, industry skill alpha and stock selection alpha) is reported in parentheses								
Hausman specification test								
Test summary	Chi-sq. Statistic		Chi-sq. d.f		Prob		Result	
CAPM	0.000		2.000		1.000		Fail to reject H_0	
Four-factor model	0.000		4.000		1.000		Fail to reject H_0	
Five-factor model	0.270		5.000		1.000		Fail to reject H_0	
Note(s): H_0 : Difference in coefficients is non-systematic								
Source(s): The Author(s)								

Table 5.
Industry allocation:
relative contribution of
the skill

	2011	2012	2013	2014	2015	2016	2017	2018	2019–20
<i>I. Alpha contributed by industry allocation skill</i>									
CAPM	0.383	0.9	0.563	0.49	0.546	0.446	0.479	0.398	0.582
Four factor	0.881	0.627	0.649	0.846	0.913	0.611	0.844	0.345	0.457
Five factor	0.866	0.658	0.851	0.562	0.602	0.82	0.81	0.882	0.61
<i>II. Alpha contributed by style selection skill</i>									
CAPM	0.941	0.791	0.516	0.597	0.94	0.909	0.602	0.611	0.951
Four factor	0.571	0.597	0.71	0.64	0.498	0.491	0.778	0.458	0.328
Five factor	0.525	0.597	0.663	0.659	0.487	0.652	0.739	0.44	0.73
Source(s): The Author(s)									

overall alpha computed basis all the three asset pricing models. On a comparative scale, style contributes a much higher percentage of the overall alpha in the case of the single-factor model vis a vis model with more factors. Four-factor and five-factor models control for size, value and momentum, factors that define the style of a fund, hence in these models, style explains less of the remaining portion of superior performance in comparison to the industry.

We calculate the correlation between estimates of industry selection skill, measured by alpha and selected fund characteristics, namely, fund age, expense ratio, turnover ratio, *m*Monthly corpus and cash reserves maintained by the fund; the correlation is calculated on the overall values for the sample period. A very low degree of correlation exists between various selected fund characteristics and the industry selection estimate; the values have not

been reported in the table due to space constraints. A significantly low degree of correlation with expense ratio (0.049, at 1% level of significance), however, does indicate no extra cost being incurred by the fund for careful industry selection. Industry selection also does not have a bearing on the turnover or churning of the portfolio (−0.015 correlation) consistent with the hypothesis that broader industry allocation does not imply repeated rotation into new industries. A correlation as low as 0.018 with the log values of monthly corpus suggests that industry selection ability and superior performance generated attributable to that does not suffer from diseconomies of scale. Furthermore, industry selection alpha is also not dependant on the age of the fund; younger funds can capitalize on the expertise of fund managers in picking the right broader industries and generate superior performance. In our sample of funds, the overall correlation between five-factor industry skill estimates and stock selection skill estimates is a negative statistic with a value of −0.392 significant at a 1% level of significance. This further goes on to prove the point that two sets of skills drive the performance differently.

4.5 Does industry skill persist?

The γ coefficients tabulated above in panel I report overall alpha and results are significant at the 5% confidence level for a five-factor model up to four quarters and up to two quarters in case of single factor and four-factor models. The alpha is persistent even for shorter intervals of up to one and two quarters. Panel II reports industry selection skill alpha, the values are significant at 5% confidence level up to six quarters for five-factor and single-factor models, while results are significant at 5% level up to four quarters for the four-factor model. The alpha values attributable to industry selection skills are persistent for all quarters reported, consistent with findings of [Bollen and Busse \(2004\)](#) and [Busse and Tong \(2012\)](#). Persistence is observed even in the case of models controlling for the momentum factor, which signifies the role of fund manager in broader industry allocation and that the ability to pick outperforming industries and shifting portfolios in varied macroeconomic conditions continues even in the next several months.

Panel III results relate to the stock selection associated alpha. In contrast to values reported in panel I and panel II, results show weak to no evidence of significance at the 5% level. Few results, however, do sustain significance at a 10% level of confidence. The finding is consistent with the findings of [Busse and Tong \(2012\)](#) that evidence of persistence in relative performance emerges more from the industry selection ability of the fund manager than the skill of picking stocks that outperform. The bias in results that could have emerged from the utilization of gross returns instead of the net returns in the estimation process also gets eliminated owing to the poor correlation between five-factor estimates and several fund characteristics, reported in [Table 6](#). Hence, our conclusion of industry skill driving persistence holds good.

4.6 Does the age of the fund matter?

[Table 7](#) offers performance estimates for funds classified into deciles based on their portfolio age for the data period 2011–2020. Panel I contain estimates of the overall skill alpha for all funds. Consistent with [Elton et al. \(2012\)](#) and more in line with [Busse and Tong's \(2012\)](#) findings, we observe a very weak to nonexistent negative correlation between fund alpha attributable to industry selection and turnover estimates. We find no evidence of depletion in the performance estimates, or total alpha, across deciles sorted in order of fund age in panel I.

Panel II reports industry selection skills measured by the intercept α_{pi} in the regression model as per [Equation \(2\)](#). Stock selection skill, α_s is essentially the difference between overall skill and industry skill. Decile 1 represents the top decile based on fund age, while decile 10 refers to the bottom decile, the youngest funds in the category. The results report no evidence of deterioration in the case of industry selection skill as measured by alpha, α_{pi} . This is

Table 6.
Whether industry
selection skill exhibits
persistence

	Q1	Q2	Q3	Q4	Q6	Q8
<i>I. Overall alpha</i>						
CAPM	0.9841 (37.8)	0.9967 (24.4)	1.0742 (21.3)	1.0745 (18.5)	0.9229 (12.5)	0.9594 (11.9)
Four factor	0.9858 (37.5)	1.0127 (24.5)	1.0811 (21.4)	1.0989 (19.1)	0.9108 (12.4)	0.9546 (12)
Five factor	0.9848 (37.4)	1.0145 (24.5)	1.0852 (21.4)	1.0942 (18.8)	0.8996 (12.2)	0.9343 (11.6)
<i>II. Industry allocation</i>						
CAPM	0.4782 (18.4)	0.5224 (13.7)	0.5345 (11.5)	0.5487 (10.8)	0.3509 (6.1)	0.3811 (6.4)
Four factor	0.9836 (38.1)	0.9362 (21.3)	1.0996 (20.0)	1.1839 (18.9)	1.0288 (13.4)	1.1048 (13.6)
Five factor	0.9848 (37.3)	1.0145 (24.5)	1.0852 (21.4)	1.0942 (18.8)	0.8996 (12.2)	0.9343 (11.6)
<i>III. Stock selection</i>						
CAPM	0.9762 (38.6)	0.9164 (22.7)	1.0004 (20.1)	1.0923 (19.3)	1.0511 (15.9)	0.9681 (13.8)
Four factor	0.9673 (38.4)	0.9282 (23.8)	0.9929 (20.8)	1.0634 (19.7)	1.0095 (16.1)	0.9482 (14.1)
Five factor	0.9669 (37.5)	0.9326 (23.1)	1.0352 (21.2)	1.1057 (20.3)	1.0389 (16.6)	0.9476 (14.2)

Source(s): The Author(s). *t*-statistic are reported in parentheses

Table 7.
Decile-wise Analysis:
Industry allocation,
fund age and turnover

	Bottom	9	5	2	Top	Correlation with turnover
<i>I. Composite alpha</i>						
CAPM	0.56561*	1.03545*	1.62483*	0.7483	1.38591*	-0.0002
Carhart four factor	0.30758*	0.3286	0.61938*	0.1822	1.29103*	0.0125
Five factor	0.1107	-0.1166	0.0583	-0.3681	0.6447	0.0067
<i>II. Industry allocation</i>						
CAPM	0.60512*	0.97014*	1.17916*	0.91028	1.43868*	-0.0222
Carhart four factor	0.14965*	0.05572**	0.34824*	0.27661	1.32971*	-0.0128
Five factor	0.069215	-0.02586	-0.10572	-0.29414	0.62929	-0.0141
<i>III. Stock selection</i>						
CAPM	-0.03951	0.06536	-0.44568	-0.16197	-0.05276	0.0236
Carhart four factor	0.15792	0.27288	0.27114	-0.09441	-0.03868	0.0272
Five factor	0.041506	-0.09072	0.16405	-0.07393	0.01543	0.0216

Source(s): The Author(s). **, * indicates 10 and 5% significance level respectively

strongly evident in single-factor and four-factor alpha estimates, while five-factor estimates do exhibit some but very weak evidence of low negative correlation. Industry selection skill also exhibits weak negative to no correlation with turnover ratio, which strengthens the argument that alpha attributable to industry selection is not an outcome of frequent churning of the portfolio. These results highlight a very important characteristic of fund management that fund managers continue to find industries that outperform or perhaps maintain the performance level even as the fund continues to grow in volume.

The stock selection alpha estimate reported in panel III exhibits weak but statistically insignificant evidence of the negative correlation with fund age. Our results differ from the findings of Busse and Tong (2012) of statistically significant evidence of diseconomies of scale in case of stock selection. Our findings indicate that while there exists a weak negative correlation between stock selection and the fund age, industry selection persists and younger funds find equal opportunities to offer superior returns with statistically significant alpha estimates across all the models. While funds manage to pick stocks that outperform even as the funds' age, they excel at picking the right industries in varying macroeconomic market conditions, and industry selection, unlike stock selection, does not require regular portfolio churning, signifying lower transaction costs.

5. Conclusion

The outperformance of mutual funds has long been attributed to the fund manager's stock selection and market timing skills. Our study conducted on a robust sample of 34 Indian equity mutual funds, over a 10-year horizon, clarifies the role of conventional measures cited in the extant literature with the reiteration that both stock selection and industry allocation contribute to superior performance.

Our results provide significant evidence of persistence in industry selection alpha, which is consistent with the empirical literature. While some funds excel at identifying the companies with high profitability and scalability, and others focus on analyzing macroeconomic factors, key policy changes and trends in their quest of finding the right industries, both skills work together to create winning funds. Winner funds also attract bigger flows as investors chase outperformance. The impact of increasing fund AUM on risk-adjusted returns must next be investigated. We demonstrate that increasing fund flows do not affect the superior performance attributable to industry allocation. One reason for no evidence of diseconomies of scale could be enough room available to shift the portfolio to more attractive industries in a top-bottom approach. In contrast to previous findings, we discover a weak negative correlation between rising fund corpus and stock selection ability. Comparatively, increasing fund AUM does not influence industry selection skill.

The conclusions of our study can benefit a wide spectrum of stakeholders. Policymakers gain crucial insight into the economic ramifications of key policy changes affecting specific industries, while investment advisors gain a new perspective on judging fund manager performance. Mutual funds have emerged as the most important source of funding and support for the government securities market. Our findings may also shed light on how a fund manager's industry selection impacts the amount of investable surplus available. Investors are perpetually perplexed as to why certain funds outperform and continue to add to investors' wealth. Our study attempts to decode the superior returns and also provide educational value to investors.

Note

1. ACE Mutual Fund is a dedicated database for mutual fund research, encompassing all existing participants and over 16,000 mutual fund schemes across all asset classes. As a result, the data given is free of survivorship bias and has been referred to the research.

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