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Investment style consistency and performance of Indian fixed income mutual funds

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Abstract In this study, we examine investment style, and style consistency and its relationship with risk-adjusted performance of the Indian fixed income mutual funds (MFs) using a sample of 242 funds across 16 categories over a period from April 2015 to March 2020. Our findings indicate that (a) fund managers practice securities selection, but their securities selection ability fails to improve risk-adjusted returns; (b) higher style consistency leads to better risk-adjusted performance; and (c) investment style and style consistency have considerable impact on fund performance. This is possibly the first comprehensive study that analyses investment style and its relationship with the performance of Indian fixed income MFs and contributes to the growing body of research on performance evaluation of fixed income funds.
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Introduction

Connecting fund surplus investors with fund deficit businesses is one of the most significant functions of the financial markets. Investors and businesses approach markets to move funds across time and geography and trade various investment products to negotiate future cash flows and manage risk. Common stock and fixed income securities are the primary instruments of investment to achieve these objectives. As the complexity of investment management processes and investment instruments has increased, the task of achieving these objectives is being outsourced to professional investment managers. This has resulted in the emergence of a number of investment products such as mutual funds (MFs), pension funds, endowments, portfolio management services and hedge funds. As MFs offer a number of advantages such as liquidity, diversification, ease of access, professional management and, at times, tax benefits, they are generally the most popular investment avenue with the largest amount of assets under management (AUM) in an economy.

MFs were introduced in India with the enactment of the Unit Trust of India Act of 1963 (AMFI, 2021a). However, a significant growth in MF AUM has been recorded only in the last 2 decades owing to market-oriented calibration of the economy, introduction of electronic exchanges, increase in per capita income and financialisation of savings (Chakrabarti, 2010; Shah, Kumar, Garg & Mehta, 2019). As of December 2020, more than 40 asset management companies (AMCs) in India offer over 1200 fund alternatives and in-turn manage more than USD 360 billion in assets (AMFI, 2021b). Having said so, the ratio of MF AUM to GDP for India is less than 11%

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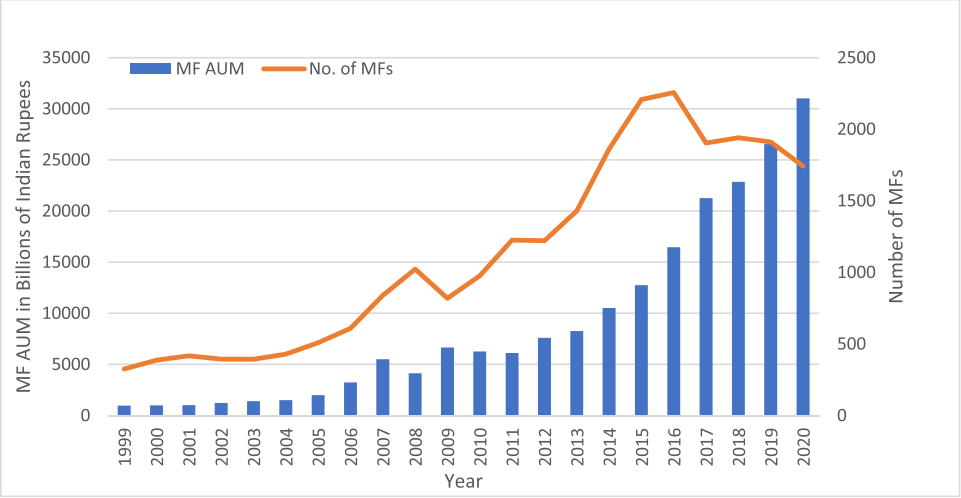


Fig. 1 Growth of the Indian MF industry. *Source*: Association of Mutual Funds of India (AMFI).

as compared to 103% for the United States and the world average of 55% (Investment Company Institute, 2020). This indicates not only the diversity of MF in India but also the immense potential for growth of the Indian MF industry (Fig. 1).

According to Investment Company Institute (2020), nearly 45% of the worldwide assets of open-ended MFs are managed by equity MFs and only 34% of assets are managed by fixed income MFs. However, when it comes to India, equity and fixed income MFs manage 27% and 53% of total Indian assets, respectively (SEBI, 2020). Thus, all over the world, open-ended MF AUM is skewed towards equities, but the same in India is skewed towards fixed income. India is an emerging capital market with very low equity penetration and a substantial proportion of savings in the form of non-financial investments. For instance, there are only 89.7 million demat accounts in a population of more than 1300 million (Sethuraman, 2022). A possible rationale for MF AUM being skewed towards fixed-income funds is that there is a gradual shift in investors' preferences from bank deposits to fixed-income funds in India because of (1) favourable tax treatment of income from fixed-income MFs vis-à-vis income from bank deposits; (2) better liquidity offered by fixed-income funds as compared to bank deposits; and (3) a multitude of investment avenues based on maturity and risk that are available with fixed-income funds. To be specific, long-term capital gain from fixed-income funds is taxed at a rate of 10% with indexation, and 20% without indexation, while the income from bank deposit is taxed at the rate applicable according to the tax payer's income tax slab. This differential taxation makes fixed-income funds more attractive as compared to bank deposit for large investors.

MF AUM proportions, as seen in Fig. 2, pinpoint the significance of fixed income MFs for Indian investors. Considering the large amount of assets managed by MFs and the economically significant role played by MFs for investors and financial markets, performance evaluation of MFs is all the more important for investors, AMCs and market regulators. However, prior scholarly studies on performance evaluations have focused more on equity MFs and that too in the context of developed economies. Blake, Elton and Gruber (1993) and Clare, O'Sullivan, Sherman, and Zhu (2019) have pointed out

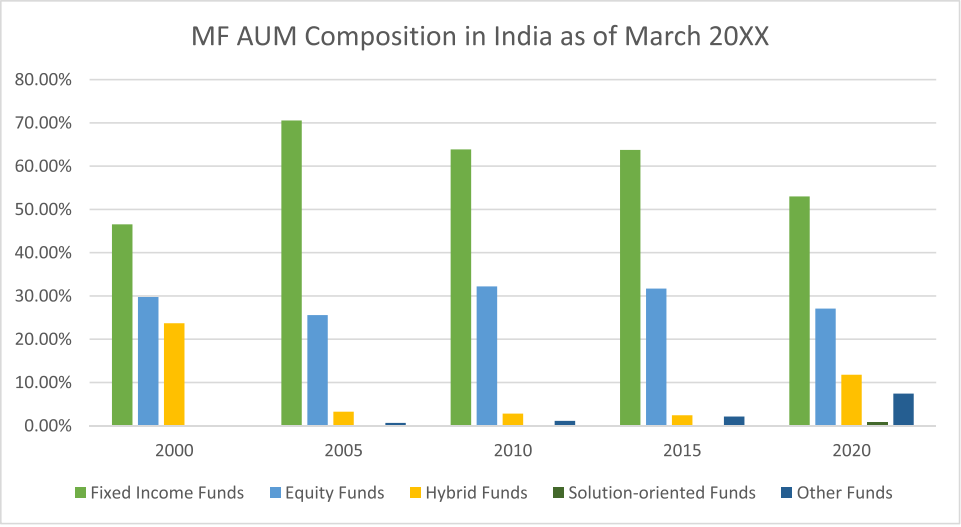


Fig. 2 MF industry asset class composition. *Source*: Securities and Exchange Board of India (SEBI).

the scarcity of scholarly literature on performance evaluation of fixed income MFs. Performance evaluation of emerging market fixed income MFs is even scarcer. This study aims to fill the gap in the literature on performance evaluation of fixed income MFs from a large developing country such as India.

Scholarly research on performance evaluation of MFs has examined the selection ability using Jensen's alpha. Further, literature offers ample evidence of the role of fund's investment style when it comes to fund performance. This study examines the relatively unexplored relationship between the investment style, style consistency and the risk-adjusted performance of Indian fixed income MFs and in turn augments the literature on performance evaluation of fixed income MFs. The study stands apart from a broad body of work in this area, as it shows that selection ability is not rewarded, and that consistent behaviour style generates better risk-adjusted returns. The study's takeaways are two-fold in nature. First, Indian fixed income MFs exhibit large-scale non-adherence to the stated investment style. Second, fund's adherence to investment style is positively associated with better risk-adjusted performance. Towards the end of this exercise, the authors offer a rationale for underperformance of Indian fixed income MFs, and in doing so, discuss the study's implications for the asset management industry and regulators.

The rest of the paper is organised as follows. The second section discusses the relevant literature for investment style analysis, while the third and fourth sections explain the methodology, and sample and data, respectively. The results and attendant inferences are made available in the fifth section, followed by the sixth section that provides the conclusion.

Literature review

Active investment management methods involve a diverse range of disciplines. To categorise and explain this diversity, regulators, investment analysts and research scholars refer to the concept of investment styles. Investment style is defined as a natural assemblage of investment disciplines that has some predictive power in explaining the future variability in returns across portfolios (Maginn, Tuttle, Pinto & McLeavey, 2007). It also comprises the analysis of the returns (Return-based style analysis, RBSA) and the holdings (Holding-based style analysis, HBSA) of a fund with an objective to draw inferences about the types of biases and quality of views of the fund managers (Maginn et al., 2007). HBSA and RBSA are the two widely used methods for style analysis of MFs. Sharpe (1988 and 1992) and Daniel, Grinblatt, Titman and Wermers (1997) were the pioneers who undertook original studies on RBSA and HBSA of MFs, respectively. We have employed RBSA in this study, as it offers a more aggregated view of a fund's style in terms of the actual benefit (return) an investor receives. Also, unlike fund holdings data, fund returns are reported more frequently and without substantial time lags and this offers greater avenues in discerning investment styles.

While expounding the procedure for performing RBSA, Sharpe (1992) indicated that investment style accounts for a large part of the dispersion in portfolio returns. RBSA attempts to explain the systematic exposures that a fund has, as compared to a series of benchmark portfolios designed to capture the essence of a particular investment characteristic. This process involves using the past returns to a fund and a set of indices representing different investment styles to determine the relationship between the two. Generally, higher the correlation of a fund's returns with a given style index, greater the weight of that style index. Sharpe (1992) also showed that the coefficient of determination (R-Square) of the model can be used as a measure of style consistency. Brown, Harlow and Zhang (2009) applied both HBSA and RBSA to a large sample of US equity funds to examine (a) style consistency; (b) correlation of style consistency with risk-adjusted returns; and (c) the impact of style consistency on performance persistence. The authors show a negative relationship between investment style consistency and portfolio turnover; a positive relationship between a fund's style consistency and its risk-adjusted return and a positive relationship between investment style consistency and performance persistence. In a related study, Brown, Harlow and Zhang (2015) found style volatility to have a distinct impact on future fund performance as compared to fund expenses or past risk-adjusted returns. They also showed that funds with less style volatility significantly outperformed those with more style volatility on a risk-adjusted basis. Cao, Iliev and Velthuis (2017) showed that while funds drifting from their investment style do not offer higher abnormal return or performance persistence, they do outperform their peers. Chua and Tam (2020) demonstrated that style drift leads to an increase in a fund's subsequent net inflows and this in turn enhances AUM-linked compensation of the manager. As a result, larger funds have a greater incentive to drift. Further, their findings indicate that style drift interferes with securities selection, and it harms investors' interests and undermines market integrity.

Analysing investment style of bond funds, Blake et al. (1993) proved that the quadratic programming technique used in RBSA yielded weights on the passive indices that closely matched the actual investment style of the fund. This study provided confidence in quadratic programming as a procedure, and its application as a method to determine investment style based on historic returns of MFs. Subsequently, Kahn and Rudd (1995) employed Sharpe's style analysis to decompose fund total returns into style and selection components. In doing so, they found that investors select a benchmark for investment and then choose fund mangers to outperform that benchmark. Trzcinka (1995) and Gallo and Lockwood (1997) have demonstrated that RBSA is useful in classifying MFs due to its model simplicity, cost-effectiveness and reduced incentive for the management to manipulate ex-post ranking.

Bogle (1998), using RBSA, showed that actively managed funds are unable to outperform passively managed investment indices. The author explained that performance evaluation of US MFs has changed from using a simple market model to peer-style comparison as MFs' investment styles evolved from being relatively homogenous during 1970s to being heterogeneous in 1990s. Maag and Zimmermann (2000) applied style analysis to examine performance of German deuschemark bond funds. While their overall findings were consistent with prior notable works (Blake et al., 1993; Elton, Gruber & Blake, 1995; Kahn & Rudd, 1995), they found that the out-of-sample results of a dynamic style

analysis were similar to that of the most simple single-index in-sample models. They also highlighted significant difference between index models and style analysis. Unlike index models, style analysis incorporates the investment restrictions such as no short-sale and restrictions on borrowing that are faced by MFs when it comes to implementing their strategies.

Brown and Marshall (2001) showed how three sets of regressions using historical returns can be utilised to estimate the extent to which a fund manager systematically over-weights or under-weights sectors keeping in view, interest rate trajectory, volatility plays and sectoral performance over a particular time period. They suggested that the investment style of an active fixed-income manager is not appropriately explained by the relationship between fund returns and factor realisations such as interest rate changes and sector spread changes. To outperform a benchmark, an active manager takes position on the portfolio duration based on his/her view on the likely interest rate changes. Such a manager would have interest rate exposure each period, but it is likely that his/her interest rate exposure would be very little on average. In such circumstances, a time series regression of portfolio excess returns on interest rate changes would disclose no systematic relationship, notwithstanding the interest rate exposure of the manager. Style analysis, according to Brown and Marshall (2001), provides better insights into such relationships.

Scher and Muller (2005) examined equity style and performance persistence of South African MFs. They found small cap and value funds to exhibit negative performance persistence and fund management cost being the prime differentiator amongst the different equity styles. Comer and Rodriguez (2006, 2013) analysed the investment style, performance and cash flows of investment grade corporate and government bond funds. Their style analysis focused on understanding the conceptual differences across the groups. Using style analysis and two index models based on sector and duration allocation, they discovered distinct style differences across asset categories and in turn examined the risk-adjusted performance of the funds across categories. Domian and Reichenstein (2008, 2009) applied RBSA for high-yield and convertible bond funds. They suggested that RBSA should improve investors' understanding of their true asset allocations and help them to manage their portfolios better. They showed that high-yield bonds are hybrid assets that replicate returns of a portfolio holding stocks, high-grade bonds and cash. They also showed that differences in style weights across funds were consistent with differences in the fund holdings and investment styles.

Deb, Banerjee and Chakrabarti (2007) and Mohanti and Priyan (2018) are the two notable prior studies on investment styles of Indian equity MFs. Both the studies employ RBSA over monthly returns over a period of three to four years for a sample of equity funds in India. While Deb et al. (2007) show that Indian equity funds are unable to outperform their style benchmarks on average, Mohanti and Priyan (2018) provide evidence of active management and good selection ability.

Previous scholarly literature demonstrates superiority of applying style analysis when it comes to classifying MFs and unearthing factors affecting its performance. The literature also demonstrates replicability of the performance of actively managed MFs as a portfolio of passive investment indices. Some scholarly literature has also thrown light on the relationship of investment style and risk-adjusted performance, and investment style and performance persistence. We contribute towards this strand of literature by undertaking an in-depth examination of the relationship between investment style consistency and risk-adjusted performance of Indian fixed income MFs.

Conceptual framework

The objectives of this study are to analyse investment styles of Indian fixed income MFs and examine style consistency and relationship of style consistency with risk-adjusted fund performance. To be specific, Sharpe's (1992) RBSA framework is employed to measure style consistency. Further, Clare et al.'s (2019) single and multifactor models were employed to estimate risk-adjusted returns for all the funds. Lastly, in line with precedence in the literature, the Pearson correlation coefficient is estimated to examine the relationship between investment style consistency and risk-adjusted returns of funds (Brown et al., 2009).

Sharpe's RBSA framework estimates the following asset class factor model:

$$R_{i,t} = \sum_{i=1}^{p} b_{ip} R_{p,t} + e_{i,t} \quad (1)$$

where $R_{i,t}$ represents the total return of the fund i at time t, b_{ip} represents exposure of fund i to asset class p, $R_{p,t}$ represents the total return of asset class p, and $e_{i,t}$ represents the unexplained component of fund return.

For any fund, the average exposure to each index, b_{ip}, during a given observation period can be estimated by minimising the variance of the error term ($e_{i,t}$) by imposing the following constraints:

$$\sum_{p=1}^{r} b_{ip} = 1 \quad (2)$$

and

$$0 \leq b_{ip} \leq 1 \ \ \forall \ \ i \quad (3)$$

Sharpe (1992) terms analysis as per Eq. (1) as 'Unconstrained Regression'. Imposition of a constraint, as shown in Eq. (2), yields estimations that are termed as 'Constrained Regression'. Imposition of two constraints, as shown in Eqs. (2) and (3), yield outcomes that are referred to as 'Quadratic Programming'. The objectives of the analysis are (a) to estimate a set of coefficients that minimises the variance of $e_{i,t}$, subject to the stated constraints and (b) to maximise the associated value of R-square, subject to the stated constraints. The imposition of the constraints brings the analysis closer to the realities of the funds' investment style and paves way for meaningful insights. The constraints are a reflection of investment realities of MFs such as investment of the entire corpus, no short selling and restriction on borrowing. Eqs. (2) and (3) mimic the following two investment constraints faced by MF managers: (1) the funds cannot borrow and invest and (2) the funds cannot deal in short sales. These constraints impact the parameter estimations, whereby the sum of all the estimated parameters would be

100% and none of the parameters can assume a negative value.

The investment style, thus estimated using this methodology, is an average of potentially changing style over the time of analysis (Sharpe, 1992). Resulting R-square from the analysis denotes the percentage of variance of the fund return ($R_{i,t}$) that is explained by the style-based passive portfolio. R-square is also the percentage of a fund's return attributed to its investment style, while (1-R-square) denotes the return attributed to selection ability of the fund manager. Atkinson and Choi (2001), Brown et al. (2009) and Sharpe (1992) consider R-square as the measure of a fund's style consistency and [1-R-square] as the measure of a fund's style inconsistency. Kahn and Rudd (1995), Brown et al. (2009) and Domian and Reichestein (2008, 2009) have also termed [1-R-square] as securities selection ability of a fund manager.

For this study, we have divided our sample of 242 Indian fixed income MFs in-to four distinct clusters. Quadratic programming was employed for each MF by considering pertinent passive portfolios, so as to estimate its investment style coefficients and R-square. Since our clusters are based on risk attributes such as Liquidty, Duration, Credit Risk and Risk-free (gilt), the pertinent passive portfolios are different for different clusters and the benchmark index varies across fund categories.

Further, we employed Clare et al. (2019) single-factor and multi-factor models to estimate risk-adjusted returns (Jensen's alpha or abnormal return) for all the funds. The models estimate risk-adjusted returns as follows:

$$R_{pt} - R_{ft} = \alpha_{1p} + \beta_{1p} \times ERM_t + \varepsilon_{pt} \quad (4)$$

where R_{pt} is the monthly return at time t for MF p and R_{ft} is the monthly risk-free return, ERM_t is the excess return (over R_{ft}) in month t for CRISIL Composite Bond Fund Index, α_{1p} is the Jensen's alpha for MF p, β_{1p} is the sensitivity to excess market return for excess returns of a fund p and ε_{pt} is a white noise error term.

$$R_{pt} - R_{ft} = \alpha_{1p} + \beta_{1p} \times (R_{bt} - R_{ft}) + \beta_{2p} \times ERM_t + \beta_{3p} \times TS_t + \beta_{4p} \times CS_t + \varepsilon_{pt} \quad (5)$$

where R_{bt} is the monthly return on the benchmark index of fund p at time t, TS_t and CS_t are the term spread and credit spread respectively, at time t. TS indicates the steepness of term structure of interest rates, and CS captures the credit risk. TS is calculated as the monthly returns of CRISIL 10-year Gilt Index minus monthly returns of CRISIL 1-month T-Bill Index; and CS as the monthly return of CRISIL A Medium to Long Term Index minus monthly return of CRISIL AAA Medium Term Index. β_{1p}, β_{2p}, β_{3p} and β_{4p} indicate the sensitivity of excess return of a fund p to excess benchmark return, excess market return, term spread and credit spread, respectively.

In order to examine the relationship between investment style consistency and risk-adjusted performance of MFs, the variables of interest are R-squares estimated using Sharpe's quadratic programming and α_{1p} estimated using Clare et al. (2019) single-factor and multi-factor models. Pearson correlation coefficients between R-squares and α_{1p} are calculated for all the funds and averages of correlation coefficients are calculated for all the fund categories.

Sample and data

Securities and Exchange Board of India (SEBI), the MF regulator, has notified 16 mutually exclusive and collectively exhaustive categories of open-ended fixed income MFs. The SEBI notification defines categories based on average Macaulay's duration and the type of fixed income securities that are available for investment (SEBI, 2017). The fund managers are required to adhere to the notification and classify their fund in any and only one of the sixteen categories. Consequently, distinct investment styles that match SEBI definition of the fund category enables us to select one passive portfolio as a benchmark index when it comes to performance evaluation of funds pertaining to a category. SEBI's prescriptions at such a disaggregated level do not allow much scope for fund managers to deviate from the stated investment objective or definition of fund category.

As of March 2020, there are a total number of 329 open-ended fixed income Indian MFs, out of which 242 funds are included in our sample. Table 1 offers a snapshot of the fixed income fund categories, benchmark index for each category, number of funds in each category as of March 2020 and the number of funds considered for our study. There is a tradeoff between the number of funds that form part of the study and the time period of the study. Put differently, as the timeline of the study increases, the number of funds in the sample declines. We have selected the period 2015–2020 so as to include the maximum number of funds for the study. In the process, we ended up with a sample size of 242 funds for the study with nearly 73% of AUM of all the 329 funds put together. If the sample period is increased to 10 years, the number of funds that form part of the sample will be 190 and they would constitute less than 40% of the AUM of all Indian fixed income MFs put together as of March 2020.

Additionally, we have created four clusters based on 16 fund categories with an objective to identify and quantify funds' investment style that is deviating into a nearby fund category. We have named these clusters as (1) liquidity, (2) duration, (3) credit risk and (4) gilt clusters. The liquidity cluster comprises of overnight funds, liquid funds, ultra-short duration funds, low duration funds and money market funds. The duration cluster comprises of short duration funds, medium duration funds, medium to long duration funds, long duration funds and dynamic duration funds. Corporate bond funds, credit risk funds and banking and PSU debt funds constitute the credit risk cluster. The gilt cluster includes gilt funds, gilt 10-year duration funds and floater funds. As stated earlier, we use Sharpe's quadratic programming with six passive portfolios (style indices), to estimate investment style coefficients and R-square. Five different passive portfolios (style indices) are considered for each of the clusters, and the CRISIL Composite Bond Fund Index is taken as a proxy for market return because it provides a comprehensive snapshot of the Indian bond market. It is a total return index that tracks performance of a debt portfolio that includes government securities and AAA/AA+/AA rated corporate bonds for short-term, medium-term and long-term maturities. It is composed of seven debt indices: (1)

Table 1 Fixed income fund categories, benchmarks, number of funds as on March 2020 and no. of funds selected in the sample.

Sr. No.	Open-ended fixed income fund category	Benchmark	Number of funds as on March 2020	Number of funds in the sample
1	Overnight Funds (OF)	CRISIL Overnight Index	30	4
2	Liquid Funds (LF)	CRISIL Liquid Fund Index	39	34
3	Ultra-Short Duration Funds (USDF)	CRISIL Ultra Short-Term Debt Index	29	18
4	Low Duration Funds (LDF)	CRISIL Low Duration Debt Index	26	22
5	Money Market Funds (MMF)	CRISIL Money Market Index	20	15
6	Short Duration Funds (SDF)	CRISIL Short Term Bond Index	28	25
7	Medium Duration Funds (MDF)	CRISIL Medium Term Debt Index	18	15
8	Medium to Long Term Funds (MTLDF)	CRISIL Medium to Long Term Debt Index	14	13
9	Long Term Funds (LTF)	CRISIL Long Term Debt Index	2	1
10	Dynamic Duration Funds (DDF)	CRISIL Dynamic Debt Index	29	24
11	Corporate Bond Funds (CBF)	CRISIL Corporate Bond Composite Index	20	13
12	Credit Risk Funds (CRF)	CRISIL Composite Credit Risk Index	23	14
13	Banking & PSU* Funds (BPSUF)	CRISIL Banking and PSU Debt Index	19	16
14	Gilt Funds (GF)	CRISIL Dynamic Gilt Index	21	20
15	Gilt 10-year Funds (G10YF)	CRISIL 10-year Gilt Index	4	4
16	Floater Funds (FF)	CRISIL Equal Weighted Index	7	4
		Total	**329**	**242**

Note:
*PSU = Public Sector Undertaking.

CRISIL Composite Gilt Index with 45% weight, (2) CRISIL AAA Long Term Bond Index with 17% weight, (3) CRISIL AAA Medium Term Bond Index with 11% weight, (4) CRISIL AAA Short Term Bond Index with 20% weight, (5) CRISIL AA and AA+ Long Term Bond Index with 2% weight, (6) CRISIL AA and AA+ Medium Term Bond Index with 2% weight and (7) CRISIL AA and AA+ Short Term Bond Index with 3% weight. The index is one of the most widely followed bond indices in India with more than 20 years of history. The index portfolio is marked-to-market on a daily basis with CRISIL gilt and bond valuation (CRISIL, 2022).

RBSA is performed on monthly return over the period starting from April 2015 to March 2020 for this sample of funds. Data of monthly returns of funds has been obtained from ACE MF database. CRISIL, an S & P Company, provides the data for all the fixed income category indices. We have used monthly return data for 16 benchmark indices and 5 widely followed style indices. These style indices are (1) CRISIL Composite Bond Fund Index as proxy for market return, (2) CRISIL Short Term Credit Risk Index, (3) CRISIL Composite Gilt Index, (4) CRISIL Medium Term Gilt Index and (5) CRISIL Long Term Gilt Index. Table 2 provides details about the four clusters and passive portfolios selected for style analysis. Using these indices, we performed RBSA using quadratic programming technique for 60 months of holding period returns (from April 2015 to March 2020) for all the funds. Additionally, monthly return data for the same period of CRISIL 10-year Gilt Index, CRISIL 1-month T-Bill Index, CRISIL A Medium to Long Term Index and CRISIL AAA Medium Term Index are used to compute term spread and credit spread for they form part of Clare et al. (2019) single-factor and multi-factor models. Further, CRISIL 1-Year T-Bill Index is the source of monthly risk-free returns in estimating single-factor and multi-factor models.

Results and analysis

As stated earlier, the Sharpe (1992) asset class model measures investment style as parameter estimates, style consistency as R-square of the model and securities selection ability as [1-R-square]. Jensen's alphas from the single-factor and multi-factor models are the risk-adjusted returns for the funds. Table 3 presents style consistency (R-Square), size (AUM) and risk-adjusted performance (Jensen's alpha) for all the categories. In the interest of brevity, test outcomes of style analysis of the four clusters are made available in supplementary tables.

In a way, results shown in Table 3 and supplementary tables quantifies Indian fixed income MF managers' adherence to or deviation from stated investment objectives. The coefficient for a passive portfolio indicates the weight assigned to that passive portfolio so as to create a combination of passive portfolios that replicates the return of a fund. The general expectation is that the coefficient (weight) for the benchmark of a fund would be the largest, so that it reflects adherence to the stated investment style. However, a large number funds in all categories except Overnight Funds, Liquid Funds, Short Duration Funds and Long-Term Funds show deviations from benchmarks, indicating that the risk-return characteristics of the funds are different from the stated investment objective or style. Deviation from the benchmark occurs due to selecting securities that do not constitute the benchmark and/or apportioning weights to securities that are not the same as benchmark weights. It is believed that deviation from a benchmark can generate better risk-adjusted performance, but our results present a different picture. Of all the funds that exhibited deviations from the benchmark, our findings show that only 35 (14.46%) funds report positive risk-adjusted returns for

Table 2 Clusters, fund categories and indices for style analysis.

Cluster	Fund category	Passive portfolios (Indices) for style analysis
Liquidity	Overnight Funds (OF) Liquid Funds (LF) Ultra-Short Duration Funds (USDF) Low Duration Funds (LDF) Money Market Funds (MMF)	CRISIL Overnight Index (OI) CRISIL Liquid Fund Index (LFI) CRISIL Ultra-Short Term Debt Index (USTDI) CRISIL Low Duration Debt Index (LDDI) CRISIL Money Market Index (MMI) CRISIL Composite Bond Fund Index (MR)
Duration	Short Duration Funds (SDF) Medium Duration Funds (MDF) Medium to Long Term Funds (MTLDF) Long Term Funds (LTF) Dynamic Duration Funds (DDF)	CRISIL Short Term Bond Index (STBI) CRISIL Medium Term Debt Index (MBI) CRISIL Medium to Long Term Debt Index (MLBI) CRISIL Long Term Debt Index (LDI) CRISIL Dynamic Debt Index (DDI) CRISIL Composite Bond Fund Index (MR)
Credit Risk	Corporate Bond Funds (CBF) Credit Risk Funds (CRF) Banking PSU Funds (BPSUF)	CRISIL Corporate Bond Composite Index (CBCI) CRISIL Composite Credit Risk Index (CCRI) CRISIL Banking and PSU Debt Index (BPSUDI) CRISIL Short Term Credit Risk Index (STCRI) CRISIL Short Term Bond Index (STBI) CRISIL Composite Bond Fund Index (MR)
Risk Free (Gilt)	Gilt Funds (GF) Gilt 10-year Funds (G10YF)	CRISIL Dynamic Gilt Total Return Index (DGTRI) CRISIL 10 Year Gilt Index (G10Y) CRISIL Composite Gilt Index (CGI) CRISIL Medium Term Gilt Index (MTGI) CRISIL Long Term Gilt Index (LTGI) CRISIL Composite Bond Fund Index (MR)
	Floater Funds (FF)	CRISIL Equal Weighted Index (EWI) CRISIL Overnight Index (OI) CRISIL Liquid Fund Index (LFI) CRISIL Low Duration Debt Index (LDDI) CRISIL Money Market Index (MMI) CRISIL Composite Bond Fund Index (MR)

both single-factor and multi-factor models. This proves that drift in investment style vis-à-vis respective benchmarks in the case of India yields economically significant rewards only for a few fund managers. These funds also get above average performance rating from independent investment research companies in India. Contrary to SEBI's prescriptions with regard to fund categories, our results show style deviation on a large scale. Large-scale style deviation raises two questions. First, whether SEBI's prescription for fund categorisation works effectively. Second, the validity of prevailing performance evaluation practices in the Indian MF industry which tolerate such a large-scale style deviation.

Table 4 presents cluster-wise and category-wise average style weights and, measure of style consistency (R-square). On average, funds in the Cluster 4 (Gilts) exhibit the most style consistent behaviour, while funds in Cluster 2 (Duration) exhibit the least style consistent behaviour. As seen in Table 3, the funds in the Duration Cluster seems to be offering the poorest risk-adjusted returns, followed by the funds in Credit Risk Cluster. Looking at the average R-squares for fund categories in table 4, Credit Risk Funds and Gilt Funds seem to offer the largest and the smallest scope for securities selection respectively, but average risk-adjusted return for Credit Risk Funds is one of the lowest. At an aggregate level, cluster and category averages of R-square and risk-adjusted returns prove that security selection skills of Indian fixed income fund managers do not create value for the investors.

Fig. 3 presents the relationship between style consistency (R-Square) and risk-adjusted performance as measured by Jensen's alpha of multifactor model for five select categories of funds, namely, Liquid Funds, Medium to Long Duration Funds, Dynamic Duration Funds, Corporate Bond Funds and Banking and PSU Funds. These categories form part of Fig. 3, as they exhibit average R-square of 0.70 or more and each of these categories comprises a sizeable number of funds. In other words, funds in these five categories are highly consistent in their investment style. Fig. 3 indicates a positive relationship between style consistency and risk-adjusted performance. Table 5 provides further details pertaining to this relationship, across all categories.

Table 5 presents the Pearson correlation coefficients between R-square of a fund category and Jensen's alphas for single-factor model and multi-factor model. Interestingly, for 13 out of 16 fund categories, the correlation between R-square and single factor as well as multi-factor model alphas is positive. The correlation coefficient for long-term funds cannot be calculated as this category has only one fund. Further, for 11 categories, the correlation coefficient is greater for multi-factor models than the same for single-factor models. High correlation coefficients confirm the Brown et al. (2009) hypothesis that higher the style consistency, greater is the risk-adjusted return. In other words, style consistent funds outperform style inconsistent funds on risk-adjusted basis.

The broader takeaways from Tables 3 to 5 are as follows: Indian fixed income fund managers practice securities selection, but their security selection skills fail to improve risk-adjusted performance of funds. This is contrary to the findings of Mohanti and Priyan (2018) that indicate some degree of securities selection ability improves risk-adjusted performance of the Indian equity MFs. The paper also shows higher style consistency leads to greater risk-adjusted return. Put simply, our findings indicate that investors would be better off with Indian fixed income funds maintaining style consistency. Also, investment style and style consistency have a considerable impact on performance of Indian fixed income MFs.

Table 3 Fixed income MF category-wise style consistency, size and performance.

Fund Categories	Number of funds	Style Consistency			Size			Monthly Performance			Annualised Performance		
		Minimum R-Square	Maximum R-Square	Median R-Square	AUM (Rs. Crores)	AUM as a% of Cluster AUM	AUM as a% of Total AUM	Minimum Jensen's alpha	Maximum Jensen's alpha	Median Jensen's alpha	Minimum Jensen's alpha	Maximum Jensen's alpha	Median Jensen's alpha
Liquidity Cluster													
Liquid Funds	34	0.0171	0.8938	0.7296	378,031	59.83%	37.36%	−0.0020	0.0001	0.0000	−2.41%	0.14%	−0.03%
Low Duration Funds	22	0.0015	0.8795	0.3849	85,258	13.49%	0.19%	−0.0041	0.0003	−0.0002	−4.95%	0.34%	−0.27%
Overnight Funds	4	0.5039	0.9066	0.6675	41,886	6.63%	4.14%	−0.0004	0.0000	−0.0001	−0.51%	−0.05%	−0.14%
Money Market Funds	15	0.0030	1.0000	0.6388	71,870	11.37%	7.10%	−0.0015	0.0006	0.0000	−1.74%	0.68%	0.02%
Ultra Short Duration Funds	18	0.0058	0.8607	0.5993	54,804	8.67%	5.42%	−0.0023	0.0011	−0.0001	−2.78%	1.33%	−0.11%
Cluster Statistics	93	0.0015	1.0000	0.6704	631,849	100.00%	62.45%	−0.0041	0.0011	−0.0001	−4.95%	1.33%	−0.08%
Duration Cluster													
Short Duration Funds	25	0.0002	0.9282	0.6135	98,368	63.13%	9.72%	−0.0076	0.0003	−0.0008	−9.12%	0.36%	−0.96%
Medium Duration Funds	15	0.0768	0.9014	0.6368	28,457	18.26%	2.81%	−0.0071	0.0004	−0.0014	−8.55%	0.49%	−1.62%
Medium to Long Duration Funds	13	0.0776	0.9340	0.8726	9824	6.31%	0.97%	−0.0057	−0.0002	−0.0016	−6.84%	−0.24%	−1.92%
Long Duration Funds	1	0.9065	0.9065	0.9065	840	0.54%	0.08%	−0.0009	−0.0009	−0.0009	−1.04%	−1.04%	−1.04%
Dynamic Duration Funds	24	0.1501	0.9130	0.7965	18,323	11.76%	1.81%	−0.0037	0.0003	−0.0013	−4.44%	0.36%	−1.50%
Cluster Statistics	78	0.0002	0.9340	0.7952	155,812	100.00%	15.40%	−0.0076	0.0004	−0.0013	−9.12%	0.49%	−1.50%
Credit Risk Cluster													
Corporate Bond Funds	13	0.0711	0.9378	0.8086	55,431	30.72%	5.48%	−0.0033	0.0005	−0.0004	−3.95%	0.56%	−0.46%
Credit Risk Funds	14	0.0208	0.9029	0.2724	54,932	30.44%	5.43%	−0.0045	0.0001	−0.0013	−5.39%	0.15%	−1.55%
Banking & PSU Funds	16	0.2460	0.9146	0.7316	70,082	38.84%	6.93%	−0.0016	0.0006	0.0000	−1.95%	0.66%	0.02%
Cluster Statistics	43	0.0208	0.9378	0.6968	180,445	100.00%	17.83%	−0.0045	0.0006	−0.0002	−5.39%	0.66%	−0.26%
Risk-Free(Gilt) Cluster													
Gilt Funds	20	0.5686	0.9588	0.9007	8962	20.52%	0.89%	−0.0021	0.0004	−0.0004	−2.48%	0.49%	−0.48%
Gilt 10 Year Funds	4	0.4538	0.9470	0.7541	895	2.05%	0.09%	−0.0001	0.0022	0.0014	−0.08%	2.60%	1.66%
Floater Funds	4	0.7229	0.8457	0.8365	33,808	77.43%	3.34%	−0.0003	0.0003	0.0000	−0.33%	0.36%	−0.04%
Cluster Statistics	28	0.4538	0.9588	0.8987	43,666	100.00%	4.32%	−0.0021	0.0022	−0.0002	−2.48%	2.60%	−0.29%

Note: Annualised performance is calculated based on monthly performance.

Table 4 Cluster-wise and category-wise average style weights and R-square.

Cluster	Fund categories	Indices and average style weights						R-square
Liquidity		**OI**	**LFI**	**USTDI**	**LDDI**	**MMI**	**MR**	
	Cluster Average	**0.2956**	**0.2863**	**0.2033**	**0.1375**	**0.0364**	**0.0410**	**0.5606**
	Overnight Funds	0.9189	0.0335	0.0000	0.0000	0.0000	0.0477	0.6864
	Liquid Funds	0.2616	0.7122	0.0014	0.0119	0.0000	0.0129	0.6781
	Ultra Short Duration Funds	0.3207	0.0454	0.2719	0.1855	0.1311	0.0455	0.4287
	Low Duration Funds	0.2629	0.0000	0.3222	0.3653	0.0000	0.0496	0.4354
	Money Market Funds	0.2241	0.0975	0.4584	0.0671	0.0681	0.0849	0.6030
Duration		**STBI**	**MBI**	**MLBI**	**LDI**	**DDI**	**MR**	
	Cluster Average	**0.4441**	**0.1090**	**0.0738**	**0.0922**	**0.0082**	**0.2727**	**0.6177**
	Short Duration Funds	0.8886	0.0833	0.0079	0.0000	0.0030	0.0173	0.4985
	Medium Duration Funds	0.5122	0.3088	0.0839	0.0354	0.0142	0.0454	0.5397
	Medium to Long Term Funds	0.0893	0.0329	0.0857	0.2450	0.0015	0.5456	0.7714
	Long Term Funds	0.0000	0.0000	0.0000	0.9941	0.0000	0.0059	0.9065
	Dynamic Duration Funds	0.1493	0.0568	0.1328	0.1033	0.0138	0.5440	0.6955
Credit Risk		**CBCI**	**CCRI**	**BPSUDI**	**STCRI**	**STBI**	**MR**	
	Cluster Average	**0.0247**	**0.0975**	**0.1777**	**0.1627**	**0.4479**	**0.0895**	**0.6089**
	Corporate Bond Funds	0.0573	0.0808	0.1520	0.0881	0.4311	0.1907	0.7114
	Credit Risk Funds	0.0161	0.1788	0.1591	0.3119	0.3341	0.0000	0.3661
	Banking & PSU Funds	0.0058	0.0398	0.2148	0.0928	0.5611	0.0857	0.7380
Risk Free (Gilt)		**DGTRI**	**G10Y**	**CGI**	**MTGI**	**LTGI**	**MR**	
	Cluster Average	**0.4786**	**0.0735**	**0.0441**	**0.0641**	**0.1571**	**0.1827**	**0.8508**
	Gilt Funds	0.5956	0.0522	0.0305	0.0000	0.2121	0.1097	0.8836
	Gilt 10 Year Funds	0.0250	0.1400	0.1562	0.0627	0.0391	0.5770	0.7272
		EWI	**OI**	**LFI**	**LDDI**	**MMI**	**MR**	
	Floater Funds	0.3472	0.1135	0.0000	0.3859	0.0000	0.1534	0.8104

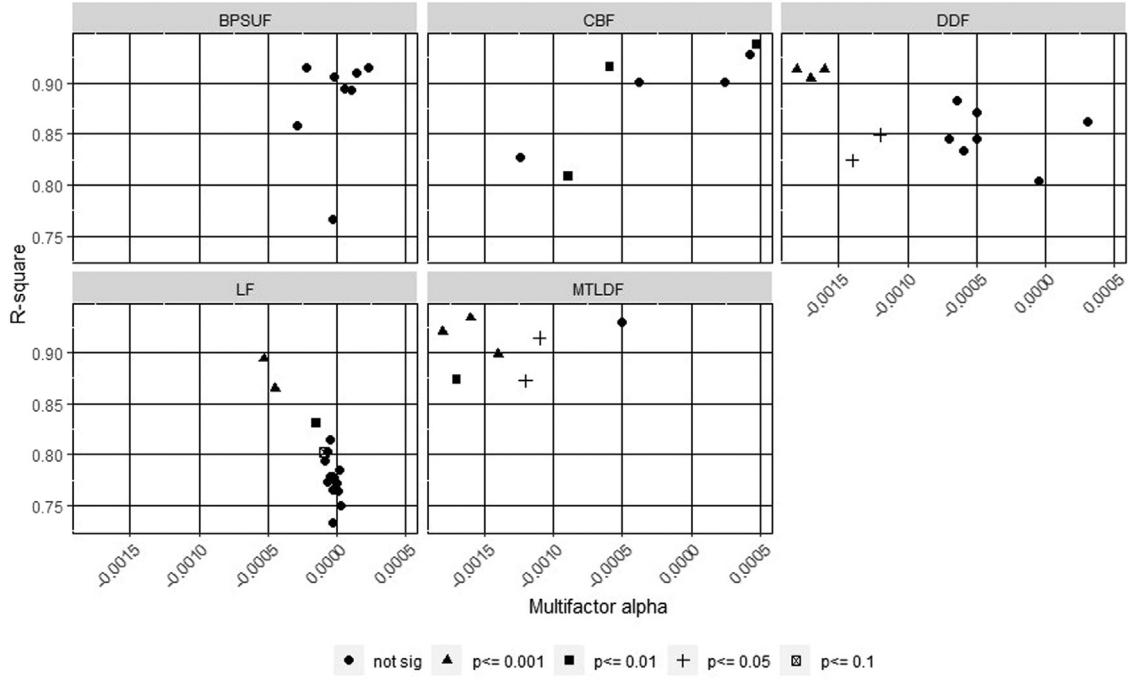


Fig. 3 Style consistency and risk-adjusted performance of selected fixed income funds. *Note*: BPSUF = Banking & PSU Funds, CBF = Corporate Bond Funds, DDF = Dynamic Duration Funds, LF = Liquid Funds, MTLDF = Medium to Long Duration Funds.

Conclusion

Prior scholarly research on performance evaluation of fixed income or equity MFs has generally examined securities selection skill, timing ability, performance persistence and investment style analysis. However, defining investment style of a fund and exploring the impact of style on fund performance is still one of the most intriguing aspects in the

Table 5 Relationship between style consistency and risk-adjusted returns.

Cluster	Fund categories	Pearson correlation coefficient of R-square with	
		Single-factor Alpha	Multifactor Alpha
Liquidity	Overnight Funds	0.3772	0.5367
	Liquid Funds	0.7479***	0.7590***
	Ultra-Short Duration Funds	0.4397*	0.3704*
	Low Duration Funds	0.8046**	0.8089**
	Money Market Funds	0.2859	0.2946
Duration	Short Duration Funds	0.7847***	0.8019***
	Medium Duration Funds	0.7149**	0.7082***
	Medium to Long Term Funds	0.8767***	0.9026***
	Long Term Funds	Not Calculated	Not Calculated
	Dynamic Duration Funds	0.3290	0.4201**
Credit Risk	Corporate Bond Funds	0.6242*	0.7565**
	Credit Risk Funds	0.8251**	0.8233**
	Banking & PSU Funds	0.6144*	0.6231
Risk Free (Gilt)	Gilt Funds	−0.1737	−0.0444
	Gilt 10 Year Funds	−0.8913	−0.9231#
	Floater Funds	0.2701	0.4657#

Note:
***$p < 0.001$.
**$p < 0.01$.
*$p < 0.05$, #$p < 0.1$.

professional asset management industry (Brown et al., 2009). HBSA and RBSA are popular methods geared towards exploring the investment style of funds. While scholars acknowledge that a fund's investment style influences its performance, little is known about the impact of investment style consistency on abnormal returns of the funds. Notable prior scholarly works have focused on investment style analysis and style consistency for equity MFs, but the literature on style analysis for fixed income MF is still scarce.

This study examines the investment style, style consistency and the relationship between style consistency and risk-adjusted returns for a comprehensive sample of 242 fixed income funds across 16 different style categories encompassing the entire fixed income MF landscape in India. We show that there is large-scale style deviation (style drift) from the stated investment style in Indian fixed income MF industry. Fund managers appear to deviate from the investment style with an objective to generate better risk-adjusted returns, but in reality, fund performance is poor. We provide evidence that investment style consistency is an important tool for performance evaluation of a fund. Using R-square, a simple measure of investment style consistency from Sharpe (1992) asset class model, we show that there is significant positive linear relationship between investment style consistency and risk-adjusted returns of funds in India. Funds with high investment style consistency tend to have higher risk-adjusted returns within a given investment style category. Our results also suggest that style inconsistency, or in other words, style drift, leads to inferior risk-adjusted returns.

Our results show that maintaining a consistent investment style is a valuable skill in professional asset management. This skill should be incorporated in the fund's communication to investors and performance reporting. Assessing this skill would go a long way in enabling AMCs to develop pertinent recruitment, retention and remuneration policies for fund managers.

We demonstrate that investment style analysis can aid in identifying misclassification of funds. The regulatory approach in India is to classify fixed income funds on the basis of their average Macaulay's duration and the characteristics of the securities held in the portfolio, and the periodic reporting requirement for both. This leaves some scope for fund managers to window dress and ensure classification of their funds in certain category. Classifying funds based on coefficients of pre-defined investment style, as we have demonstrated in our study, would ensure that funds do not deviate from their stated investment objective or style and also offer some leeway for fund managers to practice securities selection. Such an approach to fund classification will also mitigate the likelihood of investors investing in funds that do not match their desired risk-return expectations. Substantial style inconsistency for a long time period may also signal potential change in risk characteristics of a fund.

While we have assessed the linear relationship between investment style consistency and risk-adjusted return, we believe there is scope to examine the relationship between investment style consistency and performance persistence of funds applying HBSA and for a longer time period. Further, recursive investment style analysis over a longer time period that is aimed at measuring the evolution of investment style drift, identifying factors responsible for style drift and examining the impact of style drift on fund performance would offer deeper insights on style consistency and performance persistence of Indian fixed income MFs. Another avenue for future research could be to examine the association of governance practices of an AMC and the investment style consistency of its funds.

Supplementary materials

Supplementary material associated with this article can be found in the online version at doi:10.1016/j.iimb.2023.07.002.

References

AMFI. (2021a). MF history. Retrieved from AMFI India: https://www.amfiindia.com/research-information/mf-history

AMFI. (2021b). MF monthly. Retrieved from AMFI India: https://www.amfiindia.com/research-information/amfi-monthly

Blake, C., Elton, E., & Gruber, M. (1993). The performance of bond mutual funds. *Journal of Business* 66 (3), 371–403.

Bogle, J.C. (1998). The implications of style analysis for mutual fund performance evaluation. *Journal of Portfolio Management* 24 (4), 34–42.

Brown, D., & Marshall, W. (2001). Assessing fixed income manager style and performance from historical returns. *Journal of Fixed Income* 10 (4), 15–25.

Brown, K.C., Harlow, W.V., & Zhang, H. (2009). Styaing the course: The role of investment style consistency in the performance of mutual funds. Working paper. University of Texas, Austin.

Brown, K.C., Harlow, W.V., & Zhang, H. (2015). Investment style volatility and mutual fund performance. Working paper. University of Texas, Austin.

Cao, C., Iliev, P., & Velthuis, R. (2017). Style drift: Evidence from small-cap mutual funds. *Journal of Banking and Finance* 78, 42–57.

Chakrabarti, R. (2010). The asset management industry in India. In: Chakrabarti, R., De, & S. (Eds.), Capital markets in India. Sage Publication India Pvt. Ltd, New Delhi, pp. 225–279.

Chua, A.K., & Tam, O.K. (2020). The shrouded business of style drift in active mutual funds. *Journal of Corporate Finance* 64, 1–20.

Clare, A., O'Sullivan, N., Sherman, M., & Zhu, S. (2019). The performance of US bond mutual funds. *International Review of Financial Analysis* 61 (1), 1–8.

Comer, G., & Rodriguez, J. (2006). Corporate and government bond funds: An analysis of investment style, performance and cash flow. Working Paper. Georgetown University.

Comer, G., & Rodriguez, J. (2013). A comparison of corporate versus government bond funds. *Journal of Economics and Finance* 37 (4), 495–510.

CRISIL. (2022). Financial products. Retrieved from CRISIL: https://www.crisil.com/en/home/what-we-do/financial-products/indices.html

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance* 52 (3), 1035–1058.

Deb, S.G., Banerjee, A., & Chakrabarti, B.B. (2007). Performance of Indian equity mutual funds vis-a vis their style benchmarks: An empirical exploration. 10th Capital Markets Conference, Indian Institute of Capital Markets. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=962827.

Domian, D.L., & Reichenstein, W. (2008). Return-based style analysis of high yield bond funds. *Journal of Fixed Income* 17 (4), 72–87.

Domian, D.L., & Reichenstein, W. (2009). Return-based style analysis of convertible bond funds. *Journal of Fixed Income* 18 (3), 52–64.

Elton, E., Gruber, M., & Blake, C. (1995). Fundamental variables, APT and bond fund performance. *Journal of Finance* 50 (4), 1229–1256.

Gallo, J., & Lockwood, L. (1997). Benefits of proper style classification of equity portfolio managers. *Journal of Portfolio Management* 23 (3), 47–55.

Investment Company Institute. (2020). *In investment company fact-book 2020*. ICI Publications.

Kahn, R., & Rudd, A. (1995). Does historical performance predict future performance? *Financial Analysts Journal* 51 (6), 43–52.

Maag, F., & Zimmermann, H. (2000). On benchmarks and performance of DEM bond mutual funds. *Journal of Fixed Income* 10 (3), 31–45.

Maginn, J.L., Tuttle, D.L., Pinto, J.E., & McLeavey, D.W. (2007). Managing investment portfolios: A dynamic process. John Wiley & Sons, Inc, Hoboken, NJ.

Mohanti, D., & Priyan, P.K. (2018). Style-exposure analysis of large-cap equity mutual funds in India. *IIMB Management Review* 30 (3), 219–228.

Scher, N., & Muller, C. (2005). Equity style and performance persistence in South African unit trusts. *Investment Analysts Journal* 34 (61), 5–16.

SEBI. (2017). *https://www.sebi.gov.in/sebiweb/home/HomeAction.do?doListing=yes&sid=1&ssid=7&smid=0*. Retrieved May 24, 2020, from https://www/sebi.gov.in: https://www.sebi.gov.in/legal/circulars/oct-2017/categorization-and-rationalization-of-mutual-fund-schemes_36199.html

SEBI. (2020). Monthly bulletin April 2020. Retrieved from www.sebi.gov.in: https://www.sebi.gov.in/sebiweb/home/HomeAction.do?doListing=yes&sid=4&ssid=80&smid=107

Sethuraman, S. (2022). Retrieved from business standard: https://www.business-standard.com/article/markets/india-s-demat-account-tally-up-63-to-89-7-million-in-fy22-shows-data-122041401088_1.html

Shah, A., Kumar, A., Garg, A., & Mehta, S. (2019). Unlocking the Rs. 100 Trillion opportunity: Asset management industry in India. Retrieved from www.amfiindia.com: https://www.amfiindia.com/Themes/Theme1/downloads/BCG-Banner7.pdf

Sharpe, W. (1988). Determining a fund's effective asset mix. *Investment Management Review* 2 (6), 59–69.

Sharpe, W. (1992). Asset allocation, management style, and performance measurement. *Journal of Portfolio Management* 18 (2), 7–19.

Trzcinka, C.A. (1995). Equity style classification: Comment. *Journal of Portfolio Management* 21 (3), 44–46.