Journal of Banking, Information Technology and Management
Volume 12 No. 2 • July-December 2015

Performance Evaluation of Indian Equity Diversified Mutual Funds Using Carhart's Four-Factor Model

Parag Rijwani

Abstract

Mutual funds institutions are gaining popularity in developing financial markets and have been growing faster than the developed markets. The amount of funds that are under the purview of professional management is large and increasing. This phenomenal growth in the mutual fund industry in these emerging markets has resulted in an increase in the number of investment companies offering a range of funds. Due to the great number of funds in existence, evaluating managers' performance and selecting funds with relatively high risk-adjusted returns can be an especially difficult and challenging task. With all the effort spent in selecting and evaluating mutual funds, there is one natural question to ask: Can investors forecast mutual fund performance? Much of research has been done based on Mutual Funds, their performance and the fund selection models used for the same. In this context, the addition of the fourth factor in the Carhart Model is still under surveillance regarding the efficiency and role played by that factor in fund selection in various economies/markets. This paper aims at evaluating the performance of Indian equity diversified mutual funds using the Carhart's 4-factor Model. As a performance attribution model, the four-factor model captures the risk and return characteristics of four elementary equity investment strategies viz. investing in high versus low market sensitivity stocks, investing in small versus large market capitalization stocks, investing in value versus growth stocks, investing in momentum versus contrarian stocks.

Keywords: *Carhart's Four-Factor Model, Diversified Mutual Funds, Performance Attribution*

1. Introduction

Mutual funds are an established institution in developed financial markets. In emerging markets, growth of mutual funds has been robust. The amount of funds that are under the purview of professional management is large and increasing. Due to the large number of funds in existence, evaluating managers' performance and selecting funds with relatively high risk-adjusted returns can be an especially difficult and challenging task. With all the effort spent in selecting and evaluating mutual funds, there is one natural question to ask: Can investors forecast mutual fund performance? Much of research has been done based on Mutual Funds, their performance and the fund selection models used for the same. Most of these researches have not been done in the Indian Context. Moreover, addition of the fourth factor in the Carhart Model by him is still under surveillance regarding the efficiency and role played by that factor in fund selection in various economies/markets. No such research on evaluation of performance of Carhart model for Mutual Fund Selection has been observed to take place in the Indian Context.

The mutual funds offered vary enormously in terms of their investment objectives, types of securities held, historical returns and risk levels, load and management fees, levels of diversification, quality of service, and so on (Cook W.D., Hebner K.J. (1993)),. Similarly, fund shareholders vary enormously in terms of their wealth levels, rates of portfolio turnover, degrees of risk tolerance, understanding of financial markets, beliefs in the ability of mutual funds to outperform the market, their own portfolio's level of diversification, and so on. Saraoglu H, Detzler M.L. (2002), Modern portfolio theory (MPT) states that the investment decision process can be separated into two independent processes. In one, investment professionals, such as mutual fund managers, specialize in constructing a variety of risky portfolios. In a second process, individual investors choose complete portfolios by combining the optimal risky portfolio, based on their risk tolerances, and the risk-free asset. With this impressive growth record and the increasing complexity, diversity and competitiveness of the mutual fund industry, it is important to examine the approach adopted by investors and mutual fund managers.

The proliferation of mutual funds has made choosing the right funds a challenge to many investors. In response, many magazines and news services designed to assist investors in mutual fund selection have emerged. These sources provide performance statistics and fund attributes, such as information on fund managers, expense ratios, and turnover, but an individual investor seldom has the time or the expertise to analyze the vast amount of data available on mutual funds. Therefore, some financial software and finance Web sites now offer mutual fund screening tools. Unfortunately, these tools range from the inadequate to the useless. First, few investors have sufficient financial knowledge to input the appropriate values for the screening variables. Second, the tools do not consider the preferences of individual investors; the tools implicitly assume that each screening variable is equally important to all investors. Finally, such a large number of funds may meet the screening criteria (a common occurrence) that investors still need to make selections from the list.

Analytical Hierarchy Process:

A structural approach to selecting mutual funds is based on the analytic hierarchy process (AHP) and overcomes some of the shortcomings of typical screening tools. The approach thus adds to financial advisors' toolkit an objective procedure for choosing mutual funds. The AHP model has the following distinct advantages. It provides a systematic approach to ranking mutual funds for individuals based on each individual's unique investment objectives and constraints. The complete portfolio of funds selected by the AHP model is customized for a particular investor. Second, the AHP prevents the investor from making inconsistent preference assignments. Because fund selection involves more than one parameter (for example, it may involve investment objectives, tax efficiency, risk, and expense ratios), enforcing consistency in the decisions is difficult if the selection method is unstructured. The AHP helps steer investors away from rules of thumb that do not reflect their personal preferences. Unlike the typical screening tool, which produces a list of funds that meet certain criteria, the AHP ranks the selected mutual funds on the basis of the investor's preferences, making the final decision much easier. Third, this approach minimizes the amount of technical input required from investors.

The AHP methodology consists of the following four major steps:

1. Develop the hierarchical structure:
   - Mission.
   - Selection criteria.

- Alternatives.

2. Assign a relative importance of each selection criterion to the mission.
3. Rank alternatives under each criterion.
4. Rank each alternative's contribution to the mission.

Fama-French's 3 Factor Model:

Fama-French Model is a factor model that expands on the CAPM by adding size and value factors in addition to the market risk factor in CAPM. This model considers the fact that value and small cap stocks outperform on a regular basis. By including these two additional factors, the model adjusts for the outperformance tendency, which is thought to make it a better tool for evaluating manager performance.

The three factor model is motivated by the empirical finding that size and the ratio of book to market equity have consistent and significant explanatory power for US stock returns at the very least (Fama and French, 1992:427-465 and 1993:3-56), Ondes T., Bali S. (2010)). The Fama-French three factor model is

$$E(Ri) = Rf + \beta[E(Rm) - Rf] + siSMB + hiHML$$

where SMB and HML capture the size and book to market effects, respectively. SMB and HML are factor mimicking hedge portfolios constructed from stock returns. This model performs very well empirically and is capable of explaining many of the anomalies that the CAPM is not capable of explaining such as the overreaction effect (Fama and French 1996:55-84). One possible objection to the model is that it is an empirically driven one designed to capture anomalies such as the size effect that the CAPM is incapable of explaining, however argue that the premium associated with SMB and HML are consistent with a multi factor version of Merton's ICAPM (1973:867-887)

Carhart's 4 Factor Model:

The Carhart's model (1997) appears to improve upon the Fama-French model in terms of reducing mean absolute pricing errors of mutual fund returns. By now the Fama-French and Carhart models have become quite popular and have been widely used for estimating costs of capital, computing optimal asset allocations and measuring performance evaluations. The lack of theoretical grounds for the Fama-French and Carhart's momentum factor-mimicking portfolios to be cross-sectionally priced risk factors has spawned a lot of research aimed at either identifying the economic reasons for these portfolios to be priced factors or discrediting the validity of the two multifactor models on statistical grounds and risk-return relation misspecifications.

2. Literature Review

Evaluation of Carhart's 4 Factor Model

Kan R., Zhang C. (1999), in empirical tests of asset pricing models, macroeconomic variables are often proposed as candidates for systematic factors. The macroeconomic variables are typically motivated by theory or economic intuition, but many have statistically insignificant correlations with the returns on financial assets. Taking a skeptic's point of view, some of these macroeconomic variables might be useless "factors," in the sense that they are independent of all the asset returns. The paper tried to establish, in a sense, that the seriousness of the problem caused by a useless factor is related to the degree of model misspecification. The issue is whether the over-identifying restriction (OIR) test in Generalized Method of Moments (GMM) can reliably detect misspecified models that contain useless factors. As we remarked in the last paragraph, a useless factor causes serious problems primarily when the model is misspecified, which is exactly what the OIR test is designed to detect. It is natural to conjecture that the OIR test will effectively reject a misspecified model with a useless factor. But can we really count on the OIR test to detect a misspecified model that contains a useless factor? Surprisingly, the answer is "no." By definition, the presence of a useless factor does not make a misspecified first-moment condition more, or less, incorrect. However, it blows up the estimated second-moment function whose inverse is used as a weighting matrix in estimation and testing. As a result, the OIR test becomes less powerful and a misspecified model with a useless factor may pass as a correct one.

The paper emphasizes that the results do not imply a flaw in the GMM itself. The validity of the GMM requires some regularity conditions that are sometimes overlooked by empirical researchers and sometimes difficult to verify. Many macroeconomic variables used in empirical asset pricing studies have low sample correlations with asset returns. Although the hypothesis that a macroeconomic variable has zero correlations with the returns on a set of assets cannot be rejected, researchers often find themselves reluctant to throw away the variable because of the concern about statistical power. On the other hand, a useless factor could pass the test for zero correlations due to a few outliers, or violations of other joint hypotheses in forming the test of zero correlations. These possibilities complicate direct tests of useless factors. It is important, therefore, to understand the statistical properties of asset pricing tests in the presence of a useless factor. It is important also because a pure useless factor serves as the limiting case of a true factor observed with noise when the amount of noise increases.

Martín C. Lozano B. (2006), the linear factor models, as the Fama-French (1993; 1996) and Carhart (1997), are by far the most common in empirical asset pricing. The paper has focused on the questions: how to estimate parameters, how to calculate standard errors of the estimated parameters, how to calculate standard errors of the pricing errors, and how to test the model. The two basic ideas for the estimation and evaluation are: time-series regression or cross-sectional regression. Time-series regression turns out to be a limiting case of cross-sectional regression. The GMM, p = E(mx) approach turns out to be almost identical to cross-sectional regressions. The GMM/discount factor, time-series, and cross-sectional regression procedures and distribution theory are similar but not identical. Cross-sectional regressions on betas are not the same thing as cross-sectional regressions on second moments. Cross-sectional regressions weighted by the residual covariance matrix are not the same thing as cross-sectional regressions weighted by the spectral density matrix. The GMM/stochastic discount factor approach is still a "new" procedure (see Cochrane, 2005). Thus, it is important to verify that it produces similar results and well-behaved test statistics in the setups of the classic regression tests1. To address these questions, they applied various methods to a classic empirical question. How do time-series regression, cross-sectional regression, Fama-MacBeth procedure, and GMM/SDF compare when applied to a test of the Fama-French and Carhart models? They found that three methods produce practically the same results for this classic exercise. They produced almost exactly the same estimates, standard errors, t-statistics, and -?2 statistics that the pricing errors are jointly zero.

Lozano and Irigoyen (2006), said that Carhart model is able to price the 25 test portfolios while Fama-French model fails on specific ones. Finally, according to their findings, Lozano and

Irigoyen proposed a slightly different specification that works somewhat better than Fama-French and Carhart models on explaining cross-sectional returns. Extensions should go over the economic interpretation of the smb, hml and umd factors. Among the many competing explanations behind the success of these models is the one based on time-varying investment opportunities. Specifically, Fama and French (1993) suggest that hml and smb might proxy for state variables that describe time variation in the investment opportunity set. This is done by relating the Fama-French factors to macroeconomic variables and business cycle fluctuations. Liew and Vassalou (2000), for instance, show that hml and smb help forecast future rates of economic growth, and both Lettau and Ludvigson (2001) and Vassalou (2003) show that accounting for macroeconomic risk reduces the information content of hml and smb. On the other hand, authors such as Petkova (2005) argue that changes in financial investment opportunities are not necessarily exclusively related to news about future macro variables; furthermore, Campbell (1996) points out that the factors in the model should be related to innovations in state variables that forecast future investment opportunities.

Common Risk Factors In the Returns of Stocks and Bonds

Fama and French (1993): The paper identifies five common risk factors in the returns on stock and bonds. There are three stock-market factors: an overall market factor and factors relate to firm size and book-to-market equity. There are two bond-market factors, related to maturity and default risks. Stock returns have shared variation due to the stock-market factors, and they are linked to bond returns through shared variation in the bond-market factors. Except for low-grade corporates, the bond-market factors capture the common variation in bond returns. Most important, the five factors seem to explain average returns on stocks and bonds. Variables that have no special standing in asset-pricing theory show reliable power to explain the cross-section of average returns. The list of empirically determined average-return variables includes size, leverage, earnings/price and book-to-market equity.

Fama and French (1992) studied the joint roles of market ?, size, E/P, leverage, and book-to-market equity in cross-section of average stock returns. They find that used alone or in combination with other variables, ? (the slope in the regression of a stock's return on a market return) has little information about average returns. Used alone, size, E/P, leverage, and book-to-market equity have explanatory power. The bottom line result is that two empirically determined variables, size and book-to-market equity, do a god job explaining the cross-section of average returns on NYSE, Amex, and NASDAQ stocks for the 1963-1990 period.

3. Research Methodology

3.1. Objective: To evaluate performance of Indian equity diversified mutual funds using Carhart's 4-factor model

3.2. Scope: Equity diversified Mutual Funds in India

3.3. Data Source: Ace Mutual Fund database

3.4. Sampling: 188 Indian equity diversified open-ended Mutual Fund Schemes

3.5. Data Analysis: This research is based on secondary data. In this study, we examine the efficiency of Carhart's 4-Factor Model in Mutual fund selection in the Indian Context. As a performance attribution model, the four-factor model captures the risk and return characteristics of four elementary equity investment strategies:

1. Investing in high versus low market sensitivity stocks

2. Investing in small versus large market capitalization stocks
3. Investing in value versus growth stocks
4. Investing in momentum versus contrarian stocks

The four-factor performance attribution model can be mathematically represented as

$$RP - RF = \beta P + \beta M{*}RMRF + \beta S{**}SMB + \beta B{*}HML + \beta O{*}PR1YR$$

Where RP – RF = Portfolio excess return

RMRF = Market factor return

SMB = Size factor return

HML = BTM factor return

PR1YR = Momentum factor return

α_P = Portfolio risk-adjusted return

β_{RMRF} = Portfolio market beta

β_{SMB} = Portfolio size beta

β_{HML} = Portfolio BTM beta

β_{PR1YR} = Portfolio momentum beta

The size, BTM, and momentum factor returns are the return to a portfolio of small-cap stocks minus the return to a portfolio of large-cap stocks, the return to a portfolio of value stocks [stocks with a high ratio of book to market value] minus the return to a portfolio of growth stocks [stocks with a low ratio of book to market value], and the return to a portfolio of momentum stocks [stocks that outperformed in the recent past] minus the return to a portfolio of contrarian stocks [stocks that underperformed in the recent past], respectively. The portfolio betas are the sensitivities of the portfolio excess return to the factor returns and hence the model's measures of the risk exposures of the portfolio. In other words, the betas of a portfolio are measures of the extent to which the portfolio return varies with the factor returns. We perform time-series regression on the past data available for various Mutual Funds in the Indian Market using Carhart 4-Factor Model for fund selection.

3.6. Data Analysis:

Carhart Mark (1997): Mutual funds are sorted on January 1 of each year, from 2011 to 2015 into decile portfolios based on their previous calendar year's return. The portfolios are equally-weighted, using reported returns. Reported returns are net of all operating expenses (expense ratios) and security-level transaction costs, but do not include sales charges. Funds with the lowest past one-year return comprise decile 1 and funds with the highest comprise decile 10. Within each decile: 6 portfolios to be formed (S/L, S/M, S/H, B/L, B/M, and B/H) where

S = Small firms and B = Big firms (based on Asset under Management) and L = Low, M = Medium and H = High (based on the market cap to which the mutual fund belong: Small, Mid and Large).

SMB is the difference between the returns on small and big stock portfolios with about the same weighted average asset under management.

HML is the difference, between simple average returns on the mutual funds having fund class as Large Cap (S/H and B/H) and the average returns on the mutual funds having fund class as Small Cap (S/L and B/L).

The Fund Classification (Value Research: New Fund Classification) is done based as Large Cap if more than 80 percent of its investments are in Equity Stocks which belong to Large Cap and as Small Cap if more than 60 percent of its investments are in Equity Stocks which belong to Small Cap or Others.

PR1YR is the equal-weight average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight average of firms with the lowest 30 percent eleven-month returns lagged one month.

RM is return on the value weighted portfolio of the stocks in the six size BE/ME portfolios.

Rf is 90 days T-bill rate which is 5 percent.

RpRf is the excess return, which is the difference between market return on S&P CNX 500 index since last 5 years from National Stock Exchange website and the portfolio return.

4. Empirical Results

Adjusted R Square:

Table 4.1 Adjusted R-square & coefficients from Time-series Regression Results

Year-end March 31	*Adjusted R square*	*Intercept*	*?RMRF*	*?SMB*	*?HML*	*?PR1YR*
2011	0.997	0.517	0.954	-1.163	-0.010	0.202
2012	0.999	-0.103	1.051	0.262	0.003	0.310
2013	0.712	0.283	0.320	4.270	-0.134	-0.820
2014	1.000	0.337	1.000	0.000	0.000	0.000
2015	1.000	-0.153	1.000	0.000	0.000	0.000
2011-2015	0.718	0.179	0.567	-3.383	-0.088	0.798

Dependent Variable: Excess Return on Portfolio

Independent Variables: RMRF (Market Risk Premium),
SMB (Size Factor Return),
HML (BTM Factor Return) and
PR1YR (Momentum Factor Return)

In the year 2011, the adjusted R square indicates that the result of dependent variable could be explained to an extent of 99.73% by the four independent variables.

In the year 2012, the adjusted R square indicates that the result of dependent variable could be explained to an extent of 99.94% by the four independent variables.

In the year 2013, the adjusted R square indicates that the result of dependent variable could be explained to an extent of 71.21% by the four independent variables.

In the year 2014, the adjusted R square indicates that the result of dependent variable could be explained to an extent of 100% by the four independent variables.

In the year 2015, the adjusted R square indicates that the result of dependent variable could be explained to an extent of 100% by the four independent variables.

When the data was analysed for all the five years put together, it was observed that excess return on portfolio could be explained to an extent of 71.81% by the four independent variables.

This variation in the overall five years is because of the recession which resulted in fluctuating economy.

P-value:

Table 1.2 P-value from Time-series Regression Results

Year-end March 31	*Intercept*	*βRMRF*	*βSMB*	*βHML*	*βPR1YR*
2011	<0.00	<0.00	0.125	0.461	0.043
2012	<0.00	<0.00	0.333	0.596	0.006
2013	0.003	0.379	0.106	0.530	0.455
2014	<0.00	<0.00	0.646	0.524	0.325
2015	<0.00	<0.00	0.122	0.212	0.281
2011-2015	<0.00	<0.00	0.061	0.191	0.062

Dependent Variable: Excess Return on Portfolio

Independent Variables: RMRF (Market Risk Premium),
SMB (Size Factor Return),
HML (BTM Factor Return) and
PR1YR (Momentum Factor Return)

In the year 2011, the p-value for the independent variables RMRF and PR1YR is less than 0.05 i.e. 5% and hence the dependent variable (Excess Return on Portfolio) is dependent more on these two factors.

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In the year 2013, the p-value for none of the independent variables RMRF and PR1YR is less than 0.05 i.e. 5% and hence the dependent variable (Excess Return on Portfolio) is independent of these factors.

In the year 2014, the p-value for the independent variables RMRF is less than 0.05 i.e. 5% and hence the dependent variable (Excess Return on Portfolio) is dependent more on this factor.

In the year 2015, the p-value for the independent variables RMRF is less than 0.05 i.e. 5% and hence the dependent variable (Excess Return on Portfolio) is dependent more on this factor.

When the data was analysed for all the five years put together, it was observed that the p-value for the independent variable RMRF was less than 0.05 i.e. 5%, hence the dependent variable (Excess Return on Portfolio) is dependent on this factor. It was also observed, that for all the five years combined together, the p-value for SMB and PR1YR is near 0.06 i.e. 6%, hence though their acceptance level of significance is out of range they still cannot be ignored.

5. Findings & Conclusion

The 4 factor model is consistent with a model of market equilibrium with four risk factors. Alternatively, it may be interpreted as a performance attribution model, where the coefficients and premia on the factor mimicking portfolios indicate the proportion of mean return attributable to four elementary strategies: high versus low beta stocks, large versus small market capitalization stocks, value versus growth stocks and one-year return momentum versus contrarian stocks.

The 4-factor model can explain considerable variation in returns. The relatively high variance of the SMB, HML and PR1YR zero-investment portfolios and their low correlations with each other and the market proxies which suggest the 4-factor model can explain sizeable time-series variation (Appendix 1). For Mutual Fund portfolios constructed to mimic risk factors related to Size, BTM and PR1YR (one –year return momentum) capture strong variation in returns, no matter what else is in the time-series regressions. This is evident that size, book to market equity and one-year momentum return indeed proxy for sensitivity to common risk factors in returns. Nowhere in the research, it is observed that though HML (BTM factor return) is out of significance level or does not have an impact on the dependent variable for the specified period, this model as explained by Carhart in his paper (On Persistence In Mutual Funds) has proved valid and all the four factors are of importance in the selection of Mutual Fund Schemes.

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Appendix 1

Table 2.1: Correlation amongst factors in 2011

	RMRF	SMB	HML	PR1YR
RMRF	1.0000	-0.4725	0.0198	-0.0044
SMB	-0.4725	1.0000	-0.1134	-0.4411
HML	0.0198	-0.1134	1.0000	0.5455
PR1YR	-0.0044	-0.4411	0.5455	1.0000

Table 2.2: Correlation amongst factors in 2012

	RMRF	SMB	HML	PR1YR
RMRF	1.0000	-0.5248	0.0274	-0.2083
SMB	-0.5248	1.0000	-0.1991	0.7977
HML	0.0274	-0.1991	1.0000	-0.1539
PR1YR	-0.2083	0.7977	-0.1539	1.0000

Table 2.3: Correlation amongst factors in 2013

	RMRF	SMB	HML	PR1YR
RMRF	1.0000	0.7487	0.3771	-0.4270
SMB	0.7487	1.0000	-0.0048	-0.1894
HML	0.3771	-0.0048	1.0000	-0.6856
PR1YR	-0.4270	-0.1894	-0.6856	1.0000

Table 2.4: Correlation amongst factors in 2014

	RMRF	SMB	HML	PR1YR
RMRF	1.0000	-0.6907	-0.3532	0.2612
SMB	-0.6907	1.0000	0.6677	0.4437
HML	-0.3532	0.6677	1.0000	0.4103
PR1YR	0.2612	0.4437	0.4103	1.0000

Table 2.5: Correlation amongst factors in 2015

	RMRF	SMB	HML	PR1YR
RMRF	1.0000	-0.1169	0.1627	-0.1015
SMB	-0.1169	1.0000	-0.1920	0.3455
HML	0.1627	-0.1920	1.0000	0.0164
PR1YR	-0.1015	0.3455	0.0164	1.0000

Parag Rijwani, Assistant Professor, Institute of Management, Nirma University, Ahmedabad, Gujarat, India