"The effect of performance manipulation on fund flows under different market conditions in South Africa"

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THE EFFECT OF PERFORMANCE MANIPULATION ON FUND FLOWS UNDER DIFFERENT MARKET CONDITIONS IN SOUTH AFRICA

Abstract

This study analyzes the effect of performance manipulation on mutual fund flows under different market conditions to provide explanations to the increased flow of investors' funds to persistently underperforming active mutual fund managers in South Africa. The study employs a system GMM technique to analyze panel data of 52 South African actively managed equity mutual funds for the 2006–2019 period. From the analysis, it is found that past fund flows and fund size constitute a set of fund-level factors with predictive influences on fund flows, while market risk exerts systemic effect on the flow of investors' assets to fund managers. The results show that market conditions do not impact the relationship between mutual fund flows and performance manipulation, which implies that manipulation strategies implemented by fund managers do not engender increased funds' flow from asset owners. This study thus concludes that other non-performance factors drive convexity in the relationship between fund flows and performance in South Africa.

Keywords	performance manipulation, fund flows, market conditions, outperformance, underperformance, mutual funds
JEL Classification	G11, G14, G23

INTRODUCTION

Analysts continue to demand explanations to the continuous cash flow of investors to active funds despite their inability to exhibit superior performance relative to the market, while active management is premised on the ability to outperform the market (Ellis, 2015). However, beyond outperformance, drivers of the flow-performance inconsistency may include performance manipulation through which fund managers adapt to changing market conditions to sustain the attraction of investors' cash, while manipulation strategies alter the efficient asset pricing mechanism of the financial system and allow arbitrageurs to achieve extraordinary returns. Evidence (S&P, 2019) suggests that in one-year, active fund portfolios in South Africa underperformed the market by 34.01 percent, underperformed it by 84.66 percent in three years, and trailed it significantly by 91.03 percent in five years (as cited in Apau et al., 2021a). In the period under review (2014–2018), the inflow of new cash from investors to fund managers increased significantly, with over R1.9 trillion worth of assets under administration as of the end of the third quarter of 2018, while the current combined assets of the fund industry stand more than R2.49 (ASISA, 2021; Rangongo, 2018) as cited in Apau et al. (2021a). The asymmetric flow-performance patterns in South Africa suggest that the dynamics of their interactions adapt to different market conditions and hence require nonlinear conditional modelling to obtain accurate inferences about their behavior.

1. LITERATURE REVIEW

Mutual fund management, like other forms of business, goes through cycles of change from time to time, which results in differences in the relationship between fund flows and performance across different conditions of the market (Jun et al., 2014). As such, active fund managers vary their trading strategies under different market conditions as a means of adapting to prevailing trends to sustain performance momentum and fund flows. Scholars explain that active managers maintain a stable strategy during bullish markets but implement new investment strategies during bearish markets because systemic uncertainties deteriorate investors' confidence in the ability of fund managers to deliver outperformance (Kacperczyk et al., 2014). While some new strategies are recognized as prototypical style of active management, others are mainly driven by manipulation motives to tamper with fund trading results to project a more impressive performance outlook to current and prospective investors.

Wang (2018) employs Carhart four-factor and rolling window models to analyze the rise and fall of portfolio pumping in US mutual fund families. The results show that portfolio pumping (otherwise known as portfolio padding) represents an effective means by which fund managers sustain cash flows while maintaining recent superior performance momentum, at least in the short run. Through portfolio pumping strategy, fund managers augment the market value of investment portfolios by means of a purposeful acquisition a significant percentage of the company's outstanding shares, specifically towards the closing periods of trading cycles. This strategy is recognized as a deceptive trading approach and, thus, a form of manipulation as the unsophisticated investor is misled into acquiring stakes in an obviously bloated fund portfolio.

The findings of Wang (2018) show that pumped funds report extraordinary performance and remain industrially competitive compared to their unpumped counterparts. In this way, fund contributors compensate outperforming fund managers with additional cash allocations, while such managers experience minimal administrative overheads and dispersions in returns. However, the market value of pumped portfolios is swelled towards the end of a trading cycle, and declines at the start of a new trad-

ing cycle. This affects adversely the long-run performance of funds and thus drives mass redemption actions among fund contributors. Duong and Meschke (2019) explain that active strategists involved in portfolio pumping include restrictive withdrawal clauses in asset administration contracts, as a means of controlling rapid redemption actions by investors while sustaining fund liquidity positions.

Huang et al. (2011) investigate the incentive behind mutual fund risk-taking and the effect of fund managers' risk-taking on the overall fund performance, using one-factor CAPM, the Fama and French three-factor, Carhart four-factor, and Ferson and Schadt (1996) models. The study's results show that fund managers minimize the level of risks on underlying investments in subsequent trading periods when their recent performance were superior to the market. Frequent change in risk strategy represents a form of manipulation as fund managers utilize this strategy to smoothen their trading results, although this approach is recognized as a common active management style. By minimizing the associated risk of fund portfolios, fund managers can smoothen returns over multiple periods, where they act swiftly in publishing superior returns but hesitate in disclosing inferior performance (Qian & Yu, 2015). Fund managers tamper with conventional performance measure like the Sharpe ratio and Jensen Alpha in the implementation of return smoothing strategy, by purposefully minimizing portfolio risk to boost risk-adjusted performance (Bollen & Pool, 2008).

Chen (2011) employs time-series linear regression models to analyze the use of derivative and risk-taking among fund managers. From the study, fund managers who maintain significant holdings in derivative investments generally, exhibit minimal levels of portfolio risk. Hence, such managers are less likely to indulge risk-shifting behaviors during market downturns as the use of derivatives sustains fund performance under fluctuating market condition. Fund managers persist in performance enhancing strategies with derivatives because the average investor exhibits less sophistication in distinguishing between derivative-induced performance and performance driven by superior trading ability. Evidence from the analysis of Huang et al. (2011) indicates that the drivers of risk-shifting through derivative investments are more linked career concerns of hired investment professionals than their ability to opti-

mize trading opportunities across bullish and bearish conditions of the market. Fund managers attach significant interest to career security and bonus payment when defining the composition of their portfolio holdings, while the unsophisticated investor is unable to analyze the risk associated with derivative portfolios during stock-picking. However, less-sophisticated investments generally yield more sustainable returns in the long run than high-risk derivative portfolios. This is because prolonged market volatility diminishes the value of underlying high-risk assets (Natter et al., 2014).

Scholars prescribe various ways by which the prevalence of deceptive trading strategies among active managers could be mitigated, to ensure the protection of the financial interest of the average fund contributor while engendering a more robust financial system. Qian et al. (2014) suggest that the actual performance of active managers relative to the performance of passive strategies is efficiently evaluated by the application of a more encompassing metric, the Manipulation Proof Performance Measure (MPPM) proposed by Goetzmann et al. (2007). The MPPM is a standardized performance metric used as a benchmark measure to ascertain the degree of manipulation of fund performance. The degree of manipulation is the margin of variance in the performance of funds as measured by the MPPM and the performance values of funds as measured by conventional performance measures (CPMs), namely, Jensen's Alpha, Sharpe ratio, Treynor ratio and the Treynor & Mazuy (TM) and Henriksson & Merton (TM Gamma) analysis. The creation of manipulation degrees involves prior ranking of fund performance, where the performance of a fund is ranked based on its performance in terms of the Manipulation Proof Performance Measure (MPPM) and the CPMs. Funds are ranked on a scale of one to five based on their performance relative to the industry average in the past trading period.

In the analysis, funds that exhibited exceptional performance are assigned high ranking scores, while those with average performances relative to the MPPM and the CPMs are allotted low ranking scores. The difference between the fund's performance as per the MPPM and the CPMs shows the degree of manipulation of the fund. A larger ranking difference implies a higher degree of manipulation. In a typical scenario, the manipulation degree for the

Sharpe ratio of a particular fund is denoted by the difference between MPPM ranking of the fund and its ranking as per the Sharpe ratio for the fund in period under review. The rates at which a particular portfolio outperforms the benchmark relative to the different indices (MPPM inclusive) are recorded together with the approximate rate of occurrences as an indication of a portfolio's level of significance of outperformance or underperformance. Performance indices employed in the analysis are based on published returns of the funds (after adjusting for overhead expenditure) in the past period. The frequency at which the ratio of a fund outperforms that of the benchmark is computed as the basis for assessing manipulation.

Scholars (Goetzmann et al., 2007) explain that the efficiency of the MPPM is recognized in its strong independence feature that enables funds to withstand complex manipulation strategies as cited in Qian et al. (2014, p. 4). This measure possesses an element derived from utility function that makes it independent and resilient against dynamic manipulation (Brown et al., 2010). The MPPM is formulated such that its output rises in returns and, hence, has a concave outcome. In practice, most conventional measures of performance are based on the assumption that fund returns are independent and have identical distributions. However, this assumption does not hold for the Sharpe ratio because of how it is statistically formulated and thus makes it vulnerable to manipulation. Fund managers can manipulate the Sharpe ratio if the interim results achieved through the Sharpe ratio are maintained around the theoretical optimal level. In this way, the Sharpe ratio can report a high value at the end of the entire trading period. However, the utility function property of the MPPM makes it robust to modifications typical of the Sharpe ratio manipulation, where the difference in the distributions between the achieved and expected returns are captured as though the returns distribution was actual and identically distributed across different periods (Goetzmann et al., 2007).

Tan (2015) explains that TM and HM measures of market timing and selectivity are purposefully formulated to account for the timing ability of the sophisticated trader, without capturing loss incurred by the unsophisticated market timer. In this way, comparable returns are achieved by the unsophisticated timer, as well as the trader who does not

implement timing strategies altogether. However, through MPPM, the loss incurred as a result of lack of sophistication in market timing is captured and adequately accounted for (Brown et al., 2010). Practically, the MPPM evaluates the trading results of fund managers by adequately capturing the cost of holding undiversified portfolios. As a result, it allows more weight to be assigned to risk in the approach, particularly where minimal risk aversion is assumed because of dependence on the standard deviation of funds' performance values. Smoothing of returns over multiple periods, where fund managers are quick to report trading gains but delay in reporting losses, is regarded as a typical manipulation strategy (Titman & Tiu, 2011). From the literature (Bollen & Pool, 2008), through this mechanism, funds can maintain marginal extraordinary returns while reducing the standard deviation concurrently as cited in Qian et al. (2014, p. 5). However, with the application of the MPPM, the impact of this strategy on fund performance become limited, since the MPPM by formulation is dependent on the relative uniqueness of the marginal and variation of extraordinary returns (Qian et al., 2014). Thus, the MPPM represents effect metric of differentiating between manipulated funds and those who achieve extraordinary returns through superior trading ability.

Based on the preceding discussion on the dynamics of manipulation and its impact on fund flows and market robustness, a contextual analysis of the manipulation in the fund management industry of South Africa becomes essential for effective investment planning and regulation. This is because the South African financial market is still an emerging one and thus vulnerable to the dynamic activities of opportunistic traders who exploit market inefficiencies for extraordinary gains. From the statistics, the average return of the fund industry in South Africa was 41.2 percent in 2006, 19.2 percent in 2007, –23.2 percent in 2008, while 32.1 and 19.0 percentages were recorded in 2009 and 2010, respectively (ASISA, 2021). An average market return of 2.6 recorded in 2011 represents the lowest positive for the period under study. The lowest negative average return is denoted by the 2016 figure of –0.06 percent. For the period under review, the rate of market volatility (which indicates the level of dispersions in market returns) ranges from a minimum of 0.64 percent to a maximum of 2.20 percent.

The above dynamics show the existence of a significant range of market volatility in South Africa. Moreover, following a rebound in equity investments in 2019 and beyond, a significant increase in South African funds' assets is forecasted by analysts which is expected to activate agency issues between the career concerns of hired investment professionals and the financial interest of investors (Glow, 2020). Altogether, active fund managers, especially regular underperformers, employ diverse methods such as return smoothing, portfolio pumping, the use of derivative instruments and risk-shifting in deceptive trade strategies of performance manipulation to sustain fund flow under time-varying conditions of the market. However, the application of the standardized performance metric (MPPM) to the analysis of funds' performance represents an effective means of mitigating the impact of manipulation on the efficiency of the financial system while protecting optimal financial interests of fund contributors.

In the above context, questions regarding the effect of manipulation on fund flows under different market conditions remain a gap in the literature that calls for an investigation. Moreover, questions rooted in agency theory and behavioral hazards relative to fund managers career concerns, the mechanisms of manipulation, characteristics associated with manipulation prone stocks and the resultant effect of manipulation on fund contributors provide adequate incentive to model performance manipulation (Dyakov et al., 2022). To this effect, this study aims to analyze the effect of performance manipulation on fund flows under bullish and bearish market conditions in South Africa.

2. METHODOLOGY

2.1. Data sources and sample selection

The study employs quarterly data spanning from the end of the first quarter of 2006 to the end of the last quarter of 2019 of 52 active equity obtained from S&P Capital IQ, McGregor BFA Library, and the Association of Savings and Investment South (ASISA) website to achieve the aim of the study. GDP data for economic size is sourced from the South African Reserve Bank's website. The sample is selected based on data availability, with a

minimum of six years of data as the criteria for including a fund. This study follows Nenninger and Rakowski (2014) and formulates the computation of fund flows as the net quarterly percentage of cash flows accruing to a fund as a result of investor stock purchasing and redemption activity. In this way, a fund's flow is computed as:

$$Flow_{it} = \left(TNA_{it} - TNA_{it-1}\left(1 + r_{it}\right)\right)/TNA_{it-1}, \quad (1)$$

where $Flow_{it}$ denotes the total net assets of fund i at quarter t; TNA_{it} represents the fund's total net assets at quarter t; TNA_{it-1} is fund i total net assets in the past quarter $t - 1$. Fund $i's$ return in quarter t is denoted by r_{it}, which accounts for reinvested dividends and adjusted for the fund's overheads. The performance of equity funds in South Africa is logarithmically calculated quarterly returns of fund price index. Following Rupande et al. (2019), fund performance by raw returns is formulated as follows:

$$R_{it} = \ln\left(P_{it}/P_{it-1}\right) \cdot 100 , \quad (2)$$

where R_{it} is the return on fund i in quarter t; P_{it} represents the current price of fund i in quarter t; P_{it-1} denotes the price of fund in the previous period $t - 1$; and ln is the natural logarithm of the price index. The Johannesburg Stock Exchange All Share Index (JSE ALSI) is employed as a proxy for market performance for the past trading year for the sample period.

2.2. Analysis of the effect of performance manipulation on fund flows under different market conditions

To assess the effect of performance on fund flows under different market conditions, a dynamic panel system GMM model with a conditional variable nested in to capture the effect of market conditions on manipulation is estimated. Scholars (Arellano & Bond, 1991) explain that a dynamic panel Generalized Method of Moments technique is capable of accounting for likely dynamic endogeneity biases which Ordinary Least Squares (OLS) approach does not eliminate by its estimation (as cited in Kripfganz & Schwarz, 2015, pp. 1, 2). The GMM approach presents a theoretical and

more enhanced estimation instrument that captures endogeneity problems of simultaneity and unobservable heterogeneity (Wintoki et al., 2012). From the literature (Blundell & Bond, 1998), the two-stage approach is more robust than difference GMM estimator that obtains all parameter estimates simultaneously as cited in Roodman (2009, pp. 27, 29). Following Qian et al. (2014), the effect of performance manipulation on fund flow under different market conditions is estimated with the following empirical model:

$$
\begin{aligned}
Flow_{it} = {} & \beta_0 + \beta_1 Flow_{i,t-1} + \beta_2 Mdg_{i,t-1} + \\
& + \beta_3 r_{i,t-1} + \beta_4 \ln(TNA_{i,t-1}) + B_5 \ln\left(Age_{i,t-1}\right) + \\
& + B_6 Std_{i,[t-4,t-1]} + B_7 Std_{M,[t-4,t-1]} + \\
& + B_8 E \cos ize_{[t-4,t-1]} + \beta_9 Mktcon_{[t-4,t-1]} + \mu_{it},
\end{aligned}
\quad (3)
$$

where $Flow_{it}$ is the net flow of fund i at time t, where $Flow_{i,t-1}$ is the net flow of fund i in time t; $r_{i,t-1}$ denote fund $i's$ raw returns in time t-1; $Mdg_{i,t-1}$ is the degree of manipulation of fund i in time t-1; computed for each of selected five commonly used performance measures in South Africa (namely Jensen's alpha, Sharpe ratio, Treynor ratio, TM alpha, and TM gamma). Following prior studies (Fletcher, 2000; Pettengill et al., 1995), the dummy variable $Mktcon$ that represents the market condition takes a value of 1 if the market return for the past trading period is greater than zero, $R_{m,[t-4,t-1]} > 0$, indicating a bullish condition and takes a value of 0 if the market return for the past period [$t – 4, t – 1$] is less than or equal to zero, $R_{m,[t-4,t-1]} \leq 0$, denoting a bearish condition as cited in Jun et al. (2014, p. 23). The natural logarithm of funds' total net assets denoted by $\ln(TNA_{i,t-1})$ and the natural logarithm of the fund age represented as $\ln(Age_{i,t-1})$ are included in the analysis to control for fund size and age as the growth pace of large and older funds is generally slower than small and younger ones. As such, scholars (Del Guercio & Tkac, 2002) explain that these dynamics can drive fund flows, as cited in Jun et al. (2014, p. 16). The annualized standard deviation of fund monthly returns in the past year $Std_{i,[t-4,t-1]}$ is included in the equation to control for the effect of fund risk, while the equity market's daily returns in the past year denoted by $Std_{M,[t-4,t-1]}$ are included in the analysis to account for the effect of market risk as reflected in return volatility of the benchmark in-

dex on fund flows. Barber et al. (2016) explain that investors' decisions on mutual funds are affected by portfolio risk and market volatility. It is known in the literature that the direction of the economy in which funds operate in terms of gross domestic product (GDP) rate impacts the overall performance of mutual fund portfolios, which includes the level of fund flows (Fuerst et al., 2013). As a result, the variable for economic size ($Ecosize_{[t-4,t-1]}$), measured as the natural logarithm gross domestic product (*lgdp*), is included in the equation to capture the effect of national economic growth on fund flows.

3. RESULTS AND DISCUSSION

3.1. Descriptive analysis

Descriptive statistics of variables employed in the analysis are presented in Table 1. From the table, a large range exists in fund flows, raw returns (returns), fund size (Lntna) and economic size (Ecosize), while fund age (Lnage), fund risk (Stdfnd), and market risk (Stdmkt) vary between 3.9 percent and 0.0 percent, 0.2 percent and –0.0 percent and 3.4 percent and 0.5 percent, respectively.

3.2. Correlation analysis

From the literature (Dormann et al., 2013), correlation analysis is conducted to determine the presence of multicollinearity issues among the independent variables employed in the analysis to avoid spurious estimation results. Through correlation analysis, the association between the variables are established. A correlation of 0.7 and beyond among independent variables indicates the existence of a multicollinearity problem as cited in Apau et al. (2021a, p. 7). Table 2 presents the correlation matrix of variables employed in the analysis. From the table, the highest correlation (0.45) is between market risk (Stdmkt) and fund risk (stdfnd), while the rest of the values are lower than 0.7. As such, the possibility of the existence of multicollinearity issues among the set of independent variables employed in the analysis is eliminated. Furthermore, the highest variance inflation factor (VIF) value (3.645) among the independent variables is below the acceptable level of 10. Saeed (2014) explains that VIF value below 5 or 10 suggests the non-existence of the multicollinearity problem among the independent variables.

Table 1. Descriptive statistics

Source: Authors' estimation (2022).

	FLOW	**RETURNS**	**LNTNA**	**ECOSIZE**	**LNAGE**	**STDMKT**	**STDFND**
Mean	22.693	1.082	4.214	1.699	2.307	0.999	0.008
Maximum	12769.821	17.768	2.932	7.200	3.871	3.375	0.164
Minimum	−109.587	−16.000	−2.810	−6.100	0.000	0.499	−0.016
Std. dev.	339.796	4.354	3.108	2.444	0.888	0.405	0.006
Observations	2008	2008	2008	2008	2008	2008	2008

Table 2. Correlation matrix

Source: Authors' estimation (2022).

Variables	**FLOW**	**RETURNS**	**LNTNA**	**ECOSIZE**	**LNAGE**	**STDMKT**	**STDFND**	**VIF**
FLOW	1.000	–	–	–	–	–	–	1.116
RETURNS	0.018	1.000	–	–	–	–	–	1.092
LNTNA	0.042**	0.164***	1.000	–	–	–	–	2.415
ECOSIZE	0.006	0.067***	−0.121***	1.000	–	–	–	2.364
LNAGE	−0.006	−0.061***	0.199***	−0.166***	1.000	–	–	3.645
STDMKT	−0.007	−0.169***	−0.120***	−0.133***	−0.148***	1.000	–	2.647
STDFND	−0.015	−0.082***	−0.067***	−0.166***	−0.119***	0.449***	1.000	2.106

Note: 10%, 5%, and 1% levels of statistical significance are denoted by *, **, and ***, respectively.

3.3. Discussion of the effect of performance manipulation on fund flows under different market conditions

Table 3 reports system GMM results of the effect of performance manipulation on fund flows under different market conditions. In row 3 of the table, the lagged fund flow shows varied but significant effects on subsequent flows of fund managers. This evidence suggests that the past increase in investors' asset allocations drives the direction of funds' future cash flows. Yao et al. (2014) explain that fund contributors exhibit significant skepticism about the expertise of active managers relative to performance persistence in the long run and under different market conditions. While ambitious traders chase recent outperformers by allocating additional cash to them, pessimistic traders tend to focus on fund managers' ability to sustain recent performance momentum and, hence, minimize cash allocations to funds as the divers of fund performance are subject to change under different market conditions.

Lagged manipulation degree reports significant coefficients under only two (Treynor ratio and TM alpha manipulation degrees) out of the five performance indices employed in the analysis. This result suggests that generally, performance manipulation does not exert a significant impact on fund flows under changing market conditions. This evidence contradicts the findings of prior studies that document a significant positive effect of manipulation on subsequent cash flows of fund managers (Qian & Yu, 2015). The current evidence is expected as the dynamics that drive the performance of funds are unlikely to be the same under different market conditions, while the prior analyses on the effect manipulation on fund flows are conducted in the context of stable market conditions and, thus, they are unable to provide explanations to influence of manipulation on fund flow under time-varying conditions of the market (Qian et al., 2014).

Furthermore, scholars explain that manipulative managers are filtered out of competition by investors in the long run for taking up ex-

cessive risk as excess risk exposures deteriorates the long-run returns of active portfolios, while it declines investors' confidence in fund managers' expertise (Huang et al., 2011; Jones & Wermers, 2011). Moreover, the conditional variable for capturing the effect of market conditions on manipulation and its effect on fund flow reports significant coefficients under only two (TM alpha and TM Gamma) of the five CPMs. This implies that market conditions generally do not influence the effect of performance manipulation on fund flows.

In row 6, lagged raw returns report significant coefficients on subsequent fund flows only under Treynor manipulation degree, while it records insignificant coefficients under the manipulation degrees of the rest of the indices. This result indicates that the past increase in raw returns generally do not predict the future cash flow patterns of fund managers. This evidence supports the convex flow-performance contention in the literature that recent outperformers do not attract commensurately large sums of cash flows in subsequent periods, while funds that previously underperformed do not experience a significant forfeiture of stocks by investors, as explained by Fu et al. (2012). In practice, fund contributors redeem investment holdings in fund portfolios upon the achievement of extraordinary returns to avoid possible losses in the value of underlying assets under conditions of uncertainty in the market.

Yao et al. (2014) explain that mutual fund investors become less confident about fund managers' trading skills relative to performance persistence, and hence minimize stock-picking activities. As such, fund contributors quickly withdraw shareholding positions in funds after achieving enhanced returns, which impact negatively on the liquidity positions of funds in the long run (Ben-Rephael, 2017). However, evidence by Humphrey et al. (2013) suggests that lagged raw returns, which is the primary measure of a fund's past performance, exert apositive and significant effect on the subsequent fund flow of active managers.

Lagged fund size reports significant positive coefficients under manipulation degrees of all the

CPMs, except for the Sharpe ratio, where it is negative and insignificant. This result suggests that the past increase in fund assets engender enhanced assets flow to fund managers. In addition, fund contributors allocate more cash to large funds as investors trust in the capacity of large funds to withstand fluctuations in the market than their smaller counterparts. This finding is consistent with the prior evidence of Jun et al. (2014) that investor cash allocation decisions on mutual funds is driven by the size of a fund, large funds attract more investor cash flows to support long-run superior performance.

Lagged fund risk reports insignificant coefficients under manipulation degrees of four out of the five CPMs, except for the Sharpe ratio, where it is negatively significant. This evidence suggests that generally, an increase in fund returns dispersions does not influence the direction of future fund flows of active managers. This finding contradicts the position of prior studies that investors' decisions on mutual funds are significantly underpinned by fund risk (Jun et al., 2014). It can be observed from Table 3 that fund age reports significant coefficients only under Jensen's alpha and Treynor ratio manipulation degrees. This finding suggests that an increase in fund age does not exert a significant impact on its future cash flows. This evidence contradicts the position of the literature (Pástor et al., 2015; Bergstresser & Poterba, 2002) that investor decisions on mutual funds are affected by the number of years a fund has been in existence: older funds grow at a slower pace than younger funds as cited in Jun et al. (2014, pp. 16, 17).

Lagged market risk reports significant positive coefficients under three of the five manipulation degrees, namely, Jensen alpha, Sharpe ratio, and TM gamma manipulation degrees, while it reports insignificant coefficient under Treynor ratio and TM alpha. This result suggests that an increase in benchmark return volatility leads to enhancements in investor cash allocations to active portfolios. This interaction is expected because passive portfolios are designed to track the performance of a recognized market index. As such, any significant fluctuations in benchmark returns affect the performance of indexed portfolios. Kim (2019) explains fund contributors' confidence in active portfolios is bolstered during the periods of uncertainty on the equity market as increased market volatility affects investors' decisions on mutual funds.

Economic size reports insignificant coefficients under the manipulation degree of all performance measures. This result indicates that recent macroeconomic trends, as given by the direction growth of gross domestic product (GDP), does not drive the level of investor cash allocations to fund managers. This evidence contradicts the position of the literature that the performance of mutual fund portfolios is linked to the general performance of the economy in which funds operate, where fund investments become more profitable returns during expansionary phases of the national economy (Fuerst & Matysiak, 2013).

Lastly, in row 7 of Table 3, the market condition variable reports significant coefficients under only two (TM alpha and TM Gamma manipulation degrees) out of the five conventional performance measures employed in the analysis. This evidence implies that generally, market condition does not impact the direction of investors' asset flows to active portfolios. The current result does not support this study's postulation that the effect of manipulation on fund flows is more pronounced under bullish conditions of the market than in bearish conditions, as the variable capturing market conditions in the analysis is generally insignificant. However, Gottesman et al. (2013) find that investors' decisions on mutual funds are affected by market conditions, where the flow-performance interaction is more evident under bullish market conditions than bearish conditions.

Table 3. Effect of performance manipulation on fund flows under different market conditions

Independent variables	Dependent Variable: Fund Flow														
	Coefficients					Standard Errors					P–values				
	ALPHA	SHARPE	TREYNOR	TM ALPHA	TM GAMMA	ALPHA	SHARPE	TREYNOR	TM ALPHA	TM GAMMA	ALPHA	SHARPE	TREYNOR	TM ALPHA	TM GAMMA
FLOW(t–1)	−0.037***	0.198	0.112***	0.098**	0.033	0.012	0.105	0.053	0.049	0.047	0.002	0.051	0.034	0.045	0.475
MDG(t–1)	−36.131	−0.531	1.359***	−0.083	0.057**	26.303	0.693	0.518	0.072	0.028	0.170	0.443	0.009	0.246	0.043
RETURNS (t–1)	3.038	−0.149	−0.098***	0.015	−0.007	2.548	0.079	0.045	0.017	0.014	0.233	0.053	0.031	0.382	0.632
MKTCON (t–4, t–1)	−12.752	1.488	−0.821	0.217***	0.281***	7.134	0.041	0.620	0.096	0.092	0.052	0.050	0.186	0.024	0.002
ECOSIZE (t–4, t–1)	1.421	−0.144	0.023	−0.145	−0.057	0.186	0.199	0.028	0.079	0.088	0.444	0.471	0.396	0.054	0.516
LNTNA(t–1)	12.734***	−0.367	0.085***	0.146***	0.189***	4.305	0.334	0.036	0.040	0.076	0.003	0.272	0.019	0.000	0.013
LNAGE(t–1)	−30.399***	−0.746	−0.198***	−0.253	0.066	12.283	1.167	0.095	0.150	0.342	0.013	0.522	0.037	0.092	0.847
STDMKT (t–4, t–1)	21.893***	8.567***	0.164	0.458	0.706***	10.002	1.861	0.265	0.418	0.274	0.029	0.000	0.535	0.274	0.010
STDFD (t–4, t–1)	−2000.469	−1407.411***	−6.494	−59.125	−45.388	1.568	318.536	10.042	38.746	26.605	0.158	0.000	0.518	0.127	0.088

	ALPHA	SHARPE	TREYNOR	TM ALPHA	TM GAMMA
AR (2) test (*p*-value)	0.120	0.917	0.091	0.347	0.106
Hansen test of over-identification (*p*-value)	0.341	0.316	0.067	0.849	0.612
Diff-in-Hansen test of Exogeneity (*p*-value)	0.702	0.254	0.976	0.236	0.477

Note: 10%, 5%, and 1% levels of statistical significance are denoted by *, **, and ***, respectively.

CONCLUSION AND POLICY RECOMMENDATIONS

This study analyzed the effect of mutual fund performance manipulation on fund flows under different market conditions to provide explanations to the sustained flow of investors' assets to persistently underperforming fund managers in South Africa. The study employed a dynamic panel system GMM model with a conditional variable nested in to capture the effect of market conditions on manipulation and its effect on fund flows, using quarterly observations spanning from 2016 to 2019 of 52 actively managed funds.

It was found that past fund flows, fund size and market risk drive the direction of investors' cash allocations to funds, which implies that fund liquidity positions and the rate of market return volatility have a significant effect on the overall performance of mutual fund investments. This study verifies that manipulation strategies implemented by fund managers do not engender increased funds' flow from asset owners, leading to the conclusion that other non-performance metrics drive fluctuations in fund flows in South Africa.

As a policy recommendation, fund managers should invest in other non-performance assets, such as advertisement and promotional sales to sustain fund flows in the long run, as manipulation strategies do not impact flows when market condition is accounted for in the analysis. In addition, fund managers should consolidate funds' liquidity positions and asset base to sustain performance momentum as change fund size affects flows. Future studies can test the effect of advertisement and sales promotions on fund flows under different market conditions, since this study is limited in these regards due to data availability issues.

AUTHOR CONTRIBUTIONS

Conceptualization: Richard Apau, Peter Moores-Pitt, Paul-Francois Muzindutsi.
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