Prediction of Equity Mutual Fund Performance in South Africa using Regression Modelling

submitted by

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Declaration

I hereby certify that this research project was independently written by me. No material was used other than that referred to. Sources directly quoted and ideas used, including figures, tables, sketches, drawings, and photos, have been correctly referenced. Those not otherwise indicated belong to the author.

Thabo Kekana

Abstract

Studies have found that mutual funds tend to underperform the relevant benchmark index in the long term. The failure to outperform the index may be partly attributed to the fund managers' lack of tools that may assist in providing reliable estimates of how the funds are likely perform. The study uses a sample of nine South African equity mutual funds to test the predictive ability of linear and support vector regression models in predicting future mutual fund performance. Fund-specific and macroeconomic variables were used as predictor variables for predicting the year-to-date performance of the fund . The results of the study indicate that based on RMSE, support vector regression outperforms the linear regression models in predicting mutual fund performance and fund-specific and macroeconomic factors may be considered as predictor variables for fund performance.

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1. Introduction

Financial markets offer a number of ways for potential investors to invest their surplus funds. Investors with a long-term view, may for example, invest in shares of companies trading on the stock exchange. What informs the course of action followed by an investor is the objective of the investment. For an investor who is interested in the long-term growth of an investment, there are various available options to consider. An investor may adopt a passive investment strategy by constructing and investing in a well-diversified portfolio of shares that tracks the performance of the overall stock market. In the South African context, such a strategy may entail investing in companies that make up the All Share 40 Index (ALSI 40 Index). The ALSI 40 Index is an equity index made up of the top 40 largest companies listed on the Johannesburg Securities Exchange by market capitalisation. However, constructing a portfolio of this size may be a cumbersome process for any individual investor.

Alternatively, an investor may attempt to outperform the market by adopting active portfolio management strategy by investing in mispriced securities. Active portfolio management involves extensive research of the market in order identify those shares that are trading at a discount to their intrinsic value. The aim is to profit from the potential increase in the value of the shares as the market values are expected to approach the true (intrinsic) values as time elapses.

However, the investment strategies discussed above are more suitable for an investor with basic understanding of how the financial markets work. For someone without this understanding or not having a desire to put effort in this, mutual funds offer a viable option to invest surplus funds. A Mutual fund is an investment vehicle that pools funds from a number of investors and invests these funds into a portfolio of asset classes. Investors acquire shareholding in the mutual fund by purchasing mutual fund shares and their voting powers are proportional to the number of shares that they bought in the fund.

Mutual funds can be either open-end or closed-end funds. One of the difference between these funds is that investors in open-end funds can trade their shares with the fund, i.e., they buy and sell their shares in the fund at the fund's net asset value (NAV). This can happen once a day as the NAV is only determined at the close of the trading day. On the other hand, an investor in closed-end fund cannot trade their shares with fund but with other investors. Hence, trading shares in closed-end funds is similar to trading shares listed on an exchange. Another difference is that since open-end funds can trade with investors at any time, open-end funds are required to invest in liquid assets such as money market instruments. However, closed-end fund may invest in illiquid investments.

Mutual funds have board of directors who are appointed by the fund shareholders. These directors in turn appoint management companies to manage the family of funds. Each family has its own investment policy as specified in the fund prospectus. Depending on the investment policy of the fund, these funds are classified into various categories such as those that invest in equities, bonds, and money market, among others (Bodie, Kane & Marcus, 2018). Some of the funds focus on sectors of the economy such as financial services while others may have an international focus and invest in asset classes outside the borders of where the fund is managed or incorporated.

Within each of the groupings above, funds are also classified according to their investment objectives. An equity fund may for example, have income or growth as its investment objective. A fund with income objective, for example, will invest mainly in those shares of high-dividend yield companies while a growth portfolio will be made up of shares of low-dividend yield companies and those that normally retain their profits in order to fund projects with long-term prospects. Therefore, the composition of these portfolios will vary depending on the objective of the fund.

Mutual funds, particularly open-end, have gained popularity in a number of countries with Investment Company Institute (ICI) reporting that there were 46,838 open-end funds with assets of $56.2 trillion (excluding funds of funds) at the end of the third quarter of 2022 (Investment Company Institute (2022)). Of the $56.2 trillion, 44.1% were held by equity funds followed by the bond funds holding 20% of the total net assets. The mutual funds market is dominated by the United States and Europe, which had assets of $27.1 trillion and $17.3 trillion, respectively during the same period.

Despite having the largest and developed securities exchange market in Africa, the South African share of the global mutual fund industry is relatively small when compared to other regions. According to the ICI, the South African open-end funds accounted for 0.3% of the total assets with equity funds making up 0.2% of the global open-end equity funds and 24.4% of the South African funds.

For the purpose of this study, South African equity funds will be analysed as there are few studies that focus on African markets. South African equity mutual funds industry was chosen as South Africa has the biggest and most advanced securities market on the African continent. Furthermore, it has the most industrialised economy on the continent with a number of multinational companies having their headquarters in the country.

Equity mutual funds provide an alternative way for an investor to invest in a wide variety of stocks of shares issued by other companies. Among the benefits of investing in equity funds is that they invest in shares issued by several companies in different sectors of the economy, thus providing an investor with diversification benefit associated with investing in several stocks. Thus, investing in equity mutual fund is like investing in a portfolio of shares but with the selection and management of the investments delegated to the fund manager. The fund manager is compensated for the management of mutual funds by charging fees on the fund assets.

In addition to the fees payable to the fund manager for managing the fund, additional expenses, and fees such as those paid when investing and exiting the investment are payable. Furthermore, before committing funds to a mutual fund, an investor may also seek financial advice on how to allocate their funds, thus resulting in additional fees. However, the fees charged are not paid separately by the investor but deducted from the portfolio of mutual fund assets.

Irrespective of the investment objective pursued, investors prefer to put their funds in assets that will yield return that is commensurate with the risk inherent in the assets. Hence, the performance of the fund over the investment horizon is important for the investor. As such, in making a choice to invest in a particular fund, investors would prefer to invest in funds that have impressive past performance. While a number of studies have confirmed mutual fund performance persistence (Goetzmann & Ibbotson, 1994; Cuthbertson, Nitzsche & O'Sullivan, 2022), past performance is not the only factor that should be considered as the reliable predictor of what the future performance of the fund is likely to be. Success in prior periods does not guarantee that superior performance will be maintained in the future.

Research into the impact of other factors on the performance of mutual funds has been ongoing for several decades. While the investor is not involved in the management of the mutual fund, it is important for them to understand the impact of these factors as there are instances where investors have a say in how their funds are allocated among asset classes.

Despite having been extensively researched, studies on the performance of mutual funds have yielded conflicting results, particularly relative to the benchmarks measured against them. Basu, & Huang-Jones (2015) found that equity mutual funds have underperformed the stock market index in the long term. In their study of the performance of Asian mutual funds, Premaratne & Mensah (2014) found that, with exception of Hong Kong, equity and asset allocation funds underperformed the relevant benchmarks. Bodie, Kane & Marcus (2018) found periods of underperformance and superior performance between actively managed equity funds and Wilshire 5000 index over a period of 1971 to 2015.

In the study on mutual fund performance in South Africa, Tan (2015) found that there was no evidence that the mutual performance outperformed the JSE index. The result of study by Koutsokostas, Papathanasiou, & Balios (2019) shows that the Greek equity mutual funds underperformed the market index over the period studied. However, care must be taken in comparing performance between mutual fund and stock market index as the composition of each is likely to be different

(Bodie, Kane & Marcus, 2018). The market index may for example be composed mainly of stocks from large companies while the mutual fund portfolio made up of stocks with growth objective, thus making comparison challenging.

Being able to generate superior performance is key for the success of a fund manager as they are judged and rewarded according to the historical performance of their funds. Furthermore, superior performance helps in retaining clients and attracting additional investments. However, since the performance of the fund is impacted by various factors such manager's skill (Berk, & van Binsbergen, 2015;Kacperczyk, van Nieuwerburgh, & Veldkamp ,2014) and past fund performance, among others, selecting right stocks is a challenging task for the fund manager.

As the decision to invest involves making assumptions about the future performance of their investments, fund managers need guidance on how to select those assets that are expected to generate superior performance in the future. Therefore, being able to make reliable predictions about the fund performance is important for investors and fund managers as they will be in a better position to make informed investment decisions.

While mutual funds have been around for decades and there is plethora of research on mutual funds of different types, research into predictability of fund performance has not received enough attention from researchers. Most of the studies that were undertaken on fund performance prediction tend to rely on linear models and given the assumptions underlying these models, they tend to simplify reality (Belgacem & Hellara, 2011, Yadav, Sudhakar & Kumar, 2016).

While the linear models are commonly used tools, machine learning techniques offer potential alternatives to predicting mutual fund performance. Machine learning techniques offer modelling advantage as, among others, do not make assumptions about the underlying data and are able to capture nonlinearities associated with the data. Neural networks are commonly used machine learning techniques and have also found their way into the economic and financial environments (Amoako & Diawuo , 2013; Chiang, Urban & Baldridge, 1996; Indro et al., 1999; Stokes & Abou-

Zaid (2012)). However, the techniques have not yet been researched extensively and applied in forecasting mutual fund performance.

Chiang, Urban & Baldridge (1996) compared artificial neural networks (ANN), linear and nonlinear models in predicting net asset values (NAV) of mutual funds as measures of fund performance. The study used economic variables as inputs in predicting fund performance. In their study of the predictive ability of ANN, Indro et al. (1999) used fund-specific factors to predict fund performance and compared the results with linear models. The results of both studies show that ANN outperformed other models in predicting mutual fund performance.

However, one of the challenges with using ANN in forecasting is that it has overfitting problem and hence tend to yield inferior results when applied out-of-sample (Cao & Tay , 2001). Support Vector Regression (SVR), while not yet applied in forecasting fund performance, according to the researcher's knowledge, offers alternative option for improving forecasting performance as the prediction accuracy is determined by the level of error set and a cost parameter is used to penalise for overfitting. Therefore, depending on the user's objective, the predictive accuracy of the SVR can be improved by setting the level of error low.

Therefore, the objective of this study is to evaluate the forecasting ability of machine learning techniques and linear models in predicting mutual fund performance. The objective of the study will be achieved if the following research questions are answered:

- Do machine learning models provide better alternative to linear models in predicting fund performance?
- Are fund specific and macroeconomic factors able to explain variability in mutual fund performance?

The study is narrowed down to the South African context since to the best of the researcher's knowledge there is no study that was undertaken in South Africa to determine if machine learning techniques can predict mutual fund performance.

Since most of the studies on prediction of mutual fund performance use linear models, these models assume linearity between inputs and output variables and hence do not fully capture the dynamics underlying the input data. As such, the models fall short of explaining conflicting results in the literature on the fund performance. Therefore, this study proposes the use of machine learning techniques as alternatives in predicting mutual fund performance as these models do not make assumptions about the underlying input factors and have the ability to learn the underlying pattern by trial and error.

Furthermore, most of the studies on mutual fund performance have been on the impact of fund specific or macroeconomic factors, but not both. Most of these studies focus on developed markets such as the US and Europe. The availability of literature on emerging markets, especially Africa, is limited. However, given the increasing role that the Asian economies are playing on the global economy, due to their economic successes and developments in their financial markets, research that focuses on these markets has started to attract interest from several researchers (Premaratne & Mensah, 2014).

Despite having been studied extensively, the impact of fund specific factors on fund performance generated conflicting results (Chen et al. (2004); Haslem, Baker & Smith, 2008; Mahar, Mangnejo & Brohi, 2021; Nazir & Nawaz, 2010). While also yielding contradicting results, studies by various researchers have confirmed that macroeconomic factors have impact on the performance of mutual fund (Gyimah, Addai, & Asamoah, 2021; Li et al., 2021; Yadav, Sudhakar, & Kumar, 2016).

Less research has been conducted using both factors for prediction of fund performance. Apau, Moores-Pitt & Muzindutsi (2021) investigated the impact of fund specific factors and size of the economy on the performance of the mutual fund under bearish and bullish conditions. Gusni, Silviana & Faisal Hamdani (2018) investigated the impact of the fund specific factors and inflation on the performance of equity mutual funds in Indonesia.

This study will assist fund managers by providing a tool that enables a forward view of how the mutual fund performance is likely to be impacted given the anticipated economic conditions and profile of the mutual fund. In addition, the study will equip managers with the necessary skills to pick securities in the construction of a mutual fund.

2. Literature Review

In order to make informed decisions on how to allocate funds among various competing mutual funds, a manager needs a tool that can assist in the selection of funds. The selection decision will be based on among others, how the fund performed in the past and how it is likely to perform in the future. Past performance can be easily determined from the funds' past available financial information; however, how the fund is likely to perform in the future can only be predicted based on a number of factors such economic variables, and fund factors.

In forecasting performance of the fund, the manager is faced with the number of models to choose from. The selected model must give the manager confidence in its usage, as determined by its predictive accuracy. While the comparison of forecasting ability of statistical and machine learning methods has been undertaken by several researchers (Ahmed et al., 2010; Makridakis, Spiliots & Assimakopoulos, 2018), the area of mutual funds has not attracted a significant number of researchers yet.

Based on the above, the literature will focus on the following areas: (a) examination of the impact of macroeconomic factors on the performance of mutual fund, (b) impact of fund specific factors on mutual fund performance, and (c) prediction of mutual fund performance.

2.1 Impact of macroeconomic variables

Given that the performance of the mutual fund depends on the performance of the underlying financial instruments such as equities, that the fund invested in, it may be argued that events that have impact on the underlying instrument have an impact on the fund as well. Furthermore, as the financial performance of the company is impacted by local and global economic conditions (Singh, Mehta & Varsha, 2011), among others, and has a direct impact on the share price, it may be inferred that the economic factors are likely to have an impact on the financial performance of an equity fund as well. This was confirmed by a number of studies that focussed on the impact of macroeconomic factors on the fund performance (Gyimah, Addai, & Asamoah, 2021; Li et al., 2021; Panigrahi, Karwa & Joshi, 2020; Yadav, Sudhakar, & Kumar, 2016).

Changes in interest rates have an impact on the value of equities since an increase in interest rates leads to an increase in capital flows into the bond market and vice versa. Therefore, following an increase in interest rate, portfolio managers are likely to adjust their portfolio by selling off their equity holdings and invest in the bond market in an attempt to improve their portfolio return. An increase in the sale of equities will put downward pressure on the equity prices resulting in a reduction in the overall equity portfolio thus negatively impacting equity mutual funds. The study by Panigrahi, Karwa, & Joshi (2020) showed that interest rate has a negative impact on the performance of mutual funds.

Panigrahi, Karwa & Joshi (2020) analysed the impact of interest rate, inflation rate and exchange rate on the performance of four equity mutual funds in India for the period of five years, i.e., from 2015 to 2019. The study found that these economic factors had an impact on the mutual fund performance and accounted approximately 56% of the fund performance. The study also indicated, contrary to Li et al., that interest rate was the highest contributing factor to the mutual fund performance. While both studies focussed on the Indian environment, the results of Panigrahi, Karwa & Joshi (2020) contradicts the outcome of Yadav, Sudhakar & Kumar (2016) study where it was found that interest rate did not contribute to the mutual fund performance.

In their study, Gyimah, Addai & Asamoah (2021), examined the impact of macroeconomic factors on the mutual fund performance in Ghana and found that only the treasury bill rate and monetary policy rate have significant impact on fund performance in the short-run and the other factors impact the performance in the long run. The study also concluded that the treasury bill and monetary policy rates impact fund performance differently, i.e., the impact depends on the time period considered. In the short run, it was found that the treasury bill had a negative impact while the monetary policy had a positive impact on the performance. However, both rates had opposite impact in the long run.

Another study of the Ghanaian environment was undertaken by Li et al. (2021) and they concluded that macroeconomic factors have impact on the financial performance of the mutual fund in Ghana. The macroeconomic variables studied were interest rate, exchange rate, inflation, and gross domestic product (GDP) growth for the period 2008 to 2016. The study also showed that the exchange rate between Ghanaian Cedi and the US was the strongest economic factor on the performance of the mutual funds in Ghana.

Yadav, Sudhakar & Kumar (2016) used multiple regression technique to assess the impact of macroeconomic variables on the average monthly returns of eighty schemes in India for the period 2007 to 2013. The statistical technique was applied both on the average monthly returns for all funds included in the study and also at individual scheme level. The results of the study show that inflation rate and exchange rate have a negative relationship while oil prices and foreign exchange reserves show a significant positive relationship with the returns. Furthermore, the study showed that interest rate was not related to the fund performance.

2.2 Impact of fund specific factors

In addition to macroeconomic factors, several studies have found that fund specific factors such as fund size, fund age, past performance, management fees, and fund flow, among others, have an impact on the performance of the mutual fund.

In a more recent study, Mahar, Mangnejo & Brohi (2021) undertook a review of the fund attributes that have an impact on the performance of the mutual fund. The analysis was based on the results of the various studies that existed at the time of review. The study focused on how fund size, expenses, fund turnover, management effectiveness and style, liquidity, persistence in performance and fund longevity impact the fund performance. The study showed that for all attributes that were investigated, previous studies yielded conflicting results on their impact. Furthermore, it was found that some of the attributes do not have direct impact on fund performance but indirectly through others that they are related with. For example, it was found that fund size does not have a direct impact on the fund performance, but through its influence on the fund management expenses.

Since expenses and fees are levied on the portfolio value, they therefore reduce the value of the mutual fund. As the fees reduces the value of portfolio, it may be assumed that fees have a negative impact on the performance of the mutual fund. This is because the performance of the fund is determined by the income received, for example dividends distributions from the equity investments, and capital appreciation during the period under review. Therefore, any cash outflow from the portfolio will result in reduced return on investment. In their investigation of the impact of fees on mutual fund performance, Mansor, Bhatti & Ariff (2015) found that the fees have a negative impact on the mutual fund performance.

The study was based on 106 equity funds divided equally between Islamic and common equity funds in Malaysia for the period 1990 to 2009. The study also showed that both types of funds were equally impacted by the fees charged. This was also confirmed by Ahmad, Sun & Khidmat (2017) where the study used Sortino ratio as one of the performance measures for Islamic and conventional mutual funds in Pakistan and the results showed that management fees had negative influence on the ratio. Babalos, Kostakis & Philippas (2009) also found that the fund performance is negatively impacted by its expenses.

In line with Mahar, Mangnejo & Brohi (2021), Bodie, Kane & Marcus (2018) indicate that average expense ratios of larger equity funds in the US tend to be lower than the smaller ones and hence the extent to which expenses and fees impact the fund performance depends on the size of the fund. In addition to the impact of fees on the fund performance, other studies have focused on the impact of the fund size. Chen et al. (2004) investigated the impact of fund size on the fund performance and found that the size of the fund has a negative impact on performance. The analysis was based on the US equity mutual funds for the period 1962 to 1999. The study also showed that the effect of fund size is significant for funds that invest heavily in small cap stocks than other categories and hence attributes liquidity to the resulting erosion of performance.

Apau, Moores-Pitt & Muzindutsi (2021) investigated the impact of fund flow, total net assets, fund age, fund’s portfolio risk, market risk, and size of the economy under different market conditions. The study used Markov regime-switching model to investigate how these factors impact the performance of thirty-three South African equity mutual funds under the bearish and bullish states of the market. The analysis was based on equity funds data for the period from 2006 to 2019. The results of the study showed that fund age, fund risk, and market risk have significant impact on the performance of mutual funds. Furthermore, these variables have more influence on fund performance when the market is under bearish conditions than under bullish conditions.

Dahlquist, Engstrom & Soderlind (2000) investigated the impact of fund attributes on the performance of equity, bond, and money market funds in Sweden. The study analysed the impact of total net assets, fund size, fund flow, administration fees, turnover and commission based on the sample period 1992 to 1997. The results of the study indicated that there is a negative relationship between the fees and the fund performance, meaning that funds that charge high fees tend to negatively impact the performance of the fund, and vice versa. In addition, the study showed that past fund performance and fund flows had a positive impact on the fund performance.

Gusni, Silviana & Faisal Hamdani (2018) investigated the impact of the manager’s ability to select the stocks for inclusion in the fund and at the appropriate time, fund size, and inflation on the performance of equity mutual funds in Indonesia. The study was based on nineteen equity funds sampled from the 2011 to 2015. The study concluded that the manager’s stock selection skill and inflation had a significant impact on the equity fund performance; however, it may be argued that the investigation did not include adequate number of independent variables to such support such conclusion.

In one of the few studies that investigated the factors that could be driving fund performance in emerging markets, Gottesman & Morey (2007) investigated whether fund performance in these markets is driven by factors that are different from those in the developed markets like the USA. The study was motivated by increased popularity of mutual funds in emerging markets and their impressive financial performance. Gottesman & Morey (2007) were of the view that the risk and regulatory environment in which emerging funds operate could be contributing to the difference in fund performance between the markets. The investigation did not focus on specific countries, but on the diversified emerging market funds on the Morningstar database.

Gottesman & Morey (2007) analysed three distinct samples from different periods, i.e., 1997, 2000 and 2003. Furthermore, they validated the results using three-year out-of-sample data for each of the in-sample data. In their study, Gottesman & Morey (2007) confined their analysis to the impact of expense ratios, portfolio turnover, manager tenure, recent past fund performance, fund size and Morningstar mutual fund ratings. The results of the study showed that expense ratio had significant and negative impact across more several sample period than any other factor. The other factors, with the exception of Morningstar mutual fund ratings, did not have significant impact on the performance Morningstar mutual fund ratings was not a good predictor of fund performance across all sample periods.

2.3 Prediction of mutual fund performance

Since the linear relationship between input and output variables assumed by linear models does not hold in practice, these models have resulted in conflicting results on the performance of mutual funds relative to passive portfolios. Despite their limitations, linear models are widely used in assessing and predicting mutual fund performance. In investigating the ability of the Morningstar ratings to predict emerging market performance, Gottesman & Morey (2007) used a linear model.

Belgacem & Hellara (2011) used multiple regression model and correlation analysis to investigate the relationship and ability of fund characteristics to predict equity mutual fund performance in Tunisia. In their study, Belgacem & Hellara (2011) used past performance, fund size, fund age, net asset value and management fees as independent variables in the model for the period 1999 to 2006. The study showed that historical fund performance, fund size, and fund growth had significant positive influence on the fund performance while management fees had a negative and significant impact on the performance. The impact of net asset value and fund flow were found to be positive but insignificant to explain the fund performance.

Elton, Gruber & Blake (1996) applied a four-index linear model in investigating whether past fund performance can predict future performance. The results of the study indicate that past performance does provide a reliable information on the prediction of future fund performance.

3. Methodology

3.1 Data

In line with Gusni, Silviana, & Faisal Hamdani (2018), this research used purposive sampling technique in selecting mutual funds to be studied. Furthermore, consistent with the study by Apau, Moores-Pitt & Muzindutsi (2021), a fund must have at least five years of data before being considered for inclusion.

The following equity funds were chosen for the purpose of this study:

Fund Name
36One BCI SA Equity Fund (36One)
Absa Prime Equity Fund (ABSA)
Allan Gray SA Equity Fund (Allan Gray)
Aylett Equity Prescient Fund (Aylett)
Coronation SA Equity Fund (Coronation)
Fairtree Equity Prescient Fund (Fairtree)
Foord Equity fund (Foord)
Nedgroup Investments Rainmaker Fund (Nedgroup)
Old Mutual Investors' Fund (Old Mutual

Table 1: Selected Equity Mutual Funds

For fund specific factors, monthly South African equity mutual fund data on the fund size, fund age, and year-to-date fund performance for the period 01 January 2018 to 31 October 2022 for the nine equity funds was obtained from Bloomberg, and Fund Factsheets. Following Belgacem & Hellara (2011), Xiao, J., Mingsheng L., & Jing, S. (2014) and others, fund flow was determined as follows:

$$Flow_{it} = (TNA_{it} - TNA_{it-1}(1 + r_{it}))/TNA_{it-1}$$

where

$$R_{it} = \left(\ln \frac{P_{it}}{P_{it-1}}\right)$$

where R_{it} represent changes in the price of fund i between months $t-1$ and t, P_{it} is the price of fund i at time t, P_{it-1} is the price of fund i in the previous period $(t-1)$, and ln is the natural logarithm.

Thus, fund flow represents the growth of the fund that is attributable to additional money invested in the fund, not return earned by the fund on invested assets. Gross Domestic Product, Exchange rate between ZAR and USD and prime interest rate data were obtained from the South African Reserve Bank (SARB) website. The exchange rate between ZAR and USD is measured as the number of South African Rands needed to be exchanged for each US Dollar.

Data was split into two samples, i.e., one covering the period 01 January 2018 to 30 April 2022 to be used to analyse the relationship between the independent variables and the fund performance and to develop the prediction model. The other data spanning from 01 May 2022 to 31 October 2022 will be used for out-of-sampling testing, i.e., to test the predictive ability of the model outside of the data used to develop it. Out-of-sampling testing provides a certain level of assurance as the statistical models tend to be data dependent and hence may perform poorly when applied under different conditions (Jones & Mo, 2021).

3.2 Models

Multivariate linear regression models have been applied extensively in measuring mutual fund performance for a number of studies and given by the following equation:

$$YTD_{it} = \beta_0 + \beta_1 TNA_{it} + \beta_2 Flow_{it} + \beta_3 Age_{it} + \beta_4 FX_{mt} + \beta_5 Prime_{mt} + \beta_6 GDP_{mt} + \varepsilon_{it}$$

where YTD_{it} is the year-to-date performance of fund i at time t, TNA_{it} represents the natural logarithm of fund total assets of the i^{th} fund at month t, $Flow_{it}$ is the additional cash flow injected into fund i during month t, Age_{it} is the natural logarithm of the age of the i^{th} fund since its launch until time t, FX_{mt} is the exchange rate between ZAR and USD at time t, $Prime_{mt}$ is the prime interest rate at time t, GDP_{mt}

is the gross domestic product at time t, and ε_{it} is the error term associated with the model.

In order to test the ability of the independent variables to explain the variability in the dependent variable, the study uses the coefficient of determination, R^2, given below (Kutner, Nachtsheim & Neter, 2008):

$$R^2 = \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO}$$

where:

SSR refers to the sum of squared differences between the mean and predicted value of the response variable

SSE is the sum of the squared prediction errors

$SSTO$ is the total sum of squares.

SSR measures an amount of improvement in the response variable as a result of using independent variables in the regression model, SSE measures variation in the response variable not accounted for by the regression model and $SSTO$ measures uncertainty in the response variable when predictor variables are not employed.

n is the number of observations

p is the number of parameters

The coefficient of determination varies between zero and one and the larger the R^2, the greater the degree of linear association between the response and predictor variables. Hence, for the purpose of prediction, a high R^2 is recommended since it means the independent variables provides better prediction of the response variable. However, R^2 is not without limitations since it does not, among others, take into account the sample size and the number of predictor variables in the regression equation. The addition of predictor variables in the regression equation results in an increase the value of R^2 and this might be misleading since it might lead to the inclusion of independent variables that have little explanatory power in the equation.

As a way of resolving this problem, adjusted coefficient of determination (adjusted R^2) is used as a supplementary measure to the R^2. With the addition of insignificant variable in the equation, adjusted R^2 may be able to account for this. This is useful in ensuring that insignificant independent variables are not included for prediction purpose.

After the model has been built, we will perform out of sampling testing (validation) on another sample to ensure that that the results are generalisable and appropriate for our study.

In order to improve our prediction, Support Vector Machines (SVM) were also fitted to the input data. SVM are machine learning algorithms used for classification purposes (Hastie, Tibshirani and Friedman (2009)). However, SVM may be adapted and used for regression where the dependent variable is numerical instead of categorical where the technique is used for classifying the variables. When used for regression, SVM is referred to as the support vector regression (SVR) and the forecasts are derived using the following equation (Kim, 2003):

$$YTD_{it} = w_0 + w_1 TNA_{it} + w_2 Flow_{it} + w_3 Age_{it} + w_4 FX_{mt} + w_5 Prime_{mt} + w_6 GDP_{mt}$$

However, unlike the linear models, the weights w_0, w_1, w_2, w_3, w_4, w_5 and w_6 are estimated by the appropriate machine learning algorithm.

3.3 Performance Evaluation Metrics

The study will be using the Root Mean Squared Error (RMSE) to rank the predictive ability of the linear and support vector models. The RMSE is calculated as the square root of the average distance between the predicted and actual values (Rouah & Vainberg, 2007) and is given by

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{n}}$$

where *n* is the number of observations in the validations sample, y_i is the actual fund performance at time *i* and $\hat{y_i}$ is the forecast performance at time *i*. The RMSE will be determined for each model and for each fund and applied to the out-of-sample dataset. The model with the smallest RMSE value will be considered to provide a better fit.

4. Results and Discussion

4.1 Descriptive statistics

Table 2 summarises descriptive statistics for the year-to-date (YTD) performance of the nine equity funds for the sampled data.

Fund	**Minimum**	**Maximum**	**Average**	**Skewness**	**Kurtosis**
36One	-21,40%	33,00%	4,90%	0,25	-0,15
ABSA	-22,70%	27,00%	4,10%	-0,06	-0,71
Allan Gray	-30,90%	28,70%	0,80%	0,02	0,18
Aylett	-24,70%	47,70%	5,90%	0,81	1,21
Coronation	-17,90%	29,50%	2,90%	0,35	-0,38
Fairtree	-31,40%	19,80%	4,10%	-0,86	1,56
Foord	-23,50%	24,90%	0,40%	0,27	-0,22
Nedgroup	-26,30%	23,60%	-0,60%	0,02	0,05
Old Mutual	-30,90%	32,00%	1,10%	0,02	-0,31

Table 2: Summary statistics of fund performance

The YTD fund performance a widely distributed, varying from a minimum of -31,4% to a maximum of 47,7%. Most of the funds are positively skewed, indicating that a distribution with a long tail to the right will be suitable for describing fund performance. The nonnormality of the fund performance is also confirmed by the kurtosis values of all sampled equity funds, i.e., all values are below three.

4.2 Correlation Analysis

Before we estimate the models for each fund, it is important to examine the correlation between predictor variables and between predictor variables and the response variable. Likely predictor variables are those that have significant correlation with the YTD variable. Determining whether an independent variable is significant was based on their *p*-values as obtained from the correlation matrices found in the appendix. From the correlation matrices, the following were observed with respect to each fund.

For 36One, YTD is positively correlated with TNA, Age and GDP and negatively correlated with Prime. These correlations are significant at the 1% level. However, Age is highly correlated with Prime and GDP, implying that there is a possibility of collinearity among these variables. Correlation between Prime and GDP, i.e., -0,54, is not so high to imply collinearity. Therefore, in order to avoid the problem associated with multicollinearity, Age may be left out and TNA, GDP and Prime considered as suitable predictor variables for YTD.

YTD for ABSA Prime is positively correlated with Age and GDP and negatively correlated with FX. Furthermore, the former independent variables are statistically significant at 1% level while the latter independent variable is significant at 10% level. Correlation coefficient between Age and GDP is high enough to suggest collinearity.

Allan Gray has YTD that is significantly correlated with TNA, Age and GDP at 1% level and 5% level with FX. In addition, YTD is positively correlated with TNA, Age and GDP and negatively correlated with FX. The high correlation between YTD and TNA indicates that the fund performance is significantly influenced by the fund size. We find significant correlations between TNA and GDP (correlation coefficient is 0.77) and between Age and GDP (correlation coefficient is 0.80). As these coefficients are high, there is a risk that there is multicollinearity problem.

With the exception of Flow, other independent variables have significant correlation with Aylett YTD. TNA, Age and GDP correlations with YTD are significant at the 1% level while FX and Prime are statistically significant at 10% level. Correlations between independent variables are very high, suggesting the possibility of collinearity among predictor variables.

For Coronation, Age, Prime and GDP have statistically significant correlations with YTD at 1% level. YTD correlations with TNA and FX are significant at 5% level. However, Age is highly correlated with Prime and GDP, implying that there is a possibility of collinearity between the variables. Inclusion of these highly correlated variables in the prediction model has the potential to negatively impact the prediction accuracy of the model as they influence each other.

Regarding Fairtree, TNA, Age, Prime and GDP have significant correlations with YTD at 1% level and Flow has a statistically significant correlation with YTD at 5% level. Furthermore, YTD is positively correlated with TNA, Age and GDP and negatively correlated with Flow and Prime. Correlations between TNA and Prime as well as TNA and GDP are very high, with coefficients of -0.84 and 0.83, respectively. Furthermore, Age is significantly correlated with both Prime and GDP. Simultaneous inclusion of these highly correlated variables in the prediction of fund performance may distort the prediction as they are likely to influence each other.

Age and GDP have statistically significant correlation with YTD of Foord at 1% level and Prime is significantly correlated with YTD at 5% level. YTD has a positive correlation with Age and GDP and negatively correlated with Prime. However, Age is highly correlated with both Prime and GDP, implying that there might be a presence of multicollinearity.

Age and FX are significantly correlated with YTD of Nedgroup at 5% level while GDP is significantly correlated at 1% level. Age is highly correlated with GDP (correlation coefficient is 0.82), suggesting the possibility of multicollinearity presence.

For Old Mutual, TNA, Age and GDP are significantly correlated with YTD at 1% level while FX is significantly correlated at 5% level. Fund Age is highly correlated with both Prime and GDP, with correlation coefficients of -0.86 and 0.82, respectively. The high correlation coefficients between these independent variables suggest that there might be collinearity problem.

4.3 Regression results

Table 3 presents a summary of multiple linear regression results for each fund. The first row of each fund reports estimated regression coefficients and the second row reports the *p*-values for each independent variable.

Fund name	Intercept	TNA	Flow	Age	FX	Prime	GDP
36One	10.1019	0.1515**	-0.2174	0.6881***	−0.0460***	2.2023	-0.6134
	(0.3436)	(0.0722)	(0.3645)	(0.0015)	(0.0042)	(0.2094)	(0.1369)
ABSA	-13.8768	0.0543	-0.300	2.2349***	−0.0472***	4.0580**	-0.2229
	(0.0888·)	(0.6624)	(0.3643)	(0.0059)	(0.0045)	(0.0410)	(0.6169)
Allan Gray	-2.8982	0.5156***	-0.3696	0.1355	−0.0291**	-0.7953	-0.3013
	(0.7429)	(0.0000)	(0.1868)	(0.3445)	(0.0201)	(0.5442)	(0.3953)
Aylett	-10.0180	0.7759***	-0.3624	−6.3175***	-0.0223	−12.5096***	1.6575***
	(0.3373)	(0.0004)	(0.1816)	(0.0024)	(0.1923)	(0.0028)	(0.0047)
Coronation	−27.84***	-0.0051	0.0001	-0.1387	46.25	-3,181	0.9756***
	(0.0037)	(0.8551)	(0.9941)	(0.4749)	(0.0761·)	(0.2428)	(0.0060)
Fairtree	-1.6813	0.7652***	-0.5340	−1.2966**	-0.0103	1.2937	-0.1945
	(0.8535)	(0.0000)	(0.1428)	(0.0376)	(0.4878)	(0.3822)	(0.6032)
Foord	−32.4443***	0.3609***	-0.4283	2.9153***	-0.0173	1.4983	-0.0356
	(0.0009)	(0.0051)	(0.1561)	(0.0006)	(0.2649)	(0.3706)	(0.9257)
Nedgroup	−50.5318***	0.8314***	-0.7648	2.7773***	-0.0129	-2.0520	0.2428
	(0.0000)	(0.0001)	(0.4953)	(0.0002)	(0.3603)	(0.2952)	(0.5180)
Old Mutual	−27.9398***	0.6109***	-1.0699	0.7713	-0.0255	0.6127	0.2654
	(0.0049)	(0.0012)	(0.3723)	(0.1670)	(0.1581)	(0.7772)	(0.5402)

Table 3: Linear regression results

Note: *, ** and *** denote 10%, 5% and 1% levels of statistical significance respectively.

Table 4 shows the R-Square values of each fund.

Fund name	R-Square
36One	0.5903
ABSA	0.5284
Allan Gray	0.7998
Aylett	0.6555
Coronation	0.4167
Fairtree	0.6682
Foord	0.6375
Nedgroup	0.6376
Old Mutual	0.7203

Table 4: Funds R-Square values

Table 5 presents a summary of support vector regression weights for the independent variables for each fund.

Fund name	Intercept	TNA	Flow	Age	FX	Prime	GDP
36One	0.2086	5.3797	1.6843	3.3894	-3.3864	-2.0365	1.8640
ABSA	0.0208	3.0110	-4.6083	1.0095	-5.6789	1.0323	2.2992
Allan Gray	0.4442	9.1585	-0.9124	1.2450	-5.6855	-0.5816	2.0752
Aylett	0.3924	2.7419	-04509	0.1910	-6.1168	-0.8757	1.9852
Coronation	0.1825	3.0061	-4.2374	2.5506	0.2925	-1.4679	2.0111
Fairtree	0.4082	4.73	-4.8169	1.4883	-4.8145	-0.7306	0.9386
Foord	0.2060	0.4544	-4.3843	3.6339	-4.9316	-2.6126	4.0296
Nedgroup	0.1864	3.0023	-2.8979	2.1130	-5.9346	-1.1925	2.7667
Old Mutual	0.5485	9.0051	-1.7863	1.5645	-5.2531	0.1563	2.4989

Table 5: Support Vector Regression results

Table 6 shows the RMSE for models fitted to each fund.

Fund	Linear Regression	Support Vector Regression
36One	0,1606	0,0291
ABSA	0,2101	0,0447
Allan Gray	0,1149	0,0488
Aylett	0,1735	0,0461
Coronation	783,4037	0,0465
Fairtree	0,0646	0,0170
Foord	0,2062	0,0313
NedGroup	0,1239	0,0464
Old Mutual	0,1964	0,0700

Table 6: Root Mean Square Errors (RMSE)

Tables 3 and 5 indicate that the fund size, i.e., TNA variable, has contrary to Chen et al. (2004) finding, a positive relationship with the fund performance. However, the finding is consistent with the results obtained by Belgacem, and Hellara (2011). Therefore, large funds tend to perform better than the smaller ones. This may be attributable to the fact that large fund managers are able to diversify across a number of equities in different sectors of the economy than small funds can.

With the exception of Coronation and 36One, the results of both linear and support vector regression models indicate that there is an inverse relationship between the fund performance and fund flow. This implies that funds that received large cash inflows tend to underperform those that received less. The study by Apau, Moores-Pitt & Muzindutsi (2021) also shows that fund flow and fund performance are negatively related. According to Apau, Moores-Pitt & Muzindutsi (2021), this is more pronounced under the bearish state of the market.

Both linear and support vector regression models indicate that in line with Belgacem, and Hellara (2011), with the exception of Aylett, Coronation and Fairtree, the relationship between the fund age, i.e., Age and performance is positive. This may be as a result of potential investors being attracted by solid performance achieved by the fund over a period of time. Furthermore, potential investors may have confidence in placing their funds with experienced managers than newly formed funds.

The performance for equity funds studied, except for Coronation, seem to be moving in opposite direction to changes in the level of ZAR/USD exchange rate (FX). This implies that, consistent with the findings by Li et al. (2021), when ZAR depreciates against the USD, equity funds performance tend to depreciate as well. This finding is contrary to the study by Yadav, Sudhakar & Kumar (2016), where it was found that the exchange rate had a negative impact on fund performance.

Slope coefficients for linear model does not provide evidence of the relationship between the fund performance and prime interest rate. However, SVR shows that, with the exception of ABSA and Old Mutual, there is a negative relationship between the fund performance and prime interest rate. The SVR results are consistent with the results of the studies by Panigrahi, Karwa, & Joshi (2020) and Yadav, Sudhakar & Kumar (2016) where it was found that interest rate has a negative impact on equity mutual fund performance.

Linear regression model yields contradicting results on the relationship between the GDP and fund performance. however, in line with the findings by Li et al. (2021), SVR shows a positive relationship between GDP and the fund performance.

With R-Square values above 60% for six out of nine funds, we may conclude that, using the linear regression model, the predictor variables are able to explain a significant portion of fund performance variability. When applied out of sample, SVR models outperform linear regression models across all equity funds studied. This is evidenced by lower RMSE results for SVR across all funds. Based on this we may assume that SVR models provide better estimates for fund performance than the linear models.

5. Conclusions and recommendations

5.1 Conclusions

This study evaluates the predictive ability of regression models in predicting equity mutual fund performance. The study is applied to a sample of nine equity mutual funds in South Africa using monthly data for the period 01 January 2018 until 31 October 2022. The sample of funds selected invest predominantly in the shares listed on the Johannesburg Securities Exchange (JSE).

The ability of fund specific and macroeconomic factors to explain variability in equity fund performance was examined using multiple linear regression and support vector regression models. The models were compared on their ability to predict fund performance. Comparison was based on the performance of the models when applied to the out-of-sample data and it was found that support vector regression model is superior to linear model in predicting fund performance.

While fund-specific and macroeconomic factors impact different funds in different ways, it was found that these factors have impact on the performance of the equity funds and hence may be used as inputs in predicting fund performance. For fund specific factors, the results of the study show that total fund assets and fund age have a positive relationship with fund performance while fund cash inflows have a negative impact on performance. The exchange rate between ZAR and USD is negatively correlated with fund performance whereas prime rate and GDP yield conflicting results.

The study contributes to the literature by providing fund managers with alternative tools in predicting future fund performance in order to make informed investments decisions.

5.2 Recommendations

There are a number of limitations and recommendations associated with this study. Firstly, while fund-specific and macroeconomic factors selected for this study were also used by other researchers, omission of other fund-specific and economic factors might have had implications on the outcome of the investigation.

As the study is based on a sample of South African-based funds, the investigation may be extended to cover other types of mutual funds and other jurisdictions. In addition, the sample size may be increased to cover more equity funds and the sample period extended to provide a view of whether the impact of the predictor variables on the performance will change as a result of these factors.

While equity funds included in this study were randomly selected, majority of these funds follow growth investment style. Given that growth equity funds invest in growth stocks and these stocks are perceived to be riskier and tend to be highly responsive to changes in economic conditions than other stocks, the outcome of this study may not hold when applied to equity funds that follow other investment styles (Bodie, Kane & Marcus, 2018). Hence, it would be interesting, if in the future research, investigation is done after segmenting funds into different investment styles.

Finally, it would be interesting to see the outcomes of these models under changing economic environments as the underlying assets are impacted differently by changes in the macroeconomic factors.

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Appendix

36One

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	0.49	0.09	0.55	-0.05	-0.38	0.61
		(0.0002)	(0.5480)	(0.0000)	(0.7193)	(0.0051)	(0.0000)
TNA	0.49	1.00	0.24	0.09	-0.47	0.05	0.40
	(0.0002)		(0.0858)	(0.5311)	(0.0004)	(0.7332)	(0.0034)
Flow	0.09	0.24	1.00	0.12	-0.06	-0.20	0.07
	(0.5480)	(0.0858)		(0.4122)	(0.6571)	(0.1594)	(0.6036)
Age	0.55	0.09	0.12	1.00	0.60	-0.85	0.80
	(0.0000)	(0.5311)	(0.4122)		(0.0000)	(0.0000)	(0.0000)
FX	-0.05	-0.47	-0.06	0.60	1.00	-0.55	0.17
	(0.7193)	(0.0004)	(0.6571)	(0.0000)		(0.0000)	(0.2154)
Prime	-0.38	0.05	-0.20	-0.85	-0.55	1.00	-0.54
	(0.0051)	(0.7332)	(0.1594)	(0.0000)	(0.0000)		(0.0000)
GDP	0.61	0.40	0.07	0.80	0.17	-0.54	1.00
	(0.0000)	(0.0034)	(0.6036)	(0.0000)	(0.2154)	(0.0000)	

ABSA Prime

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	0.05	-0.12	0.39	-0.23	-0.16	0.56
		(0.7040)	(0.4076)	(0.0045)	(0.0963)	(0.2465)	(0.0000)
TNA	0.05	1.00	0.04	-0.67	-0.82	0.64	-0.33
	(0.7040)		(0.7850)	(0.0000)	(0.0000)	(0.0000)	(0.0165)
Flow	-0.12	0.04	1.00	0.08	0.07	-0.15	0.02
	(0.4076)	(0.7850)		(0.5964)	(0.6192)	(0.2851)	(0.9139)
Age	0.39	-0.67	0.08	1.00	0.57	-0.86	0.82
	(0.0045)	(0.0000)	(0.5964)		(0.0000)	(0.0000)	(0.0000)
FX	-0.23	-0.82	0.07	0.57	1.00	-0.55	0.17
	(0.0963)	(0.0000)	(0.6192)	(0.0000)		(0.0000)	(0.2154)
Prime	-0.16	0.64	-0.15	-0.86	-0.55	1.00	-0.54
	(0.2465)	(0.0000)	(0.2851)	(0.0000)	(0.0000)		(0.0000)
GDP	0.56	-0.33	0.02	0.82	0.17	-0.54	1.00
	(0.0000)	(0.0165)	(0.9139)	(0.0000)	(0.2154)	(0.0000)	

Allan Gray

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	0.87	-0.01	0.37	-0.33	-0.22	0.63
		(0.0000)	(0.9567)	(0.0071)	(0.0169)	(0.1159)	(0.0000)
TNA	0.87	1.00	0.10	0.45	-0.26	-0.21	0.77
	(0.0000)		(0.4969)	(0.0009)	(0.0622)	(0.1367)	(0.0000)
Flow	-0.01	0.10	1.00	0.01	-0.13	-0.01	0.19
	(0.9567)	(0.4969)		(0.9471)	(0.3473)	(0.9399)	(0.1725)
Age	0.37	0.45	0.01	1.00	0.61	-0.85	0.80
	(0.0071)	(0.0009)	(0.9471)		(0.0000)	(0.0000)	(0.0000)
FX	-0.33	-0.26	-0.13	0.61	1.00	-0.55	0.17
	(0.0169)	(0.0622)	(0.3473)	(0.0000)		(0.0000)	(0.2154)
Prime	-0.22	-0.21	-0.01	-0.85	-0.55	1.00	-0.54
	(0.1159)	(0.1367)	(0.9399)	(0.0000)	(0.0000)		(0.0000)
GDP	0.63	0.77	0.19	0.80	0.17	-0.54	1.00
	(0.0000)	(0.0000)	(0.1725)	(0.0000)	(0.2154)	(0.0000)	

Aylett

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	0.49	-0.11	0.41	-0.25	-0.26	0.61
		(0.0002)	(0.4274)	(0.0025)	(0.0725)	(0.0653)	(0.0000)
TNA	0.49	1.00	-0.21	0.97	0.50	-0.74	-.84
	(0.0002)		(0.1327)	(0.0000)	(0.0002)	(0.0000)	(0.0000)
Flow	-0.11	-0.21	1.00	-0.26	-0.12	0.23	-0.18
	(0.4274)	(0.1327)		(0.0658)	(0.4044)	(0.0982)	(0.2016)
Age	0.41	0.97	-0.26	1.00	0.57	-0.86	0.82
	(0.0025)	(0.0000)	(0.0658)		(0.0000)	(0.0000)	(0.0000)
FX	-0.25	0.50	-0.12	0.57	1.00	-0.55	0.17
	(0.0725)	(0.0002)	(0.4044)	(0.0000)		(0.0000)	(0.2154)
Prime	-0.26	-0.74	0.23	-0.86	-0.55	1.00	-0.54
	(0.0653)	(0.0000)	(0.0982)	(0.0000)	(0.0000)		(0.0000)
GDP	0.61	0.84	-0.18	0.82	0.17	-0.54	1.00
	(0.0000)	(0.0000)	(0.2016)	(0.0000)	(0.2154)	(0.0000)	

Coronation

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	0.35	-0.13	0.51	0.30	-0.37	0.61
		(0.0104)	(0.3507)	(0.0001)	(0.0306)	(0.0068)	(0.0000)
TNA	0.35	1.00	-0.15	0.73	0.29	-0.48	0.60
	(0.0104)		(0.2877)	(0.0000)	(0.0395)	(0.0003)	(0.0000)
Flow	-0.13	-0.15	1.00	-0.30	-0.17	0.17	-0.21
	(0.3507)	(0.2877)		(0.0282)	(0.2372)	(0.2194)	(0.1341)
Age	0.51	0.73	-0.30	1.00	0.21	-0.85	0.80
	(0.0001)	(0.0000)	(0.0282)		(0.1298)	(0.0000)	(0.0000)
FX	0.30	0.29	-0.17	0.21	1.00	0.17	0.27
	(0.0306)	(0.0395)	(0.2372)	(0.1298)		(0.2307)	(0.0520)
Prime	-0.37	-0.48	0.17	-0.85	0.17	1.00	-0.54
	(0.0068)	(0.0003)	(0.2194)	(0.0000)	(0.2307)		(0.0000)
GDP	0.61	0.60	-0.21	0.80	0.27	-0.54	1.00
	(0.0000)	(0.0000)	(0.1341)	(0.0000)	(0.0520)	(0.0000)	

Fairtree

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	0.60	-0.34	0.49	-0.10	-0.37	0.51
		(0.0000)	(0.0146)	(0.0002)	(0.4930)	(0.0071)	(0.0001)
TNA	0.60	1.00	-0.32	0.98	0.47	-0.84	0.83
	(0.0000)		(0.0207)	(0.0000)	(0.0005)	(0.0000)	(0.0000)
Flow	-0.34	-0.32	1.00	-0.32	-0.08	0.26	-0.20
	(0.0146)	(0.0207)		(0.0210)	(0.5867)	(0.0639)	(0.1615)
Age	0.49	0.98	-0.32	1.00	0.59	-0.86	0.81
	(0.0002)	(0.0000)	(0.0210)		(0.0000)	(0.0000)	(0.0000)
FX	-0.10	0.47	-0.08	0.59	1.00	-0.55	0.17
	(0.4930)	(0.0005)	(0.5867)	(0.0000)		(0.0000)	(0.2154)
Prime	-0.37	-0.84	0.26	-0.86	-0.55	1.00	-0.54
	(0.0071)	(0.0000)	(0.0639)	(0.0000)	(0.0000)		(0.0000)
GDP	0.51	0.83	-0.20	0.81	0.17	-0.54	1.00
	(0.0001)	(0.0000)	(0.1615)	(0.0000)	(0.2154)	(0.0000)	

Foord

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	-0.20	-0.13	0.45	-0.22	-0.28	0.61
		(0.1647)	(0.3632)	(0.0007)	(0.1212)	(0.0463)	(0.0000)
TNA	-0.20	1.00	-0.06	-0.93	-0.77	0.83	-0.65
	(0.1647)		(0.6896)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Flow	-0.13	-0.06	1.00	0.06	0.09	-0.14	0.03
	(0.3632)	(0.6896)		(0.6517)	(0.5174)	(0.3367)	(0.8350)
Age	0.45	-0.93	0.06	1.00	0.57	-0.86	0.82
	(0.0007)	(0.0000)	(0.6517)		(0.0000)	(0.0000)	(0.0000)
FX	-0.22	-0.77	0.09	0.57	1.00	-0.55	0.17
	(0.1212)	(0.0000)	(0.5174)	(0.0000)		(0.0000)	(0.2154)
Prime	-0.28	0.83	-0.14	-0.86	-0.55	1.00	-0.54
	(0.0463)	(0.0000)	(0.3367)	(0.0000)	(0.0000)		(0.0000)
GDP	0.61	-0.65	0.03	0.82	0.17	-0.54	1.00
	(0.0000)	(0.0000)	(0.8350)	(0.0000)	(0.2154)	(0.0000)	

Nedgroup Investments

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	-0.08	-0.02	0.33	-0.31	-0.17	0.49
		(0.5804)	(0.8718)	(0.0183)	(0.0257)	(0.2331)	(0.0002)
TNA	-0.08	1.00	0.33	-0.94	-0.71	0.89	-0.69
	(0.5804)		(0.0167)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Flow	-0.02	0.33	1.00	-0.27	-0.28	0.37	-0.18
	(0.8718)	(0.0167)		(0.0503)	(0.0449)	(0.0071)	(0.2057)
Age	0.33	-0.94	-0.27	1.00	0.57	-0.86	0.82
	(0.0183)	(0.0000)	(0.0503)		(0.0000)	(0.0000)	(0.0000)
FX	-0.31	-0.71	-0.28	0.57	1.00	-0.55	0.17
	(0.0257)	(0.0000)	(0.0449)	(0.0000)		(0.0000)	(0.2154)
Prime	-0.17	0.89	0.37	-0.86	-0.55	1.00	-0.54
	(0.2331)	(0.0000)	(0.0071)	(0.0000)	(0.0000)		(0.2154)
GDP	0.49	-0.69	-0.18	0.82	0.17	-0.54	1.00
	(0.0002)	(0.0000)	(0.2057)	(0.0000)	(0.2154)	(0.0000)	

Old Mutual

	YTD	TNA	Flow	Age	FX	Prime	GDP
YTD	1.00	0.67	-0.17	0.37	-0.32	-0.15	0.62
		(0.0000)	(0.2366)	(0.0062)	(0.0188)	(0.2768)	(0.0000)
TNA	0.67	1.00	-0.11	-0.16	-0.70	0.38	0.23
	(0.0000)		(0.4381)	(0.2559)	(0.0000)	(0.0061)	(0.1085)
Flow	-0.17	-0.11	1.00	-0.03	0.11	0.12	0.02
	(0.2366)	(0.4381)		(0.8245)	(0.4468)	(0.4075)	(0.9159)
Age	0.37	-0.16	-0.03	1.00	0.57	-0.86	0.82
	(0.0062)	(0.2559)	(0.8245)		(0.0000)	(0.0000)	(0.0000)
FX	-0.32	-0.70	0.11	0.57	1.00	-0.55	0.17
	(0.0188)	(0.0000)	(0.4468)	(0.0000)		(0.0000)	(0.2154)
Prime	-0.15	0.38	0.12	-0.86	-0.55	1.00	-0.54
	(0.2768)	(0.0061)	(0.4075)	(0.0000)	(0.0000)		(0.0000)
GDP	0.62	0.23	0.02	0.82	0.17	-0.54	1.00
	(0.0000)	(0.1085)	(0.9159)	(0.0000)	(0.2154)	(0.0000)	