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A Study on Relationship Between Aum (AUM) of Indian Mutual Funds and Macroeconomic Variables: A Pandemic Period Study

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Abstract

COVID-19 has affected people physically, emotionally, behaviorally, and financially. People locked themselves for safety but unlocked their funds and assets to reduce losses. Society is transforming after the pandemic. Protectionism trumps reasonable investment decisions in financial markets because individuals want to save. Early financial theories ignored human behavior, but emotions now seem to drive investors' choices. Individual, demographic, geographical, regulatory, macroeconomic, and other variables affect investors' behavior. Systemic macroeconomic difficulties directly and profoundly affect investment choices. This research uses AUM(AUM) to analyze how macroeconomic factors affect investors' mutual fund sentiments during the COVID-19 pandemic. Negative news and investor behavior are the focus of this research.

Keywords: *Financial markets, COVID-19 macroeconomic variables, AUM(AUM), VECM, E-GARCH Model.*

Introduction

Financial literature classifies risks as systemic or non-systemic, with the former being the assimilation of macro-economic factors and the latter as the amalgamation of organization-specific factors. Investors must take these risks in various amounts when investing. Diversification eliminates un-systemic risks, but cautiousness cannot decrease systemic hazards, according to literature. Investors must understand the financial climate and its effects on various investment options.

In India, security market investment relies on gut feeling, herd behavior, or apparently professional advice, which is readily available yet unreliable and may lead to losses. To address this, financial markets created mutual funds, initially established by Unit Trust of India in 1964. Mutual funds allow clients to deposit their money with an asset management business, which invests it in well-diversified, professionally managed portfolios with minimal risk for target returns. This industry has grown steadily since its founding. India has 42 Asset Management Companies (AMCs) with an Average Asset Under Management of Rs. 32,42,537 crore (in April 2021). The mutual fund industry has also experienced the impact of pandemic.

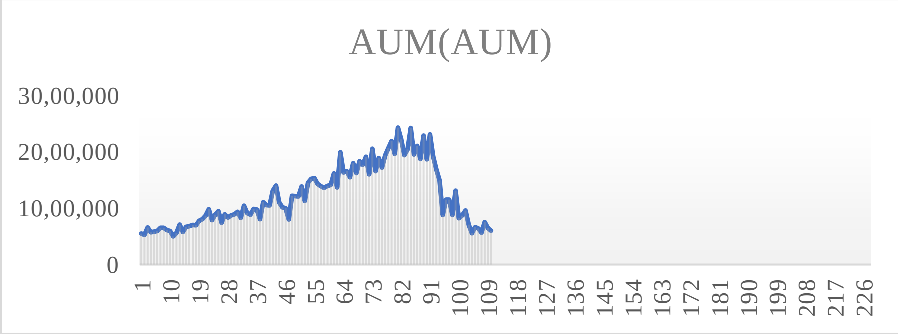

Figure 1: Chart for AUM (2012-2020): Source: Processing of Data

As shown in the image above, AUM fell sharply during the first wave of COVID-19 and is now recovering, but at a different speed.

In this work, the researcher examined the relationship between investor sentiment towards mutual funds and macro-economic indicators and the influence of COVID-19. Because AUM is the market value of AMC's investments, it is used to measure investors' views on mutual funds. This investment uses retail investor's funds. Increasing or decreasing AUM shows investors' preference for mutual funds and its relationship to other macroeconomic variables.

The article is organized into four sections: literature, data and methods, analysis and interpretation of data, and findings.

Review of Literature

The literature shows that macroeconomic variables have had many studies on their target variables using various methods.

Mishra (2012) emphasized the critical point that while there is no short-term impact, real GDP growth affects mutual funds' long-term resources. Ioana Radu (2013) examined quarterly data from 2004 to 2012 in Romania and found a link between the mutual fund market and economy. Kariuki (2014) found that macroeconomic conditions affected mutual funds' net asset values by 70.9% in Kenya.

Qureshi Kutan and Ismail (2017) evaluated market volatility and equities and balanced mutual fund flows using a panel auto-regression model. They found that equities mutual fund flows increase market volatility while balanced mutual fund flows decrease it. Imran and Ahmed (2018) used correlation and regression analysis to compare the effects of macroeconomic variables on conventional and Shariya compliant mutual funds in Pakistan and found that systematic factors affect both types of mutual funds similarly.

Panigrahi, Karwa, and Joshi (2019) discovered that macro-economic variables can explain up to 52.22% of risk-adjusted returns of selected equity mutual funds using attribute analysis. Gyimah, Addai, and Asamoah (2021) used the Auto-Regressive Distributive Lag Model

(ARDL) to track macroeconomic determinants on Ghanaian mutual fund performance and found that monetary policy had a long-term, positive effect.

With an aim to test the asymmetric effect various researchers attempted to employ E-GARCH model like Goudarzi (2010) used the Fractionally Integrated E-GARCH Model to track the Indian stock market's long-term memory and validate its long memory quality. E-GARCH and T-GARCH models were used by Goudarzi and Ramanarayanan (2011) to assess the Indian stock market's volatility and test news asymmetry. They found that bad news increased volatility more than good news. The asymmetric GARCH model produced similar results in Nairobi Stock Exchange, according to Maqsood et al. (2017), but it fit the data better. Ali et al. (2012) used the E-GARCH model to examine how the 2008 global financial crisis affected India and Pakistan's stock markets and found that both were affected.

Data and Methodology

Objectives of Study

a. To determine the association between identified macroeconomic variables and AUM

b.To identify any information asymetry that may exist regarding the AUM of mutual funds in India.

c. To test the impact of COVID-19 pandemicon the relationship of macro-economic variableswith AUM.

Database: This analysis used monthly secondary data on AUM and seven macroeconomic variables—inflation, the consumer price index, the index of industrial output, the sensex, interest rates, and the foreign exchange rate—from January 2012 to February 2021. The day the first COVID-19 case was detected in India is used to separate pre- and post-COVID-19 data. Thus, pre-pandemic data covers January 2012 to December 2019, and pandemic data covers January 2020 to February 2021. Computation uses data's inherent log values.

Tools Used

Vector Error Correction Model: Because VECM aids in the calculation of more effective estimators for co-integrating vectors, it is utilized instead of Engle and Granger's (1987) two-step error-correction model for tracking the impact of macroeconomic variables on the assets managed by various mutual funds.

$$\Delta Y_t = \sum_{j=1}^{k-1} \Gamma_j \, \Delta Y_{t-j} + \alpha\beta' Y_{t-k} + \mu + \epsilon_t \qquad \text{Eq. 1}$$

Where $\sum_{j=1}^{k-1} \Gamma_j \, \Delta Y_{t-j}$ and $\alpha\beta' Y_{t-k}$are the first difference and error correction components of equation (1), which are, respectively, the vector auto regressive (VAR) component. Yt is an order 1 integrated P*1 vector of variables, and is an ordered P*1 vector of constants. _t is a P*1 vector representing the white noise error term, and K is a lag structure. At the jth lag, _j is a P*P matrix representing short-term adjustments among variables across the p equation, is a P*R matrix of cointegrating vectors, and marks the first difference. The speed of the error correcting mechanism is represented by the P*R matrix of the speed of adjustment parameter.

E- GARCH model: Nelson (1991) created the E-GARCH model to account for the leverage effect of shock (policy, news, incidents, events, etc.) on the intended financial metrices. It aids in testing for asymmetries, or if metrics respond to both good and bad news in a similar fashion. In an E- GARCH (p, q) model conditional variance equation, the conditional variance can be expressed as

$$Log(h_t) = \varphi + \sum_{i=1}^{q} \eta \left| \frac{u_{t-1}}{\sqrt{h_{t-1}}} \right| + \sum_{i=1}^{q} \lambda_i \frac{u_{t-i}}{\sqrt{h_{t-i}}} + \sum_{k=1}^{p} \theta_k \log\left(h_{t-k}\right) \qquad \text{Eq. 2}$$

Where,φ is a constant, η represent ARCH effect, λ signifies for asymmetric effect and ϴ stands for GARCH effect. So, if in an E- GARCH model if, $\lambda_1 = \lambda_2 = \cdots = 0$ the model is said to be symmetric but if λ_i<0 it implies that negative shocks generate larger volatility than good news. The log of variance series is generally used for this model because this ensure that estimates are non- negative and the leverage effect turns out to be exponential rather quadratic. For testing the leverage effect in Asset Under Management log of the returns is used. After applying the ARCH -LM test it is known that ARCH effect is present in the series. f- statistics and the Chi-square test have probability values that are less than the 0.05 level of significance (0.0164, 0.0166), respectively. Based on the LR, FPE, AIC, SC, and HQ decision criteria, the ideal lag length is 8.

Observations and Discussion

Panel-1 Descriptive Statistics: Skewness coefficients show that assets under management, the Sensex, inflation, the consumer price index, and m3 are positively skewed, whereas the interest rate, foreign exchange rate, and industrial production index are negatively skewed.The distributions of Kurtosis of Assets Under Management, Interest rates, Sensex, Foreign Exchange rate, Consumer Price Index, Inflation, and M3 are platykurtic, while Index of Industrial Production is leptokurtic because it is higher than 3. Based on Jarque Bera test probability values, AUMand Index of Industrial Production are normally distributed since their values are less than 0.05, while the rest of the variables are non-normal since their values are greater than 0.05, accepting the null hypothesis of non-normality. Since most variables are not normally distributed, log values are utilized to obtain normal distribution.

Test of Stationarity: For this, Ajewole, Adejuwon, and Jemilohun (2020) use the Augmented Dickey Fuller and Phillip Peron tests. The null hypothesis that a unit root exists does not hold since the probability values of the T-statistics are greater than the threshold of significance of 0.05 at level. Therefore, the data is not stationary at level. The T-statistics probability values are below 0.05, rejecting the null hypothesis of a unit root. Thus, the data is non-stationary at level but stationary at first difference.

Selection of optimum lag length: Lag 3 is chosen as the optimal lag based on the AIC decision criteria (Maysami& Koh, 2000b).

Co- Integration Test: As we can see, there is only one co-integrating equation (see table No. 5 in the appendix). The Trace test and (max) both reject the null hypothesis r=0 in Favor of r=1 at the 5% level of significance. As a result, it can be said that there is only one cointegrating equation.

Vector Error Correction Model: Following are the co-integrating vectors as determined by the analytical results of the VECM model.

$$B_1' = (1.00, 1.56, 3.84, 0.26, 0.028, -0.98, -4.72, 0.37)$$

Values for AUM, CPI, FOREX, IIP, INF, INT, M3, and SENSEX that are stated above stand for long-term elasticity measuring coefficients (co-integration) and can be expressed as

$$AUM = -112.32 - 1.56CPI - 3.84FOREX - 0.26IIP - 0.028INF + 0.98INT + 4.72M3 - 0.37SENSEX. \quad \text{Eq. 3}$$

According to the equation above, AUM decreases as CPI rises and vice versa at a rate of 1.56 because the t-statistic value is higher than the cutoff rate (3.42>1.96) and the relationship is negative. FOREX and AUM have a negative relationship due to the elasticity of 3.84, which is greater than the cutoff threshold (8.54>1.96). AUM falls 0.26 per unit if IIP raises 1 unit. This link is essential since the t-statistic exceeds the cut-off rate (2.97>1.96). The link. Inverse correlation between the Sensex and AUM is minimal. The correlation between AUM and the 10-year bond interest rate is significant and has a positive elasticity of 0.98 since the t-statistic value is greater than the cut-off rate (5.27>1.96). M3 and AUM are particularly positively correlated. The change's magnitude, 4.72, exceeds the cutoff rate of |1.96 and has a t-statistic of -12.35.

The VECM model equation is as follows.

$$-0.051ECT-0.58\Delta logAUM_{(t-1)}-0.58\Delta logAUM_{(t-2)}+0.46\Delta logCPI_{(t-1)}+0.006\Delta logCPI_{(t-2)}-0.487\Delta logFOREX_{(t-1)}+0.072\Delta logFOREX_{(t-2)}+0.015\Delta logIIP_{(t-1)}-0.005\Delta logIIP_{(t-2)}+0.011\Delta logINF_{(t-1)}-0.001\Delta logINF_{(t-2)}-0.18\Delta logINTR_{(t-1)}+0.18\Delta logINTR_{(t-2)}+0.15\Delta logM3_{(t-1)}-0.14\Delta logM3_{(t-2)}+0.37\Delta logSENSEX_{(t-1)}-0.068\Delta logSENSEX_{(t-2)}+0.026 \quad \text{Eq. 4}$$

The equation above shows AUM's near-term link with macroeconomic factors.

The co-integrating equation's coefficient, -0.051, is negative but insignificant since the t statistic is smaller than |1.96| (-1.12<1.96). This coefficient measures system resilience. The coefficient indicates that the model is unreliable and that variables will not respond quickly to structural changes. The coefficients and t-statistics of the independent variables show that SENSEX at lag 1 has a strong positive relationship with AUM (t-statistic more than 1.96<2.53), In the near run, everything else is unimportant. The model's R^2 value is 0.4541, indicating that the factors under study explain 45.41% of AUM movements. The proposed model lacks autocorrelation since its Durbin Watson statistic is 1.73, which is within the permitted range of 1.5 to 2.5.

Residual Diagnostics: Serial correlation and heteroskedasticity tests diagnose residuals. Breusch-Godfrey Serial correlation LM Test, a Lagrange multiplier test for typical high-order ARMA defects, was performed. The null hypothesis for this test is that the residual has no serial correlation up to a particular order. Due to F-statistics and Chi-square statistics being larger than 0.05 (0.72, 0.46, respectively), cannot reject the null hypothesis that the recommended model has no autocorrelation. Breusch-Pagan-Godfrey test assesses model heteroskedasticity using R^2 test statistics, where N is sample size and R^2 is regression of squared residuals from first regression. Test statistics may be approximated by a Chi-square distribution. Null hypothesis: homoscedastic error variance. F-statistics and Chi-square probability values of 0.0537 and 0.149, respectively, are larger than 0.05 and indicate that the model does not contain heteroskedasticity. Thus, the null hypothesis stands.

The ARCH-LM test is used to assess the data's fitness, and the results show that the probability values for F-statistics and Chi-square are more than 5% level of significance. As a result, the null hypothesis that the model does not exhibit heteroskedasticity is not rejected. Thus, we draw the conclusion that the E-GARCH (1,1) model appropriately captures the volatility imbalance in the AUM.

$$AUMRET= -0.145-0.188AUMRET_{(t-1)} + \varepsilon_t \quad \text{Eq. 5}$$

$$Log\boldsymbol{\sigma}_t^2= 0.1398-1.16\left|\frac{u_{t-1}}{\sqrt{h_{t-1}}}\right|-0.355\frac{u_{t-i}}{\sqrt{h_{t-i}}}+0.971\ log\ (h_{t-k}) \quad \text{Eq. 6}$$

After looking at the equation (6) existence of leverage effect is also confirmed because the value of λ_i<0 (-0.355) and statistically significant (0.0045<0.05). So, it can be confirmed that bad news has a greater influence on AUM volatility than good news.

Influence of the COVID-19 pandemic on the relationship between macro- economic variables and AUM: On the association between identified macroeconomic indicators and AUM.Statistics indicate that before the pandemic, macro-economic variables under study were able to explain the variation in AUMup to 87% (R^2 values) which reduced to 78% since the first case of COVID-19 was reported in India. Further, if we look at probability F statistics it can also be visualized that the relationship between AUMand Macroeconomic variables are not significant since the inception of the pandemic as the probability value is more than 0.05 (0.16>0.05) which was significant before the crisis.

After analysis it can be observed that Consumer Price Index, M3, Inflation and Interest Rates were not contributing significantly in explaining the variations in AUM but other variables namely Sensex, M3 Inflation and Interest rates were significant contributors in above relationship whereas after the attack of pandemic, none of the variables are significant contributor in the established relationship.

Findings

Inflation and interest rates, two macroeconomic indicators, have a weakly negative relationship with assets under management, whereas the others have a weakly positive link. Pre-COVID, macroeconomic indices and AUMcorrelated strongly. During COVID-19, no substantial connection was seen. The discovered macro-economic variables can explain 45% of the variation in assets under management, but if we divide the time into pre-COVID and pandemic phases, R^2 drops sharply from 87% to 78%. VECM found that only SENSEX, at lag 1, positively affects AUM in the short term. Since the error correction term is modest, the suggested model is unsuitable for policy implications and needs more independent variables. The E-GARCH model argues that bad news influences AUM more than favorable news because to knowledge asymmetry. AUM and Consumer Price Index, AUM and M3, CPI and IIP, CPI and M3, IIP and Interest rates, and IIP and Sensex are causally linked by the Granger Causality test. The other macroeconomic elements are unrelated. COVID-19 has changed the relationship between AUM and macroeconomic parameters. In the table below, dark lines indicate significant relationships and dotted lines indicate insignificant relationships, M3, inflation, and interest rates had the greatest impact on AUM before COVID, but after COVID, they lost significance.

Conclusion

Statistical analyses of the AUM data set over 10 years and identified macroeconomic variables show that pre-pandemic macroeconomic characteristics can explain the increase or decrease in AUM by up to 87%. The pandemic reduced macroeconomic factors' explanatory power to 78%. The VECM model found that macroeconomic factors explain 48% of AUM fluctuation. Small error correction terms indicate that the model is not resilient and will not return to equilibrium if purposely changed. Long-term, CPI, FOREX, and IIP exhibit negative and strong associations with AUM, indicating that if consumer prices rise, AUM would decline as investors have less investable income, affecting market sentiment. Rising SENSEX offers investors more lucrative investment possibilities, but rising inflation reduces the amount of money that can be invested. Because mutual fund investors are more inclined to trade stocks, this association is no longer statistically significant. However, rising M3 stimulates investors to make larger investments, therefore the M3-AUM relationship is beneficial. 10-year Treasury bond-AUM relationship Favorable interest rates lower bond prices, encouraging investors to put their capital in mutual funds to protect their holdings. When discussing the short-term implications of macroeconomic issues on mutual fund AUM, the Sensex has a significant positive impact. The E-GARCH (1,1) model shows that news asymmetry dominates AUM volatility, meaning bad news affects volatility more than good news. The association was considerable before the pandemic but became insignificant during it, and the macroeconomic factors' explanatory power decreased, suggesting that COVID-19 significantly affects it. The outbreak also diminished the elements that drove this connection. Investors, policymakers, researchers, and other stakeholders can use the proposed model to assess mutual fund investors' sentiments and understand the dynamic impact of exceptional circumstances like COVID-19 on the relationship because this phase is not yet complete and India is expected to experience a third wave of the pandemic.

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