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Do Exchange Traded Funds in India Have Tracking and Pricing Efficiency?

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Abstract

Purpose: The study investigates tracking and pricing efficiencies of selected exchange traded funds (ETFs) in India.

Design/methodology/approach: The study applies different methods of determining tracking errors to assess tracking abilities of ETF managers; the average absolute differences as well as the standard deviation of differences between ETF returns and benchmark returns and standard errors from the regression of ETF returns against the benchmark. The study further uses Vector Error Correction Model (VECM) to examine the lead lag relationship between Net Asset Values (NAVs) and market prices of ETFs and pricing efficiency.

Findings: ICICI Prudential Sensex ETF exhibits the highest tracking error and Aditya Birla Sun Life Nifty ETF shows the lowest tracking error. NAVs lead their respective market prices indicating huge scope for arbitrage opportunities to authorized participants. Persistence in the deviation between NAVs and market prices is prevalent for longer period, indicating inefficient price discovery mechanism of Indian ETF market. The study confirms market inefficiency in Indian ETF market.

Originality/value: The existing literature on tracking and pricing efficiencies of ETF is largely with respect to advanced countries. There is a limited evidence of such studies in Indian context. Hence, the study adds to the literature by examining the efficient market hypothesis in Indian ETF market in terms of tracking and pricing efficiencies.

Practical Implications: The study reveals the presence of inefficient price discovery and the scope for arbitrage. This may be due to low level of trading activity and inefficient arbitrage mechanism in India. Hence, it is the need of the hour that Securities and Exchange Board of India (SEBI) and stock exchanges should take necessary initiatives to improve trading activity in ETFs and thereby to achieve market efficiency.

Keywords: Exchange Traded Funds; Tracking Error; Pricing Efficiencies; Arbitrage Opportunity; Authorized Participants; Net Asset Value

JEL Classification: G1, G2, G4

Paper Type: Research Paper

1. Introduction

Exchange traded funds (ETFs) are hybrid investments with the combined characteristics of stocks and mutual funds. They trade on organized exchanges like a stock. They invest in a portfolio of stocks or bonds or any other marketable investment avenues like mutual funds. However, unlike mutual funds, they have high liquidity, lower expenses, tax efficiency and transparency. These ETFs are passive funds, the portfolio of which resembles a selected benchmark index (Kostovetsky, L., 2003; Lettau & Madhavan, 2018; Liebi, 2020). Therefore, the performance of ETF is measured in terms of how efficiently the fund manager is able to track the benchmark. Unique trading mechanism of ETFs is that it trades in primary market and secondary market simultaneously (Kosev & Williams, 2011; Charteris et al., 2014; Rompotis, 2014). The authorized participants who are mainly institutional investors, trade in primary market and other investors trade in secondary market. In the primary market, in kind creation and redemption of ETFs take place directly from the fund house in return for a specified basket of underlying securities in the same weightage as present in the index. Investors in the secondary market buy and sell ETF shares created in the primary market on a real time basis (Kosev & Williams, 2011). Since ETFs trade like a stock in secondary market, they have a market price which is determined by the demand and supply forces. As ETFs invest in a portfolio of different underlying securities, Net Asset Value (NAV) of such funds is determined based on the performance of underlying securities in the portfolio. NAV is the basis to create and redeem units in primary market. Thus, as ETF trades in two markets, they have two prices i.e. NAV in primary market and market price in secondary market. As a result, NAVs of ETFs may be different from their market price. Such difference provides a scope for arbitrage opportunity to market makers and authorized participants (Ackert & Tian, 2008; Ben-David et al., 2017; Brown et al., 2021). If market price of ETF is less than its NAV, ETF is said to trade at a discount. To make arbitrage profits, authorized participants buy ETF units in secondary market and simultaneously sell the stocks of underlying portfolio (Dolvin, 2010; Ben-David et al, 2011; Hilliard, 2014). The buying pressure in secondary market and selling pressure on underlying stocks will correct the deviations and bring market equilibrium as per Law of One Price (LOOP) (Rompotis, 2012). In case the market price of ETF is at a premium to its NAV, authorized participants sell in secondary market and buy in primary market to take the advantage of price differential (Hilliard, 2014). Arbitrage activity brings ETF prices in line with the underlying portfolio prices and vice versa which enables improved trading activity and liquidity in underlying securities (Ben-David et al., 2017; Box et al., 2021). It further helps in price discovery. ETF market has significantly increased in terms of asset size, market significance and diversity (Lettau & Madhavan, 2018). The increased competition for large and well-performing ETF improves market quality in terms of decrease in bid-ask spread and increase in turnover (Kharma & Eugster, 2021). In an efficient market, ETFs trade at prices that are close to their NAVs. However, in practice they always trade at a premium or discount (Aditya & Desai, 2015; Yiannaki, 2015; Jares & Lavin, 2004; Goel & Ahluwalia, 2021; Göncü & Akyildirim, 2017) prove that statistical arbitrage profits are possible if at least one asset in the economy satisfies arbitrage condition. Despite arbitrage constraints are low, investors could not reduce tracking error (Goel & Ahluwalia, 2021). The presence of arbitrage indicates market inefficiency (Tripathi & Garg, 2016) and requires the attention of market regulator (Nargunam & Anuradha, 2017).

The paper makes contributions to the academic literature as follows. First, the study contributes to empirical examination of market efficiency in Indian ETF market. Error Correction Term (ECT) in Vector Error Correction Model (VECM) explains the speed of adjustment between NAVs and market prices of ETFs. The negative and significant ECT confirms the lead lag relationship and the scope for arbitrage opportunities. The study further contributes to the literature on performance evaluation by examining whether the selected ETFs in India are able to track the benchmark efficiently or not. The paper confirms the market inefficiency in Indian ETF market (Tripathi & Garg, 2016; Charupat & Miu, 2013; Aditya & Desai, 2015), as there is a scope for arbitrage. The paper further confirms the varying tracking efficiencies of the fund managers of different ETFs. This evidence draws the attention of the market regulator and stock exchanges to improve market efficiency (Jares & Lavin, 2004; Nargunam & Anuradha, 2017). The rest of the paper is organized as follows. Section two reviews prior literature; section three discusses data and methodology. Section four presents empirical results and analysis. Section five concludes the paper.

2. Literature Review

The study conducts literature survey of pricing and tracking efficiencies of ETFs across different countries. Few studies mainly focused on understanding the basic characteristics of ETFs such as analysis of the advantages and disadvantages of leveraged ETFs, the similarities and differences with classic ETFs etc. (Rompotis, 2014); significant co-movement among ETFs of different countries (Yavas & Rezayat, 2016). Charupat & Miu (2013) conducted extensive literature review to examine the key factors contributing to pricing efficiency, tracking performance and the impact on underlying portfolios of ETFs.

The conventional funds and ETFs are substitutes but not perfect substitutes and clientele effect that segregates the two vehicles into different market niches explains the existence of both instruments (Agapova, 2011). The intensity of positive feedback trading in US ETF markets is more associated with investor sentiment and such trading tends to increase when investors are optimistic (Chau et al., 2011). Feedback trading increases in the presence of lagged premiums and the effect of lagged premiums on feedback trading differs before and after the global financial crisis (Charteris et al., 2014). Investors may perceive low-beta ETFs as less desirable alternatives than high-beta ETFs (Peltomäki, 2017). ETF outflows caused by exchange rate depreciation result in less uncertainty in foreign exchange rate and large ETF inflows result in higher exchange rate uncertainty (Sakarya & Ekinci, 2020).

Tracking errors of ETFs with exposure to equities of global emerging markets are substantially higher than those of developed markets (Blitz & Huij, 2012). Chu (2011) also provided similar evidence that tracking errors in emerging markets are comparatively higher than those of US and Australia and magnitude of tracking error is negatively related to the size but positively related to expense ratio. Shin & Soydemir (2010) observes the presence of statistically significant tracking errors mainly caused by the exchange rate changes and also the presence of greater level of persistence resulting in inefficient dissemination of information. Coronado et al. (2020) reveals the presence of volatility spill-overs between dollar and pound markets.

The assets under management and the volume positively affect the tracking ability of ETFs but the volatility has negative impact on the tracking efficiency of ETFs (Singh & Kaur, 2016). The study by Qadan & Yagil (2012) also provides similar evidence that tracking error is positively correlated with daily volatility of the ETF and the trading volume has a negligible effect on reducing tracking errors. Yavas & Rezayat (2016) observe the presence of significant co-movement of returns among ETFs of different countries. Despite of such interdependencies, there is still a scope for international diversification between advanced and emerging economies. Sinha & Dutta (2013) observe that lower tracking error is the major factor for Goldman Sachs Gold ETF to exhibit consistently better performance. ETFs in the US exhibit the best performance (Janková & Doskočil 2021).

Significant tracking error between ETFs and the benchmark index explains the stock selection and market timing abilities of the fund managers who generate better than market returns (Yap et al., 2021). Excess co-movements between ETFs of similar investment style are positive and it is negative in case of ETFs of distant investment styles (Broman, 2016). The study further confirms the premise that ETFs with high liquidity attract noise traders with short horizon. Contrary to this, Nguyen & Vo (2019) find no link between liquidity and systematic risk. Kudryavtsev (2020) finds that long term stock price reversals after large price changes are more if price changes are followed by short term price drifts. DeFusco et al. (2011) document that the most important factor for the price deviation is the accumulated dividend. When the company pays out the accumulated dividend, the price deviation becomes zero. There is a clear evidence of pricing inefficiencies and unexploited arbitrage opportunities in Indian ETF market which requires immediate action of the Regulator (Tripathi & Garg, 2016). Efficient Market Hypothesis (EMH) does not hold good in case of Indian ETFs and it requires the attention of market Regulator to achieve efficient price discovery (Nargunam & Anuradha, 2017).

According to Ackert & Titan (2000), Standard and Poor's Depository Receipts, the first ETF in the world does not trade at a significant discount like closed-end mutual funds and also they are not excessively volatile. Aditya & Desai (2015) found that it takes minimum of 4 days and maximum of 10 days for the deviation between NAV and price to disappear indicating that Indian ETFs are not efficient. From the risk adjusted performance perspective, the ETFs in Luxembourg outperform the Irish ones, leading to mergers & acquisitions in the industry (Yiannaki, 2015). Asynchronous trading of the ETF and the underlying portfolio, constant flow of information in the market causes frequent discounts and premiums on such ETFs and there is a positive relationship between the returns and lagged deviations, which indicates that there is a scope for exploiting arbitrage opportunities (Jares & Lavin, 2004). The deviation between prices and NAVs of ETFs does not persist for more than two days due to effective arbitrage mechanism (Rompotis, 2010). Ivanov (2013) observes a shift of price discovery for gold and silver to the ETF market from futures market. However, futures market still dominate price discovery in oil market. Petajisto (2017) finds a significant deviation of ETF prices from their NAVs even after the arbitrage activity by authorised participants to create and redeem shares of the underlying portfolios. Such deviations are more especially in case of funds holding international or illiquid securities and it is difficult to decide NAVs of such funds. Active trading strategies generate abnormal returns before transaction costs due to mis-pricings in asset classes.

After extensive literature review, it is observed that there have been numerous studies internationally on pricing and tracking efficiencies of ETFs. However, there is a limited evidence of such studies in Indian context. Hence, the study contributes to the academic literature in terms of validity of efficient market hypothesis in Indian ETF market in terms of tracking and pricing efficiencies.

3. Data and Methodology

3.1 Data

With the listing of first ETF in 2002, the ETFs have been in existence in India for the last 20 years under different categories such as equity, gold, bond, money market instruments etc. The study currently examines tracking and pricing efficiencies of equity ETFs. Limited availability of market prices of many ETFs on a continuous basis is a constraint. As the availability of adequate data is a pre-requisite to ensure the reliable results, the study considers only nine ETFs (Appendix 1), out of which five ETFs are large cap diversified equity ETFs traded on Bombay Stock Exchange (BSE) for which S&P BSE Sensex Total Return Index (TRI) is the benchmark index. The remaining four are from National Stock Exchange (NSE) out of which three ETFs are large cap diversified equity for which the benchmark index is NIFTY 50 TRI and one ETF is banking sector ETF for which the benchmark is NIFTY Bank TRI. The sample period is from January 1, 2010 to February 28, 2019. In case, any scheme under the sample is launched after January 1, 2010, study period for the stock commences from the day on which the ETF prices are available in the market. The daily market prices of the sample ETFs and their respective benchmarks have been collected from the websites of NSE and BSE. NAVs of ETFs have been sourced from the websites of respective asset management companies (AMCs).

3.2 Methodology

The study conducts preliminary analysis of risk return characteristics of benchmark indices and ETFs based on NAVs and market prices. Benchmark index values, NAVs and market prices of ETFs are converted into log-normal returns as follows:

$$R_{B,t} = \ln(B_t) - \ln(B_{t-1}) = \ln(B_t/B_{t-1}) \quad (1)$$

where, $R_{B,t}$ is benchmark return on day t, B_t is benchmark price on day t; B_{t-1} is benchmark price on day t-1.

$$R_{NAV,t} = \ln(NAV_t) - \ln(NAV_t) = \ln(NAV_t/ NAV_{t-1}) \quad (2)$$

where, $R_{NAV,t}$ is ETF return on day t based on NAV; NAV_t is NAV of ETF on day t; NAV_{t-1} is NAV of ETF on day t-1.

$$R_{P,t} = \ln(P_t) - \ln(P_{t-1}) = \ln(P_t/P_{t-1}) \quad (3)$$

$R_{P,t}$ is return on ETF on day t based on market price; P_t is Market price of ETF on day t and P_{t-1} is market price of ETF on day t-1.

Risks associated with the returns in each case are computed as follows:

$$\sigma_{NAV} = \sqrt{\frac{\sum_{t=1}^{n}(R_{NAV,t} - \overline{R_{NAV}})^2}{n-1}} \quad (4)$$

where, σ_{NAV} is standard deviation of ETF returns based on NAV.

$$\sigma_{P} = \sqrt{\frac{\sum_{t=1}^{n}(R_{P,t} - \overline{R_{P}})^2}{n-1}} \quad (5)$$

where σ_P is standard deviation of ETF returns based on market price.

$$\sigma_{B} = \sqrt{\frac{\sum_{t=1}^{n}(R_{B,t} - \overline{R_{B}})^2}{n-1}} \quad (6)$$

where, σ_B is standard deviation of benchmark returns.

3.2.1 Tracking Efficiency

As ETF are passive funds and the portfolio of which resembles a selected benchmark index, tracking error is mainly used to assess the efficiency of the fund managers (Kostovetsky, 2003; Lettau & Madhavan, 2018). Hence, the study employs different methods of determining tracking errors to assess the ability of ETF fund managers in replicating his portfolio at par with benchmark index. Tracking error (TE) is the deviation between the performance of ETF and its benchmark. If it is high, it indicates the inferior performance of fund manager of ETF in tracking its benchmark. The lower the tracking error, the higher is the superior performance of the fund manager. Tracking error may occur due to various reasons like fund expenses, fund cash flows, dividends and changes in index composition (Milonas & Rompotis, 2006; Shin & Soydemir, 2010; Singh & Kaur, 2016).

Based on the various methods suggested by Roll (1992) and Pope & Yadav (1994), the study applies different measures of tracking errors as follows:

Rudolf et al. (1999) proposes minimization of mean absolute difference (MAD) as one of the measures of fund manager performance in terms of tracking error. MAD is a better measure (Willmott & Matsuura, 2005; Willmott et al., 2009), due its ability to cancel the differences and to avoid the problem of underestimation of tracking error.

$$TE_A = \frac{\sum_{t=1}^{n}|R_{NAV,t} - R_{B,t}|}{n} \quad (7)$$

Clarke et al. (1994) defines tracking error as the average of absolute differences between ETF NAV returns ($R_{NAV,t}$) and benchmark returns ($R_{B,t}$) as shown in equation (7). The practitioners prefer to use this measure, as quadratic functions are complex to apply.

Chai & Draxler (2014) document that when the error distribution is Gaussian and there is adequate number of observations, Root Mean Square Error (RMSE) performs better than MAD and also it satisfies the triangle inequality requirement for a distance metric. Hence, the study further applies RMSE as another method of measuring tracking error as follows:

$$TE_B = \sqrt{\frac{\sum_{t=1}^{n}(R_D,t - \overline{R_{D,t}})^2}{n-1}} \quad (8)$$

where, $R_{D,t} = R_{NAV,t} - R_{B,t}$..

Tracking error is the standard deviation of differences between ETF returns based on NAV and benchmark index returns as shown in equation (8).

The third method used in the study to measure tracking error is standard error regression.

$$R_{NAV,t} = \alpha + \beta R_{B,t} + \varepsilon_t \quad (9)$$

$$TE_C = \sqrt{\frac{\sum_{t=1}^{n} \varepsilon_t{}^2}{n-1}} \quad (10)$$

Standard errors (ε_t) derived (equation 9) by regressing ETF NAV returns against benchmark returns are used to determine Tracking Error (equation 10). If ETFs exactly resemble their benchmark indices, standard deviation of residuals from regression must be zero. If beta is one, TE_B and TE_C would be the same (Pope & Yadav, 1994). If the fund manager ensures that the fund portfolio exactly replicates its benchmark, the average tracking error should be near to zero. To test the statistical significance of tracking error, the study computes t-statistics. Insignificant tracking errors indicate that ETFs are successful in tracking their benchmarks.

3.1.2 Pricing Efficiency

The Law of One Price (LOOP) says that identical securities trading in more than one market must have the same price, otherwise, intelligent investors can generate risk free profits through arbitrage (Lamont & Thaler, 2003; Rompotis, 2012; Hilliard, 2014). Arbitrage is the simultaneous purchase and sale of the related securities at two difference prices, leading to market equilibrium. This is possible when the markets are competitive with no transaction costs and no trade constraints. However, in realty arbitrage is not risk free, as there are various limits to arbitrage such as explicit and implicit frictions (Pointiff, 2006), the positive relationship between changes in price differences and idiosyncratic risk (Gagnon & Karolyi, 2010) and quick disappearance of arbitrage opportunities due to technological development and enhanced market microstructure (Ito et al, 2012). Similarly, as ETFs trade in primary markets and secondary markets, their NAVs and prices are expected to be the same. But, the price at which they trade on stock exchanges is usually different from their NAVs, giving a scope for arbitrage opportunities (Aditya & Desai, 2015; Tripathi & Garg, 2016). Absence of LOOP leads to arbitrage, but arbitrage in turn reduces price differential and brings in market equilibrium. The pricing efficiency of ETFs is more, when both the prices come together due to the presence of arbitrage opportunities. At times, such deviations may prevail for more than a day when arbitragers are not quick enough to undertake trading activity. To investigate the persistence of premium/discount, the study regresses current period discount/premium against previous period discount/premium as follows:

$D_t = \alpha + \beta D_{t-1}$ (11)

where, $D_t = P_t - NAV_t$ i.e. rupee difference between price and NAV of an ETF at the end of the day.

Insignificant beta values indicate no persistence in deviations. In other words, such deviations disappear in a day or less. A statistically significant β indicates the presence of persistence in deviations i.e. previous period’s deviation can explain the current period’s deviation. It indicates that premium/discount will last for over a number of days. Persistence for longer period indicates the inefficiency of arbitragers in bringing the prices towards equilibrium. It may happen so when trading activity is low and liquidity is less. To further examine the scope for arbitrage opportunities the study attempts to examine the lead-lag relationship between NAVs and market prices of ETFs. This is to understand which leads in price discovery i.e. whether NAVs or market prices. For this purpose, the study applies Vector Error Correction Model to examine the price discovery process for the selected ETFs.

Financial time series are characterized by time varying correlations and variances (So et al., 2018) and have stylized facts such as fat tailed return distributions, random walk, volatility clustering etc. (Chang et al., 2014; Selim et al., 2015). As examining the stationarity of time series is a pre-requisite before applying VECM, the study uses Augmented Dickey Fuller (Dickey & Fuller,1981) test to examine the stationarity of price and return series of NAVs and market prices of ETFs. Long term dependence in agricultural futures markets suggests the fractional integration (Chang et al, 2012). Franses (2020) attempts to alleviate error in first order auto-regression using total least squares model.

When two variables are non-stationary at level, but become stationary when converted into first differences, they are said to be integrated of order (1). When two variables are non-stationary at level, if the linear combination of them is stationary, they are said to be co-integrated with each other (Engle & Granger, 1987). Another pre-requisite for examining long run association is testing co-integrating relationship between prices and NAVs. Hence, the study applies Johansen test of co-integration (1991) to confirm the presence of co-integration between NAVs and prices. Akaike Information Criterion (AIC) is used to determine optimal lag length, as it is a prerequisite for Johansen co-integration test. The study further uses Vector Error Correction Model (VECM) to assess error correction mechanism.

ECT implies deviation from long run equilibrium which is corrected through a series of short-run adjustments. Error correction model is estimated in two ways; one with NAV as the dependent variable and the other with market price of ETFs as dependent variable. The long-run and short-run causality between NAVs and prices is estimated as follows:

$$\Delta NAV_t = \alpha_1 + \gamma_1 \varepsilon_{t-1} + \sum_{k=1}^{n} \beta_{NAV,t-k} \Delta NAV_{t-k} + \sum_{k=1}^{n} \delta_{NAV,t-k} \Delta P_{t-k} + \epsilon_{NAV,t} \quad (12)$$

$$\Delta P_t = \alpha_1 + \gamma_2 \varepsilon_{t-1} + \sum_{k=1}^{n} \beta_{P,t-k} \Delta P_{t-k} + \sum_{k=1}^{n} \delta_{P,t-k} \Delta P_{t-k} + \epsilon_{P,t} \quad (13)$$

In equations (12) and (13), ε_{t-1} is the equilibrium error term which measures how the dependent variable adjusts to the previous period's deviation from long run equilibrium. It is derived as follows:

$$\varepsilon_{t-1} = NAV_{t-1} - \alpha - \beta P_{t-1} \quad (14)$$

$\epsilon_{NAV,t}$ and $\epsilon_{P,t}$ are error terms. Coefficients of equilibrium ECTs i.e. γ_1 and γ_2 imply the speed of adjustment coefficients in NAV and market prices respectively. Statistically insignificant correlation implies that current period's change in one market does not react to the previous period's deviation from equilibrium. ΔNAV and ΔP_{t-k} are the differences of NAV and market price of ETFS at lag k at time t. The second and third parts of the equations indicate the lagged first differences of both the series. The coefficients of lagged differences imply the short run effects of previous period's change in the price of current period's deviation. Statistically insignificant co-efficient values of lagged differences imply that one market does not cause another market.

4. Empirical Results and Analysis

The risk return characteristics of ETFs (Table 1) based on the NAVs and prices indicate that ICICI Prudential Sensex ETF, SBI ETF Sensex and UTI Sensex ETF outperformed their benchmark in terms of returns. However, all these ETFs exhibited more risk than the benchmark due to possible non-fundamental shocks in ETFs which cause higher volatility of underlying stocks through arbitrage (Malamud, 2016; Ben-David et al, 2018). Motilal Oswal M 50 ETF trades at significant premium of 13.88% to its NAV and is the least performer among the sample ETFs, as evident from the lowest return of 0.014%. SBI Sensex ETF and UTI Sensex ETF also trade at premium to NAV (Hilliard, 2014). This broadly explains the scope for arbitrage opportunities, where authorised participants can sell in secondary market and buy in primary market (Shin & Soydemir, 2010; Singh & Kaur, 2016; Nargunam & Anuradha, 2017; Aditya & Desai, 2015). The remaining ETFs trade at a discount to NAV, where authorised participants can buy in secondary market and sell in primary market to profit from arbitrage.

Table 1: Risk and Return Characteristics

S No	Exchange Traded Fund	ETF Price Return (%)	ETF Price Risk (%)	ETF NAV Return (%)	ETF NAV Risk (%)	Benchmark Return (%)	Benchmark Risk (%)	Deviation between Price and NAV
1	Aditya Birla Sun Life Nifty ETF	0.042	2.698	0.044	1.006	0.045	1.022	-0.68
2	ICICI Prudential Sensex ETF	0.074	4.932	0.072	1.347	0.056	0.913	-2.18
3	Kotak Nifty ETF	0.037	0.938	0.037	0.970	0.041	0.973	-0.08
4	Kotak Sensex ETF	0.033	1.167	0.033	0.969	0.032	0.962	-0.13
5	Motilal Oswal M50 ETF	0.014	1.480	0.031	1.028	0.038	0.971	13.88
6	Quantum Nifty ETF	0.042	1.067	0.042	1.067	0.047	1.118	-0.22
7	Reliance ETF Bank BeES	0.049	1.316	0.049	1.383	0.051	1.386	-0.06
8	SBI ETF Sensex	0.052	2.347	0.053	0.951	0.037	0.881	1.27
9	UTI Sensex Exchange Traded Fund	0.056	1.739	0.058	0.916	0.033	0.813	0.32

ETF Price indicates the price at which ETFs are traded on stock exchanges and ETF NAV indicates the net asset value as computed and published by the respective fund houses.

Table 2 presents tracking efficiencies of ETFs. ICICI Prudential Sensex ETF has the higher tracking errors of 0.391%, 1.01% and 1.009% respectively under all three models. The finding is in line with the evidence provided by the studies (Shin & Soydemir, 2010; Blitz & Huij, 2012; Chu, 2011; Yavas & Rezayat, 2016; Petajisto, 2017). Aditya Birla Sun Life Nifty ETF has the lowest TE_B of 0.03% and TE_C of 0.025% respectively. Reliance ETF Bank BeES has the lowest TE_A of 0.006%. Adjusted R^2 which is close to 1 also indicates the tracking efficiency of fund managers of these two ETFs and lower tracking error contributes to consistent performance (Sinha & Dutta, 2013).

Table 2: Tracking Efficiency of ETFs

S No	Exchange Traded Fund	TE_A Value (%)	TE_A t-Stat	TE_B Value (%)	TE_B t-Stat	TE_C Value (%)	TE_C t-Stat	Regression of NAV returns against Benchmark returns Coef	t-Stat	Adj R^2
1	Aditya Birla Sun Life Nifty ETF	0.02	35.15*	0.03	40.94*	0.025	40.94*	0.983	1669.83*	0.999
2	ICICI Prudential Sensex ETF	0.391	13.40*	1.01	31.84*	1.009	31.83*	0.977	28.13*	0.438
3	Kotak Nifty ETF	0.009	6.04*	0.07	46.92*	4.876	47.22*	1.056	9.95*	0.042
4	Kotak Sensex ETF	0.025	8.37*	0.14	47.21*	0.144	47.20*	0.996	314.75*	0.978
5	Motilal Oswal M50 ETF	0.148	30.41*	0.27	45.99*	0.267	45.98*	1.023	170.98*	0.933
6	Quantum Nifty ETF	0.009	2.06*	0.18	42.07*	0.179	42.06*	0.998	262.12*	0.975
7	Reliance ETF Bank BeES	0.006	5.91*	0.05	47.53*	0.047	47.52*	1.002	1406.91*	0.999
8	SBI ETF Sensex	0.069	8.59*	0.29	35.35*	0.300	36.26*	1.025	109.20*	0.901
9	UTI Sensex Exchange Traded Fund	0.141	9.50*	0.40	25.44*	0.403	25.40*	1.013	51.63*	0.805

The table presents Tracking Errors of the selected ETFs determined using various methods and regression results of NAV returns against benchmark returns

* Indicates statistically significant at 5% level.

The coefficient values which indicate the sensitivity of NAV returns to their respective benchmarks, are almost close to one (Table 3). Coefficient of lagged difference is highest for Motilal Oswal M50 at 0.996 (t value of 502.33), indicating the presence of persistence. Such persistence is present in case of all ETFs under consideration (Shin & Soydemir, 2010; Aditya & Desai, 2015; Petajisto, 2017; Tripathi & Garg, 2016). This facilitates investors to take advantage of these differences to profit from arbitrage. However, presence of persistence for a longer period is probably due to inefficient arbitrage mechanism prevalent in Indian market. It is also due to infrequent and illiquid trading of ETFs in secondary market. The study by Glosten et al. (2015) observes that higher trading activity of ETFs brings in higher information efficiency in the underlying securities market.

Table 3: Persistence in Deviations

S No	Exchange Traded Fund	Alpha	t-stat	Coefficient of Lagged Difference	t-stat	Adj R^2
1	Aditya Birla Sun Life Nifty ETF	0.001	0.018	0.924	98.88*	0.854
2	ICICI Prudential Sensex ETF	-1.197	-3.613*	0.673	28.95*	0.453
3	Kotak Nifty ETF	-0.026	0.000	0.523	28.98*	0.273
4	Kotak Sensex ETF	-0.160	-3.387*	0.443	23.31*	0.196
5	Motilal Oswal M50 ETF	0.036	1.098	0.996	502.23*	0.992
6	Quantum Nifty ETF	-1.368	-11.182*	0.186	7.98*	0.034
7	Reliance ETF Bank BeES	-0.267	-2.035*	0.592	34.89*	0.350
8	SBI ETF Sensex	0.544	3.200*	0.860	61.06*	0.739
9	UTI Sensex Exchange Traded Fund	0.689	3.452*	0.387	10.66*	0.149

The table presents persistence in deviations of selected ETFs by observing coefficient of lagged differences.

Null Hypothesis: Lag period difference is not a predictor of current period difference

* indicates statistically significant at 5% level

To further confirm such persistence and robustness of the results, the study applies VECM. The results of ADF test confirm the non-stationarity in price series and stationarity in return series of ETF based on NAV as well as price and also benchmark (Table 4). The results suggest that all ETFs under consideration are integrated of order (1).

Table 4 : Stationarity Test (Augmented Dickey Fuller Test, 1981)

S No	Exchange Traded Fund	Market Price		NAV	
		Price Series	Return Series	Price Series	Return Series
1	Aditya Birla Sun Life Nifty ETF	-2.684 (0.2429)	-18.005 (0.000)*	-2.985 (0.1362)	-13.943 (0.000)*
2	ICICI Prudential Sensex ETF	-3.052 (0.1180)	-14.041 (0.000)*	-2.646 (0.2593)	-11.368 (0.000)*
3	Kotak Nifty ETF	-2.533 (0.3118)	-13.368 (0.000)*	-2.627 (0.2676)	-14.711 (0.000)*
4	Kotak Sensex ETF	-2.554 (0.3017)	-13.239 (0.000)*	-2.658 (0.2541)	-13.308 (0.000)*
5	Motilal Oswal M50 ETF	-2.594 (0.2825)	-25.096 (0.000)*	-2.804 (0.1956)	-23.213 (0.000)*
6	Quantum Nifty ETF	-2.674 (0.2470)	-14.774 (0.000)*	-2.675 (0.2464)	-14.978 (0.000)*
7	Reliance ETF Bank BeES	-2.14 (0.5236)	-16.814 (0.000)*	-2.190 (0.4956)	-17.121 (0.000)*
8	SBI ETF Sensex	-2.348 (0.4075)	-12.233 (0.000)*	-2.470 (0.3433)	-11.092 (0.000)*
9	UTI Sensex Exchange Traded Fund	-2.752 (0.2150)	-9.005 (0.000)*	-3.231 (0.0783)	-7.074 (0.000)*

The table presents results of stationarity test for price, NAV and the respective return series of selected ETFs.

Null Hypothesis: Given series are non-stationary

* Statistically significant at 5% level

Values in paranthesis are p values

Johensen co-integration test further confirms the existence of at least one co-integrating vector i.e. there is a co-integrating relationship between NAVs and prices (Table 5).

Table 5: Results of Johansen's Cointegration Test

S.No	ETF	Lags as per AIC Lag	Max Rank	Trace Statistics	Max Statistics
1	Aditya Birla Sun Life Nifty ETF	8	0	14.8656*	14.6918
			1	0.1738	0.1738
2	ICICI Prudential Sensex ETF	7	0	26.2489*	25.6478
			1	0.6011	0.6011
3	Kotak Nifty ETF	11	0	53.5658*	53.4834
			1	0.0824	0.0824
4	Kotak Sensex ETF	12	0	43.8504*	43.8247
			1	0.0257	0.0257
5	Motilal Oswal M50 ETF	3	0	6.9998*	6.8816
			1	0.1182	0.1182
6	Quantum Nifty ETF	7	0	102.3068*	102.1664
			1	0.1404	0.1404
7	Reliance ETF Bank BeES	7	0	135.9068*	135.8717
			1	0.0351	0.0351
8	SBI ETF Sensex	11	0	19.4543*	17.8259
			1	1.6284	1.6284
9	UTI Sensex Exchange Traded Fund	10	0	49.7998*	49.6283
			1	0.1716	0.1716

The table presents the results co- integrating relationship between prices and ETFs.

Null hypothesis: There is no cointegrating vector between NAV and Price

Critical Value for Trace Statistic for max rank 0 and 1 are 15.41 and 3.76 respectively

Critical Value for Max Statistic for max rank 0 and 1 are 14.07 and 3.76 respectively

* Indicates statically significant at 5% level

In an efficient market, NAV and market price of ETF need to be equal. In case of any deviation between NAV and price, error correction mechanism helps in bringing prices to equilibrium. Statistically significant and negative coefficients of ECTs (Table 6) indicate that NAVs lead their prices for all sample ETFs.

Coefficient of ECTs explains the speed with which dependent variable corrects itself to move towards independent variable. It is highest for NAV of UTI Sensex ETF, indicating that its market price corrects at the faster rate of 55.37% (-0.5537 with p value of 0.000) to adjust towards NAVs and to reach equilibrium. Coefficient of ECM is lowest for NAV of Motilal Oswal M50, indicating that its price corrects slowly among the given sample at the rate of 0.86% to reach its NAV. Motilal Oswal takes more time to adjust towards equilibrium, as is also evident from its relatively higher tracking error and also high deviations (Chu, 2011). In other words, the scheme takes longer period to reach equilibrium, giving a lot of scope for arbitrage opportunities. The leading role of NAVs over the ETF prices is an indication of domination of noise traders over informed traders (Wermers & Xue, 2015). The findings are in line with the argument by Bradley & Litan (2010, 2011) that NAVs of the underlying should be the driving forces of ETF prices. Further, the low level of trading activity in Indian ETFs can be cause of persistence of deviation between ETFs and prices causing inefficient arbitrage mechanism.

Table 6: Results of Vector Error Correction Model (VECM)

	ETF	Lag	Variable	Coefficient of ECT	Z-Value	P-Value
1	Aditya Birla Sun Life Nifty ETF	8	Market Price	-0.0002	-0.05	0.959
			NAV	-0.0336	-3.80*	0.000
2	ICICI Prudential Sensex ETF	7	Market Price	0.0106	0.99	0.322
			NAV	-0.1421	-5.04*	0.000
3	Kotak Nifty ETF	11	Market Price	-0.0531	-0.83	0.406
			NAV	-0.1330	-2.35*	0.019
4	Kotak Sensex ETF	12	Market Price	-0.0337	-1.05	0.293
			NAV	-0.1489	-4.56*	0.000
5	Motilal Oswal M50 ETF	3	Market Price	0.0007	0.77	0.440
			NAV	-0.0086	-2.57*	0.010
6	Quantum Nifty ETF	7	Market Price	-0.1565	-1.88	0.060

			NAV	-0.2930	-4.12*	0.000
7	Reliance ETF Bank BeES	7	Market Price	0.0255	0.32	0.749
			NAV	-0.2925	-3.85*	0.000
8	SBI ETF Sensex	11	Market Price	0.0020	0.29	0.775
			NAV	-0.0617	-4.06*	0.000
9	UTI Sensex Exchange Traded Fund	10	Market Price	0.0209	0.44	0.657
			NAV	-0.5537	-6.64*	0.000

The table presents the results of VECM.

Null Hypothesis: There is no lead lag relationship between NAV and price

* Indicates statistically significant a 5% level

5. Conclusion

ETFs are passive funds which follow a selected benchmark. The tracking efficiency of the fund manager is a measure of his performance. Since ETFs trade in primary and secondary markets, any deviation between NAVs in primary market and market prices in secondary market indicates the violation of LOOP (Ben-David et al., 2017; Brown et al., 2021). Hence, it is essential to assess tracking efficiencies of the fund managers and pricing efficiencies of the market from time to time so that the market regulator can take necessary steps to improve the performance of ETF market. Thus, motivation behind the study is to measure the tracking and pricing efficiencies of selected ETFs in India. Tracking error of ICICI Prudential Sensex ETF is highest and Aditya Birla Sunlife Nifty ETF is lowest in the given sample. The persistence of deviation between NAVs and market prices of ETFs indicate the scope for arbitrage opportunities to authorized participants. The findings are in line with the other prior studies (Tripathi & Garg, 2016; Aditya & Desai, 2015; Jares & Lavin, 2004; Petajisto, 2017; Shin & Soydemir, 2010) which documented the violation of LOOP and the presence of arbitrage opportunities in ETF market. The VEC model applied in the study further confirms the pricing inefficiencies, as NAVs lead their respective market prices, providing arbitrage opportunities. Further, such deviations are prevalent in India for longer period. This may be due to low level of trading activity and inefficient arbitrage mechanism in India. However, active arbitrage activity brings ETF prices in line with the underlying portfolio NAVs and vice versa. Higher trading activity (Glosten et al. 2015) brings in higher information efficiency in the underlying securities market (Ben-David et al., 2017; Box et al., 2021) and improves price discovery mechanism. Hence, SEBI and stock exchanges should take necessary steps to improve trading activity in Indian ETFs and efficient price discovery mechanism to achieve market efficiency (Nargunam & Anuradha, 2017). The findings are useful to arbitragers and traders to develop profitable trading strategies, stock exchanges to frame better trading mechanism and market regulator to formulate policies for ensuring market efficiency. The study focuses on only equity ETFs and further research can be done in other segments such as gold, debt, leveraged, currency etc.

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Appendix 1 Exchange Traded Funds - Sample

S No	Exchange Traded Fund	Fund House	Launch Date	Benchmark	Rikometer	Category	Assets	Return since launch
1	Aditya Birla Sun Life Nifty ETF	Aditya Birla Sun Life Mutual Fund	Jul 22, 2011	NIFTY 50 Total Return	Moderately High	Equity-Largecap	Rs 212 cr (on January 31, 2019)	10.36%
2	ICICI Prudential Sensex ETF	ICICI Prudential Mutual Fund	Jan 10, 2003	S&P BSE Sensex TRI	Moderately High	Equity-Largecap	Rs 19 cr (on January 31, 2019)	17.10%
3	Kotak Nifty ETF	Kotak Mahindra Mutual Fund	Feb 02, 2010	NIFTY 50 Total Return	Moderately High	Equity-Largecap	Rs 639 crore	10.55%
4	Kotak Sensex ETF	Kotak Mahindra Mutual Fund	Jun 06, 2008	S&P BSE Sensex TRI	Moderately High	Equity-Largecap	Rs 12 crore	9.61%
5	Motilal Oswal M50 ETF	Motilal Oswal Mutual Fund	Jul 28, 2010	NIFTY 50 Total Return	Moderately High	Equity-Largecap	Rs 19 cr (on January 31, 2019)	8.06%
6	Quantum Nifty ETF	Quantum Mutual Fund	Jul 10, 2008	NIFTY 50 Total Return	Moderately High	Equity-Largecap	Rs 5 crore	11.09%
7	Reliance ETF Bank BeES	Reliance Mutual Fund	May 27, 2004	NIFTY Bank TRI	High	Equity: Sectoral-Banking	R 5,043 crore	19.01%
8	SBI ETF Sensex	SBI Mutual Fund	Mar 08, 2013	S&P BSE Sensex TRI	Moderately High	Equity-Largecap	R 14,723 cror (February 28, 2019)	13.46%
9	UTI Sensex Exchange Traded Fund	UTI Mutual Fund	Aug 26, 2015	S&P BSE Sensex TRI	Moderately High	Equity-Largecap	R 3,738 crore (As on Feb 28, 2019)	12.29%