Evaluating index fund implementation in India

Kshama Fernandes[*]
Goa Institute of Management, Goa
kshama@gim.ac.in

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Abstract

Since the first index fund launched in 1999, the index fund market in India has been growing steadily. In this paper, we seek to measure and understand the tracking error of index funds in India. The consistency and level of tracking errors obtained by some well–run index funds suggests that it is possible to attain low levels of tracking error under Indian conditions. At the same time, there do seem to be periods where certain index funds appear to depart from the discipline of indexation.

[*]The views expressed in this paper are those of the author and not of her employer.

Contents

1 Introduction

In the decade of the 1960s and 1970s, many studies indicated that actively managed funds which seek to obtain excess returns by actively forecasting returns on individual stocks, do not actually obtain statistically significant excess returns. This was consistent with the hypothesis of 'market efficiency', which suggested that obtaining excess returns should be difficult in a competitive market.

This research suggested a superior investment strategy: the index fund. This would be a portfolio which passively replicated the returns of the index. The most useful kind of market index is one where the weight attached to a stock is proportional to its market capitalisation. Index funds are easy to construct for this kind of index, since the index fund does not need to trade in response to price fluctuations. Trading is only required in response to issuance of shares, mergers, etc.

Index funds are central to the modern approach to fund management. Since the first index fund launched in 1972, investors all over the world have discovered that there are substantial benefits from utilising index funds as an alternative to actively managed funds. In many countries, assets with index funds amount to 30% to 40% of the total equity assets managed by professional fund managers.

In this study however, we do not address the question of *whether* index funds outperform actively managed funds in India; nor do we address the question of whether the agency conflicts between the investor and fund manager are better addressed by index funds. Our focus is on questions of *implementation*. Assuming that an investor *is* interested in utilising an index fund, the hurdle faced is that of *tracking error*, i.e. the annualised standard deviation of the error between index fund returns and index returns. It is argued that in developing countries, where the equity market is illiquid, the tracking error of index funds can be fairly large, thus diminishing the benefits from indexation. In this study we make a systematic effort to measure and understand tracking error of index funds in India.

We argue that correct index fund tracking error calculations require great care in data handling, and show how small mistakes in data handling can generate huge tracking errors. One problem faced is that of missing data – days where index values were available, but fund NAV values were not. Using a simulation, we show that a modest incidence of missing data can lead to an economically significant upward bias in the apparent tracking error. We offer an alternative heuristic for measuring tracking error which is unbiased in the face of such missing data.

Tracking error is typically measured as the standard deviation of difference between index returns and fund returns. The goal of an index fund is to minimise the tracking error. International evidence suggests that index funds incur a tracking error in the range of 4 basis points to about 120 basis points. We compute tracking error for the four longest existing index funds in India. Over comparable time–periods, we observe tracking error in the range of 68 basis points to 1097 basis points. In the Indian experience, we find that the Templeton Franklin funds have consistently shown low tracking error since inception. IDBI Index I-Nit Fund appears to have learned how to do index fund management and improved substantially. The UTI Nifty Index Fund exhibits unacceptably large tracking errors through out.

We go on to seek some insights into the sources of tracking error. Open-ended funds in India need to maintain buffer cash to meet redemptions. To the extent that a fund maintains buffer cash, it has $\beta \neq 1$. This inevitably induces tracking error. In addition, a fund could also incur tracking error due to active management. These constitute two competing hypotheses about the sources of tracking error.

We seek to obtain insights into this question using the single market model. We hypothesise that if the fund holds a fixed fraction of cash and does perfect indexation with the remainder, we would observe the following observable effects: (a) a highly stable beta which is less than one, (b) alpha of roughly 0 and (c) an error variance of roughly 0. We find that in the case of the UTI and IDBI products, where tracking error is clearly present, the buffer cash hypothesis does not serve to explain the bulk of tracking error.

We also explore the relationship between index volatility and index fund tracking error. When the index is more volatile, we expect index fund tracking error to be larger for two reasons: (a) Greater imprecision in achieving trades at the NSE closing price, (b) Liquidity is inferior when volatility is higher. In addition, if active management is present, then portfolio volatility is likely to be higher when index volatility is higher. We find that there is, indeed, a positive correlation between Nifty volatility and index fund tracking error. There is a remarkable homogeneity in the volatility - tracking error relationship, across different funds.

In summary, our study shows that while some funds have shown periods of very high tracking error, given the magnitude and consistency of tracking error obtained by the better performing funds, indexing as a strategy does seem implementable in India. To enable performance measurement, there is need for high quality data dissemination both by the funds and by the index provider. There is also a need for performance measurement using the methods of this paper, and their communication to customers of index funds.

The remainder of this paper is organised as follows. Section 2 is a survey of literature on index fund performance. Section 3 outlines the motivation and goals of the study. Section 4 describes the data sources employed and the methodology that is used in this paper. Section 5 documents the findings of the study. Finally, Section 6 concludes.

2 Issues

Index funds are arguably one of the most successful ideas that have flowed from academic economics into the real world. Indexing is based on the premise that if markets are fairly efficient, then it would prove difficult for active managers to obtain excess returns, after considering the higher fees and costs that they have to run up. Hence, instead of actively engaging in stock picking, index funds simply try to replicate the returns on a chosen market index and aim to deliver the returns and the risk of that index. Evaluating an index fund's performance boils down to observing how closely a fund tracks the underlying index. This is measured in terms of 'tracking error'. A well–managed index fund is one which exhibits low tracking error. The job of an index fund manager is therefore to minimise the tracking error.

In principle, managing an index portfolio requires investment in all constituent index securities in the exact proportion as the underlying benchmark. This is called a "full replication" approach. In practice, fund managers often face problems in replicating the benchmark index returns. Chiang (1998) describes the difficulties faced by managers in matching index returns. The index represents a mathematical calculation derived from a portfolio of securities that are not subject to the same market frictions as those faced by index mutual funds (Perold 1988).

Index funds incur transactions costs that are associated with portfolio implementation, re-balancing and capital flows. When the composition of the underlying index changes, either due to additions or deletions of constituents or due to corporate restructuring, the index assumes that the theoretical portfolio's new weights to each security can be achieved automatically. However, for the index fund, realigning the portfolio to mimic the underlying benchmarks involves physical trading in stock and the transactions costs incurred thereby.

Hence, factors driving tracking error include transactions costs, fund cash flows, uninvested/buffer cash, treatment of dividends by the index, corporate actions, and index composition changes. The liquidity of the underlying index securities also has implications for transaction costs (in terms of impact cost) and in turn the tracking error incurred by funds (Keim 1999).

As a result of ongoing subscriptions and redemptions, open–ended index mutual funds engage in flow–induced trading. Upon subscriptions, they are required to rapidly invest the cash flow across index securities, and upon redemptions, to sell securities to generate cash. Index funds often maintain buffer–cash to meet redemptions. This gives $\beta < 1$ and innately yields tracking error.

The size and timing of cashflows also has an impact on tracking error. Liquidity of index stocks has implications for transactions costs, both implicit and explicit. Full–replication index funds could be required to have part of their assets in illiquid index securities. When faced with large subscriptions or redemptions, the fund is forced to trade on the market under non–ideal liquidity conditions, resulting in high transactions costs and tracking error.

Typically there is a timing delay between when the index incorporates the dividend(at the ex–dividend date) and the actual receipt of the dividend by the index fund(after the ex–dividend date). Most indexes assume that accrued dividends are reinvested the day the stock goes ex–dividend. Actual receipt of dividends could take as long as several weeks.

When index securities are subject to corporate restructuring such as mergers, acquisitions or takeover by another company outside the index, there may be a timing delay between the date the company is removed from the index and the date the index fund receives the cash settlement. In addition, front–running by risk arbitrageurs who acquire securities ahead of their inclusion in the index may also have an undesirable impact (Beneish & Whaley 1996).

If the index fund is perfectly aligned with the index, the volatility of the underlying index will not result in tracking error. Since the index fund owns exactly the same portfolio as the index, however volatile the index movements are, the fund will perfectly track them. If however, the index fund portfolio does not perfectly mirror the index, volatility of the underlying index will result in tracking error.

Index volatility is of much greater concern to funds that track the index by using optimisation techniques (Rudd 1980, Jansen & van Dijk 2002). They hold a portfolio that is different from the index portfolio in the hope of minimising transactions costs associated with trading illiquid stocks. The portfolio is chosen such that it has a high correlation with the index. Under situations of normal index volatility, such an optimised portfolio will track the index closely. However during periods of high index volatility caused by index securities not held by the optimised portfolio, the fund will fail to track the index, resulting in elevated tracking error.

An ideal index fund exactly replicates index returns. Indexing achieves the investor's goal of removing discretionary powers from the fund manager. Investors would expect the index fund return to under-perform the underlying index to the extent of the management fee. In reality, index funds under-perform beyond fees charged. For reasons cited above, tracking error will be inherent in index fund performance. This can give 'cover' to discretion in fund management.

A large number of performance evaluation studies have been undertaken for actively managed funds (Elton et al. 1993, Malkiel 1995, Gruber 1996, Elton et al. 1996, Carhart 1997). However, despite the significant growth in the value of assets being indexed across the world, empirical research evaluating the performance of index funds is scarce. Frino & Gallagher (1999) examine the performance of passive equity fund managers in Australia. Frino & Gallagher (2001) evaluate the extent of S&P index fund tracking error and compare active fund and index fund performance. In this paper, we examine the tracking error experienced by index funds in India.

3 Motivation and goals of the study

The index fund industry in India is still young. Relatively little is known about the extent of tracking error experienced by index funds. Individual funds do report tracking error. However a systematic effort to measure and compare tracking error, using a consistent methodology, has not been undertaken. The short history with index funds in India implies that relatively little data is available. Yet, it is important to utilise this limited evidence in order to understand the limitations of indexing in India.

Index funds have attracted considerable attention in India. Most major fund houses have already launched index funds while many others are on way to launching. Our work is of direct usefulness to these fund houses. From the perspective of investors, our work helps in assessing the extent to which index funds deliver on their promise of exactly tracking the index. As of today, there is a lack of clarity on the extent to which index funds in India are able to accurately track the index. Our work helps produce some stylised empirical facts on this question.

Index funds may increasingly play a major role in public policy formulation. For example, the Dave Committee has recommended that equity investments by pension funds should exclusively be done using index funds. Similar arguments can, in principle, be made in the insurance sector also. While this recommendation is entirely defensible using conceptual arguments, we need to verify the extent to which accurate tracking is attainable under Indian conditions. The study helps to shed light on this, and thus advance these policy debates.

This paper is concerned with measuring and understanding the tracking error of index funds in India. We seek to address the following questions:

Q1 What are the difficulties faced in measuring tracking error and how can they be overcome?

Q2 What is the overall experience with tracking error of the competing index fund products in India today? Which are the index funds with the best fidelity?

Q3 Can we decipher the source of tracking error? Is tracking error due to buffer cash maintained or due to active management at the fund?

Q4 What can we say about the determinants of tracking error?

4 Data and Methodology

In India we have a fairly short time–series of index fund returns. The first index fund was launched in June 1999. Table 1 gives a list of existing index funds. Of these, we restrict ourselves to funds which have daily NAV data at least for a period of two years. This leaves us with four funds, IDBI Index I-Nit'99 Fund, UTI Nifty Index Fund, Templeton Franklin India Index Fund and Templeton Franklin India Tax Fund. The daily NAV data has been obtained from the funds and from CMIE[1]. We did not have access to data such as buffer cash maintained by funds, fund subscriptions/redemptions and impact cost for various basket sizes.

[1]Centre for Monitoring Indian Economy.

Fund	NAV data available from
Nifty–based	
IDBI Index I-Nit'99	July 1999
UTI Nifty Index Fund	Feb 2000
Templeton Franklin India Index Fund	Aug 2000
Templeton Franklin India Tax Fund	Mar 2001
Pioneer ITI Index Fund (NSE Nifty)	Aug 2001
FT India Index fund	Aug 2001
Benchmark ETF	Jan 2002
SBI Magnum Index Fund	Jan 2002
IL&FS Index Fund	Feb 2002
Prudential ICICI Index Fund	Feb 2002
HDFC Index Fund Nifty Plan	Jul 2002
Birla Index Fund	Sep 2002
LIC Index Fund Nifty Plan	Dec 2002
Tata Index Fund Nifty Plan(A)	Mar 2003
Tata Index Fund Nifty Plan(B)	Mar 2003
Sensex–based	
UTI Index Equity Fund	May 1997
Pioneer ITI Index Fund (BSE Sensex)	Aug 2001
FT India India Index Fund(BSE Sensex)	Aug 2001
ILFS Index Fund(BSE Sensex)	Feb 2002
LICMF Index Fund Sensex Advantage Plan	Dec 2002
LICMF Index Fund Sensex Plan	Dec 2002
Prudential ICICI ETF	Jan 2003
Tata Index Fund Sensex Plan(A)	Mar 2003
Tata Index Fund Sensex Plan(B)	Mar 2003

Table 1: Information availability about index funds in India

Foreign Index Funds	Net Assets (Million US$)	Tracking error(%)
Morgan Stanley S&P 500 Index-A	1991.90	0.041
Scudder S&P 500 Index Fd-AA	879.86	0.071
Vanguard 500 Index Fund-Inv	86298.83	0.078
Dreyfus Basic S&P 500 Stock I	1122.79	0.092
Merrill Lynch S&P 500 Index-D	1745.08	0.096
Fidelity Spartan 500 Index	7102.61	0.126
E*Trade S&P 500 Index Fund	85.30	0.153
Invesco S&P 500 Index Fund-Inv	278.19	0.157
Nationwide S&P 500 Index-A	498.89	0.177
Barclays S&P 500 Stock Fund	1420.52	1.126

Source: Bloomberg

Table 2: Some international evidence on tracking error

4.1 Tracking error

Roll[1992], Pope and Yadav[1994], and Larsen and Resnick[1998] identify a number of ways in which tracking error can be measured. We measure tracking error as the standard deviation of returns differences between the market portfolio and the index fund. Suppose we have daily time series r_{Mt}, r_{pt}, $e_p = r_{Mt} - r_{pt}$. We focus on tracking error as $\sqrt{250}\sigma_{e_p}$.

It is conventional to think of tracking error on an annualised basis. Suppose TE=0.5. Then the 95% confidence interval for index fund returns over one year will be $\pm 1\%$ compared with returns on the index. We measure the overall tracking error for the entire life of the fund. To enable comparison across funds, we compute the tracking error for the last two years ending 31/3/2003, a period for which we have NAV data for all funds under study. To capture the time dynamics of changes in tracking error, we calculate the rolling tracking error using a 250–day moving window.

Most index funds promise to maintain a particular level of tracking error. Table 2 gives some evidence of the magnitude of tracking errors incurred by index funds in the US. This suggests that the values for TE could be in the range of about 4 basis point to 120 basis points.

4.2 Difficulties in measurement

Achieving low tracking error is not easy. Suppose e is a one–day error. Further suppose $E(e) = 0$. Then the variance of the error is:

Fund	Span of data	Days with NAV missing	Percent
IDBI Index I-Nit'99 Index Fund	919	16	1.45%
UTI Nifty Index Fund	753	11	1.46%
Templeton Franklin India Index Fund	659	2	0.30%
Templeton Franklin India Tax Fund	518	3	0.60%

Table 3: Problems with Indian data

Date	Index level	Fund NAV
t_1	M_1	N_1
t_2	M_2	missing
t_3	M_3	N_2
t_4	M_4	N_3

Table 4: Snapshot of a returns series with missing data

$$\begin{aligned} \text{Var}(e) &= E(e^2) - [E(e)]^2 \\ &= E(e^2) \\ &= \frac{\text{SSE}}{T} \\ \text{so} \qquad \text{SSE} &= T\sigma_e^2 \end{aligned}$$

Suppose a fund wants to maintain an annualised tracking error of 0.5. This means its daily tracking error, σ_e, can at most be 0.0316. This implies that the SSE should be equal to 0.25. This is the 'budget' for one–year of SSE for a fund that promises a tracking error of 0.5. Now suppose we get *one day* with $r_M = 2\%$ and $r_p = 2.5\%$, i.e. $e = 0.5$ and $e^2 = 0.25$, this uses up the full year's 'budget' for SSE. Hence index funds need to be very careful in terms of consistently tracking the index.

This sensitivity also highlights the importance of sound data management. Small problems in measurement make it impossible to obtain low tracking error values like 0.5. To correctly measure index fund performance, we need high quality data.

Ideally, index fund NAVs should be available for every day that the index trades. One problem with Indian data is that of missing NAVs values. Table 3 shows the number of days of missing NAVs for the four funds under study.

We use Table 4 to try to understand the impact of missing data on tracking error. If we define $r_{M,3} = M_3/M_2$ and $r_{p,3} = N_2/N_1$, this will give a huge error $e_{p,3} = r_{M,3} - r_{p,3}$. This will throw off the TE calculation, as argued above.

We propose an alternative heuristic. Faced with the data in Table 4, we drop points t_1, t_2 and t_3. The only data-point that is used is returns from $3 \rightarrow 4$. While this appears to waste data, it avoids the bias in tracking error estimates caused by the erroneous e value.

While such an approach appears logically sound, there is a need to evaluate the economic significance of a small incidence of missing data. We conduct a Monte Carlo simulation to measure the impact of missing data on tracking error calculations. We simulate a million points of data from an imaginary index with the daily standard deviation of returns, σ_M, equal to 1.4. We focus on an index fund with a true daily tracking error σ_e, and a probability of missing data of λ.

We measure tracking error of the simulated index fund by two methods of handling missing data – one, by using the standard practice of ignoring days with missing NAVs, and two, by using the alternative heuristic suggested by us above. We calculate the exaggeration in tracking error obtained by ignoring days with missing NAVs.

We find that fairly modest rates of missing data (e.g. 0.4% or 1 point per year) suffice to bias annualised TE from 1% to 1.74%. Figure 1 shows the exaggeration observed in tracking error due to incorrect handling of missing data.

Our finding reinforces the need for high quality data. With a growing number of index funds now available to investors, measurement of tracking error becomes an important issue. Index maintainers and index funds need to ensure an identical set of dates on which r_M and r_p is reported. If this is not the case, $r_{M,t} = M_t/M_{t-1}$ should not be compared against $r_{p,t} = N_t/N_{t-2}$. In this paper, we use the 'alternative heuristic' shown above.

4.3 Buffer cash as a source of tracking error

Many index funds hold some amount of 'buffer cash', in order to cope with redemptions. This is clearly one source of tracking error.

Suppose a fund holds a λ fraction in cash which earns zero return. With the remaining $(1 - \lambda)$, the fund does perfect indexation. Further, suppose the

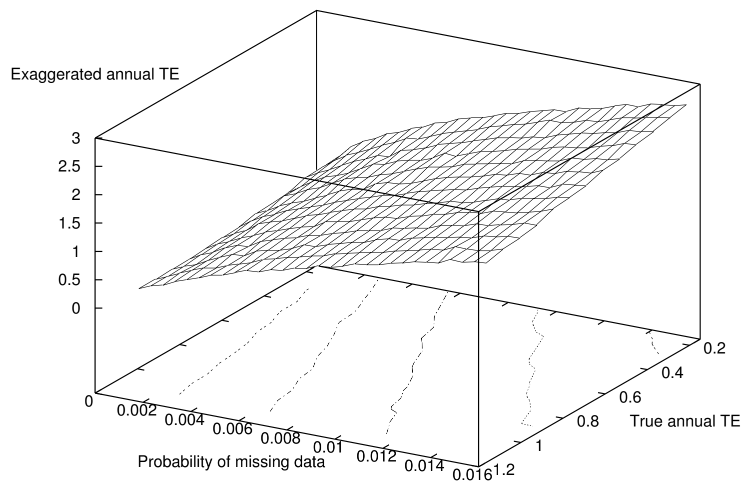

Figure 1: Exaggeration in tracking error due to incorrect handling of missing data

return on the market is normally distributed with mean zero and standard deviation σ_M^2. Then:

$$
\begin{aligned}
r_M &\sim N(0, \sigma_M^2) \\
e_j &= r_M - (1 - \lambda) r_M \\
&= \lambda r_M \\
\text{so} \quad \sigma_{e_j} &= \lambda \sigma_M
\end{aligned}
$$

If for example, $\sigma_M = 1.4$ and $\lambda = 0.01$, this suggests that $\sigma_{e_j} = 0.014$. In spite of perfectly indexing $(1 - \lambda)$, the fund would invariably incur an annualised tracking error of 0.22%, purely because of the 1% buffer cash held by it.

Broadly speaking, investors should be relatively benign towards index funds that hold buffer cash, and suffer tracking error as a consequence. In contrast, investors should be concerned when funds engage in active management. Both paths involve tracking error, and we need to find ways of distinguishing the two.

4.4 Regression framework

The market model of Sharpe (1964) captures the relationship between return on a security and the return on the market index for the same period. We use this to model the returns on an index fund. The return on the index portfolio is regressed against the return on the benchmark/index portfolio. The α provides an estimate of the excess return/value added by the index fund and the β gives an estimate of the sensitivity of index fund returns to returns on the market index.

$$r_{pt} = \alpha + \beta r_{Mt} + \epsilon_{pt} \quad (1)$$

where:

r_{pt} – return on index portfolio for a given period

r_{Mt} – return on market index for the same period

α – intercept term, represents excess return over market, should *approx* zero.

β – slope of the regression, represents systematic risk, should ideally be close to one.

Suppose the fund holds a fixed fraction λ of cash and does perfect indexing with the remainder. If this be the case, in the regression Equation 1, we will observe the following three effects:

1. A highly stable $\beta = 1 - \lambda$,
2. We should not get $\beta > 1$.
3. $\text{Var}(\epsilon) \approx 0$.
4. $\alpha \approx 0$.

We engage in rolling estimation of β, $\text{var}(\epsilon)$ and α to look for these phenomena.

4.5 Index volatility and tracking error

Research on the time-series variation of the bid/offer spread suggests that when expected volatility is high, economic agents demand a larger bid/offer spread. In addition, high volatility can yield tracking error through the imprecision introduced into index program trades, which are executed over a

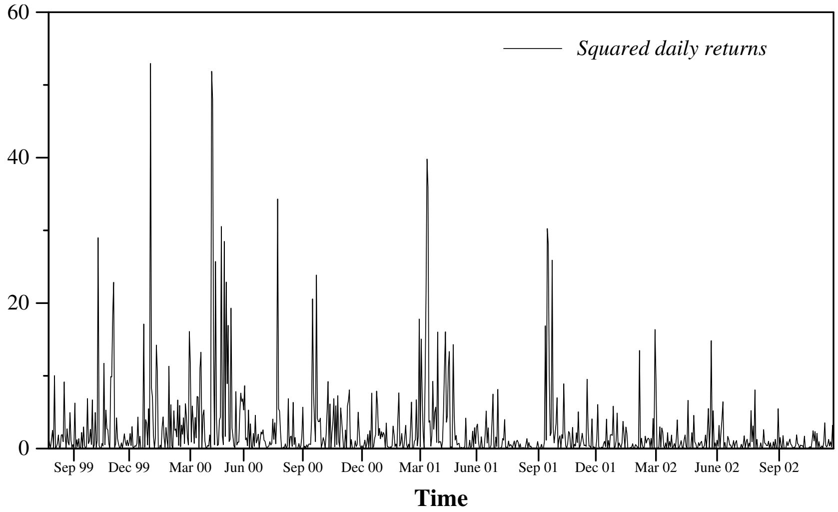

Figure 2: Time series of daily squared returns on Nifty

finite window of time. We would hence like to learn more about the relationship between tracking error and index volatility.

Towards this goal, we first need estimates of index volatility. The returns in many financial markets are not well modelled by an independent and identically distributed process. Figure 2 shows the time series of daily squared returns on Nifty. This shows time-varying volatility, and volatility clustering. A variety of tests strongly reject unconditional normality of Nifty returns. We model the time–varying volatility of Nifty returns by using an AR(1) – GARCH(1,1) model (see Appendix). We find that the AR(1) – GARCH(1,1) model mostly removes non–normality in the series.

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \epsilon_t \quad (2)$$

$$H_t = \gamma_0 + \gamma_1 \epsilon_{t-1}^2 + \gamma_2 H_{t-1} \quad (3)$$

where $\epsilon_t \sim N(0, H_t)$. Equation 2 models the autoregressive conditional mean and Equation 3 models the conditional variance of the Nifty returns series. Using this model we get a daily H_t time–series for Nifty variance. We try to explain tracking error in terms of Nifty volatility measured as the square root of conditional variance, H_t. This is done using the regression:

$$\sigma_{et} = \alpha_i + \beta_i log(\sigma_{bt}) + \epsilon_t \quad (4)$$

Product	From	Tracking error
IDBI Index I-Nit'99 Fund	26/07/1999	2.09
UTI Nifty Index Fund	27/03/2000	9.97
Templeton Franklin India Index Fund	04/08/2000	0.81
Templeton Franklin India Tax Fund	26/02/2001	0.79

Table 5: Tracking error incurred by index funds since inception

Product	Tracking error
IDBI Index I-Nit'99 Fund	0.68
UTI Nifty Index Fund	10.97
Templeton Franklin India Index Fund	0.74
Templeton Franklin India Tax Fund	0.79

Table 6: Tracking error incurred by index funds over the last two years

We use estimates of σ_e, the tracking error, over one week of fund returns at a time. These weekly estimates of index fund tracking error are regressed against σ_{bt}, weekly estimates of Nifty volatility.

5 Findings

5.1 Replicating index returns

Table 5 gives the tracking error for the funds under study from inception till 31/03/2003. The Templeton Franklin India Tax Fund has the lowest tracking error, and achieves values which compare well with those seen in developed markets. UTI Nifty Index Fund shows the highest tracking error. Table 6 gives the tracking error across a comparable time period for two years ending 31/03/2003. IDBI Index I-Nit'99 and the two Templeton Franklin Index Funds show acceptable levels of tracking error, whereas the UTI Nifty Index Funds shows a further deterioration in performance in recent times.

We do a quick comparison of the time–variation in Nifty volatility and the index fund volatility, both measured as rolling standard deviation of returns. Figure 3 shows the rolling volatily of Nifty and the four index funds across comparable time periods. The volatility of UTI Index Fund significantly deviates from that of the underlying Nifty, suggesting that the two portfolios

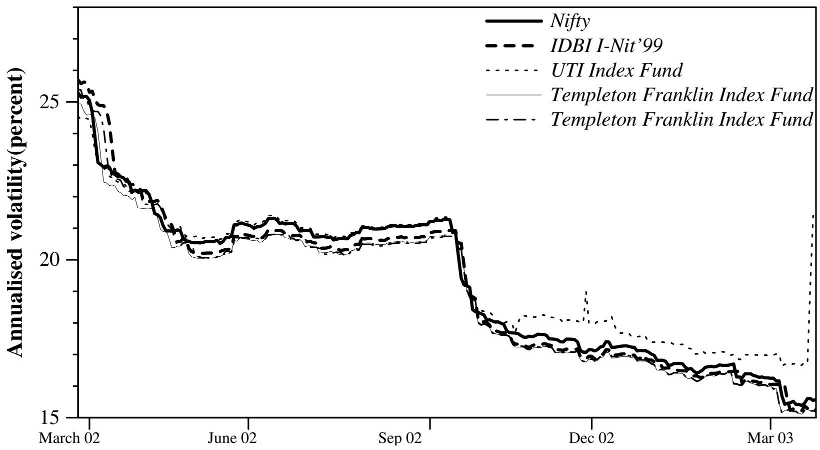

Figure 3: Rolling volatility of Nifty and Nifty–based index funds

could be different. Figure 4 to 7 show the time–variation in tracking error. IDBI Index I-Nit'99 Fund showed high tracking error during the initial year and a half, after which it has been consistent and low. The tracking error for UTI Nifty Index Fund has been highly inconsistent. Both the Templeton Franklin funds show consistently low tracking errors since inception.

5.2 Tracking error and buffer cash

We regress return on the index portfolio, r_{ip}, on return on the market, r_{Mi}, and estimate the α, β and variance of ϵ for the single market model. Table 7 gives these parameters since inception. Both the Templeton Franklin funds show a highly stable beta. The R^2 of the regression is almost one, suggesting that most of the tracking error incurred by these funds could be explained by the buffer cash held. The beta of UTI Nifty Index Fund has been highly unstable, and in recent times has hovered around 1.

To discern if the fund incurs tracking error due to buffer cash held or due to active management, we engage in rolling estimation of β, ϵ and α. Figure 8 to Figure 11 give estimations of rolling beta. Figure 12 to Figure 15 give estimations of rolling variance of errors and alpha. The two Templeton Franklin funds and the IDBI index fund exhibit the following:

1. A highly stable β.
2. $Var(\epsilon) \approx 0$.
3. $\alpha \approx 0$.

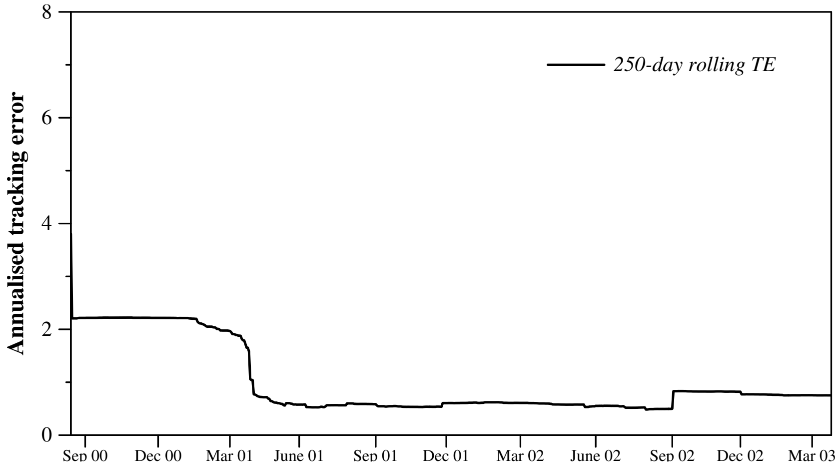

Figure 4: Rolling tracking error of IDBI Index I–Nit'99 Fund since inception

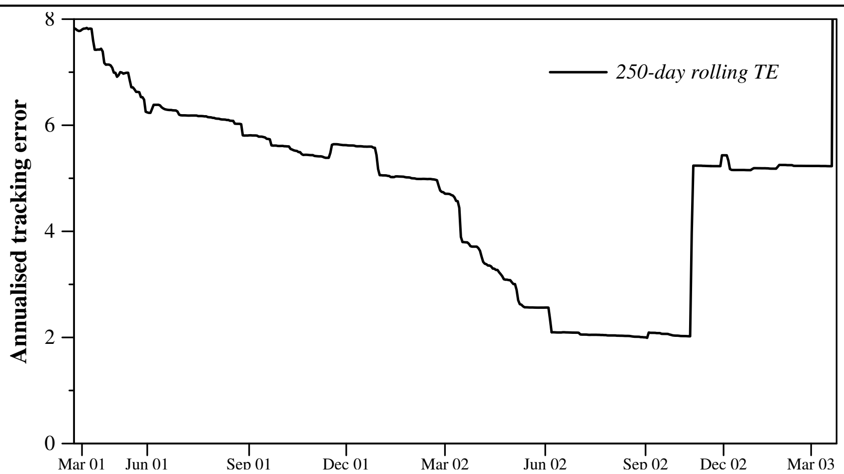

Figure 5: Rolling tracking error of UTI Nifty Index Fund since inception

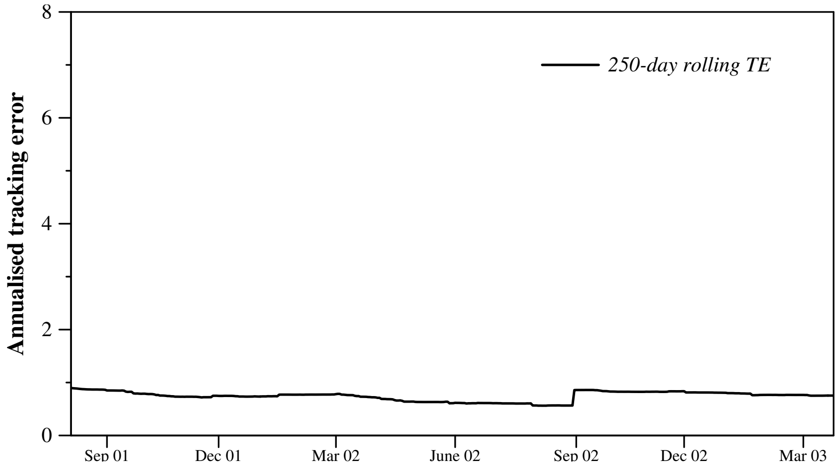

Figure 6: Rolling tracking error of Templeton Franklin India Index Fund since inception

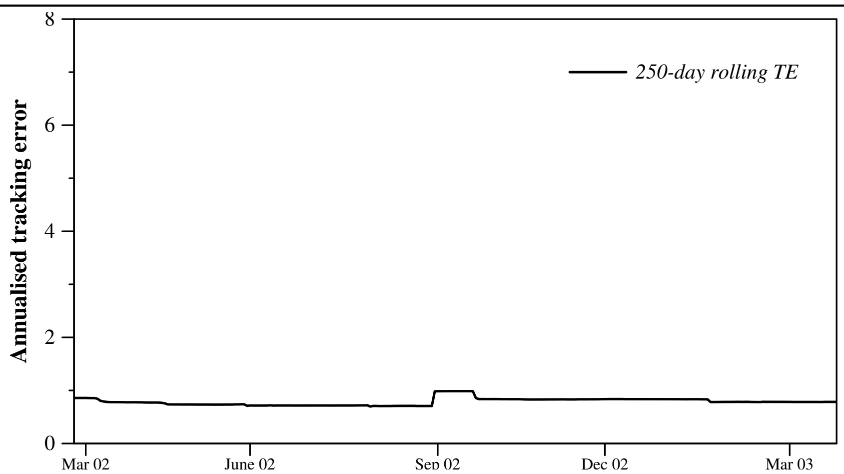

Figure 7: Rolling tracking error: Templeton Franklin India Tax Fund

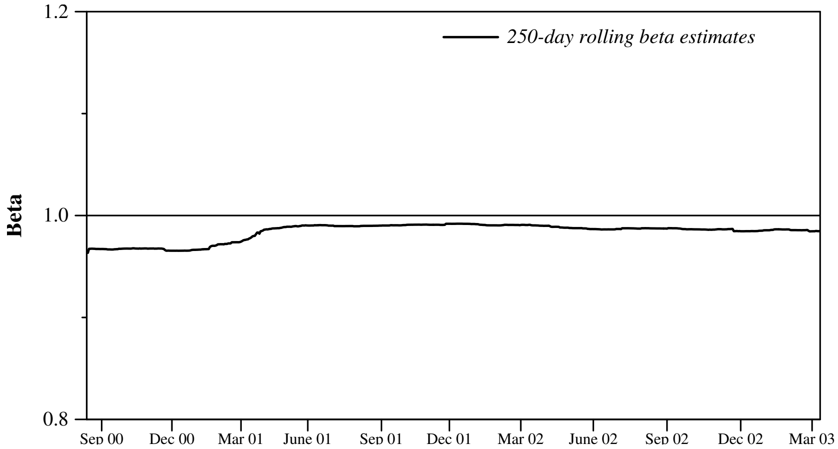

Figure 8: Rolling β : IDBI Index I-Nit'99 Fund

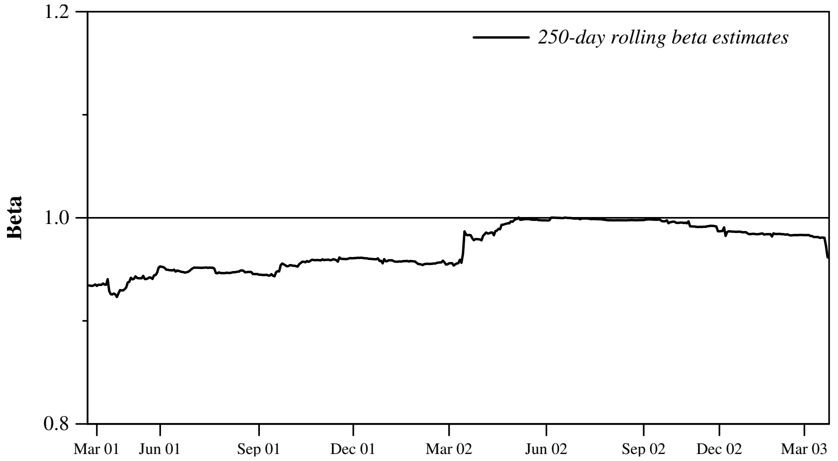

Figure 9: Rolling β : UTI Nifty Index Fund

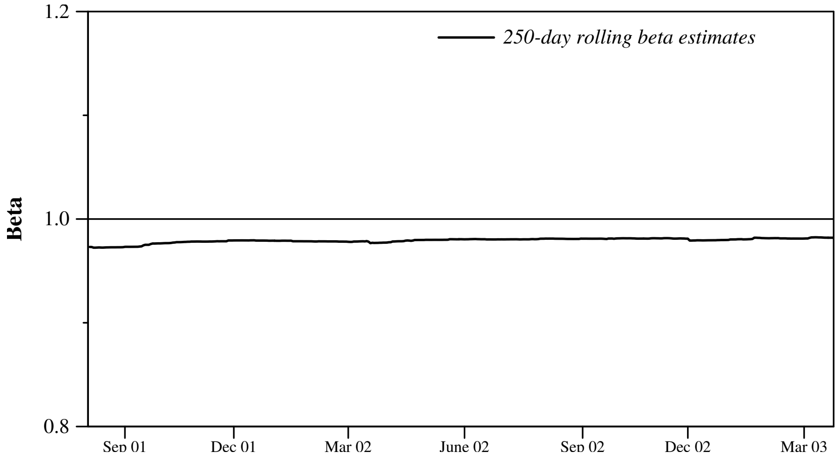

Figure 10: Rolling β : Templeton Franklin India Index Fund

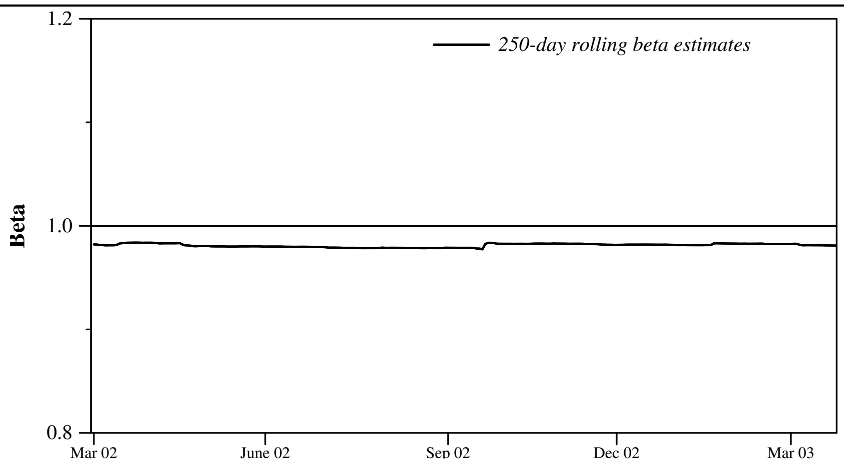

Figure 11: Rolling β : Templeton Franklin India Tax Fund

Product	Alpha	Beta	$Var(\epsilon)$	R^2
IDBI Index I-Nit'99 Fund	-0.0031	0.9774	0.0162	0.9932
UTI Nifty Index Fund	-0.0069	0.9506	0.3929	0.8423
Templeton Franklin India Index Fund	-0.0034	0.9766	0.0014	0.9992
Templeton Franklin India Tax fund	-0.0029	0.9817	0.0020	0.9988

Table 7: Single market model regression results

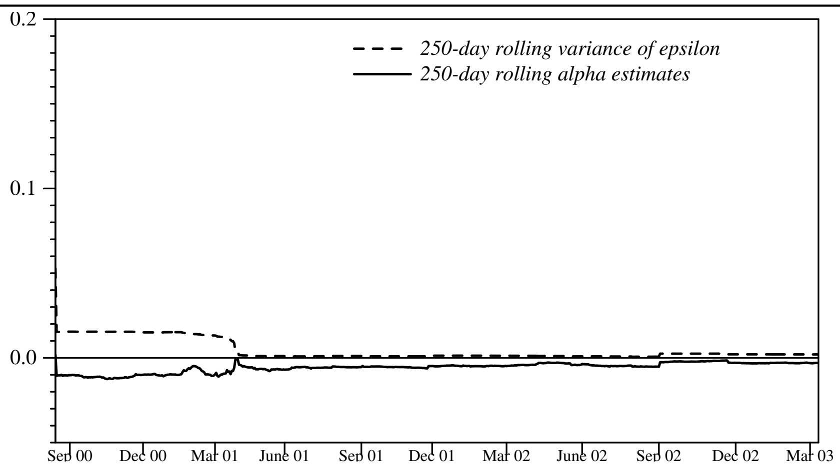

Figure 12: Rolling $Var(\epsilon)$ and α : IDBI Index I-Nit'99 Fund

The UTI fund however exhibits almost the opposite:

1. A highly unstable β.
2. A highly unstable $Var(\epsilon)$ that is different from 0.
3. $\alpha \approx 0$ and sometimes positive.

This may suggest that the tracking error obtained by UTI Nifty index fund is not due to buffer cash held, but probably due to active management.

5.3 Nifty volatility and tracking error

We model time–varying volatility of Nifty using the AR(1) – GARCH(1,1) model. Table 8 gives the model parameters for daily returns. Figure 16 shows the variance estimates obtained from the model. We try to explain tracking error in terms of Nifty volatility. Table 9 shows the regression results for the four funds. We conclude that Nifty volatility is positively correlated

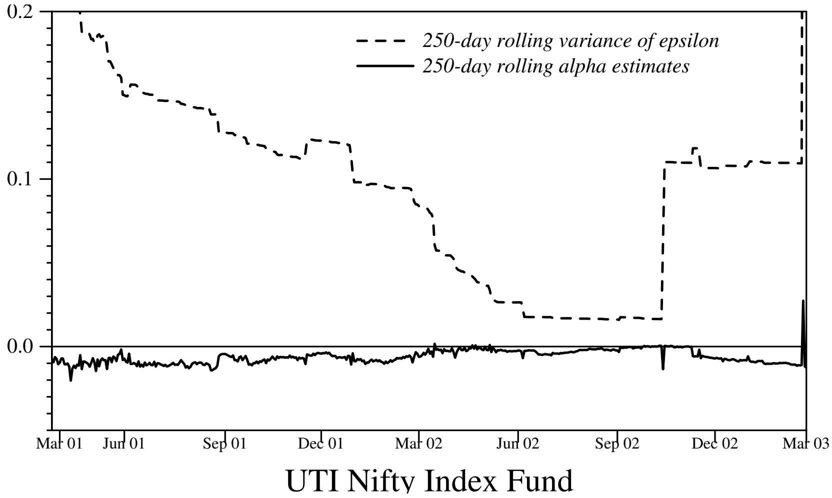

Figure 13: Rolling $Var(\epsilon)$ and α : UTI Nifty Index Fund

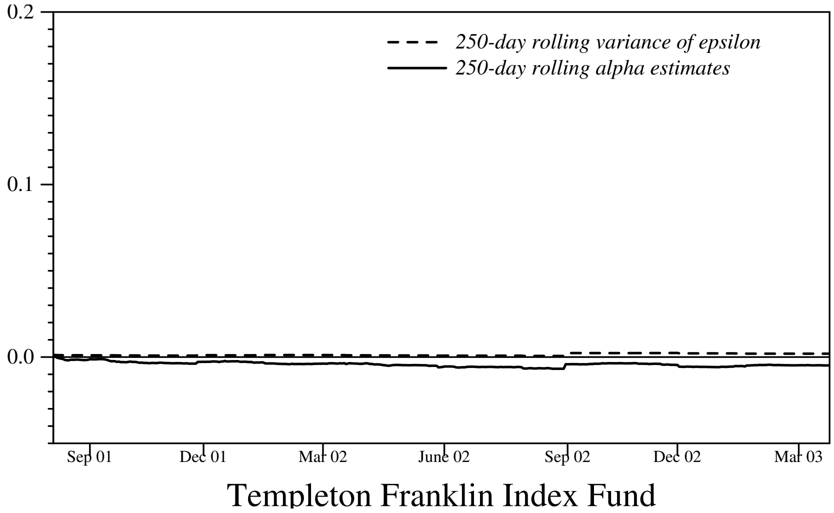

Figure 14: Rolling $Var(\epsilon)$ and α : Templeton Franklin India Index Fund

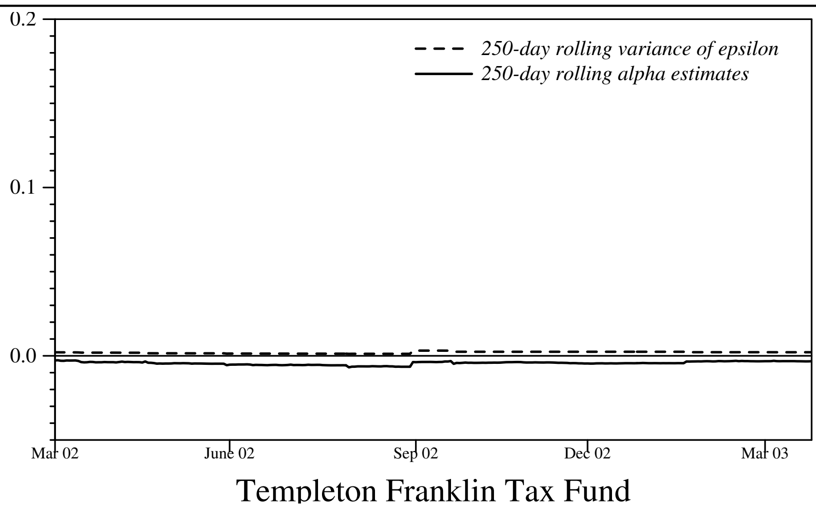

Figure 15: Rolling $Var(\epsilon)$ and α : Templeton Franklin India Tax Fund

Parameter	Coefficient	t
Mean equation		
Intercept	0.0378784	0.77
AR(1)	0.0689488	1.76
Volatility equation		
Intercept	0.1242849	5.60
ARCH(1)	0.1401796	7.30
GARCH(1)	0.8120375	41.50

Table 8: AR(1)- GARCH(1,1) model estimates for daily returns

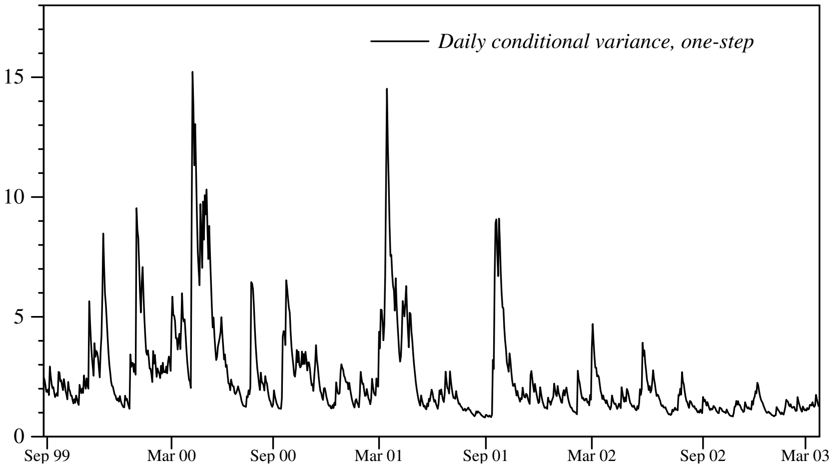

Figure 16: Variance estimates from AR(1)-GARCH(1,1) model

Fund	Intercept	Coefficient	R^2
IDBI Index I-Nit'99 Fund	0.5630496	1.977154	0.4182
UTI Nifty Index Fund	0.6979911	1.727080	0.2919
Templeton Franklin India Index Fund	0.6064298	1.729016	0.4321
Templeton Franklin India Tax Fund	0.6086619	1.691724	0.4386

Table 9: Regression estimates

with index fund tracking error. Its impact upon various highly heterogeneous funds seems to be remarkably alike.

6 Conclusion

In this study, we look at the performance of index funds in India. Index management requires supreme care in data management – by fund managers in terms of providing daily NAVs, dividend and expenses related data, and by index providers in terms of providing a neat time–series of daily index values and impact cost data for various basket sizes. It should be possible for an external observer to simulate an ideal index fund, assume zero transactions costs, and replicate the index. Our study shows that incorrect handling of data can result in significantly exaggerated values of tracking error. We suggest an alternative heuristic to handle the missing data problem encountered by us.

Using a comparable period of performance, we find that the tracking error for index funds in India ranges between 0.68% and 10.97%. The Templeton Franklin funds seem to be the best of the lot, consistently maintaining low tracking errors. The IDBI Index I-Nit'99 Fund showed high tracking error during the first half of its life, but has reduced since. The UTI Nifty Index Fund has fared very poorly on replicating index performance, exhibiting significantly high tracking error. Our rolling tracking error calculations to study the time–dynamics of tracking error suggest a *learning effect* over time.

We study buffer cash as a source of tracking error. Funds that hold buffer cash invariably run up tracking error. In the guise of holding buffer cash, funds could indulge in active management. We try to decipher this behaviour across funds by studying the single market model parameters for these funds. Except in the case of UTI Nifty Index Fund, we observe a highly stable beta, and alpha and variance of errors approximately equal to zero.

We model the time–varying volatility of Nifty returns using the AR(1)–GARCH(1,1) model and try to explain tracking error in terms of index volatility. We conclude that Nifty volatility is positively correlated with index fund tracking error.

While some funds show unacceptably high tracking error, the consistency in performance of the better run funds suggests that it is possible to attain fairly low levels of tracking error under Indian conditions.

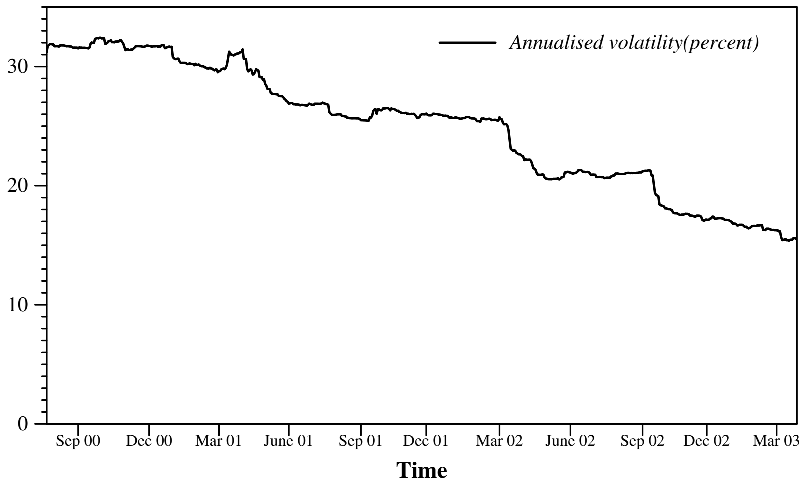

Figure 17: Rolling window annualised volatility measured as standard deviation of returns

A Modelling Nifty volatility

Historic volatility estimates based on daily squared returns assume that asset returns are independent and identically distributed and the asset return series is generated by a stationary stochastic process. We look at the Nifty returns series and find that it is not well modelled by an independent and identically distributed process. Returns and squared returns show signs of autocorrelation. Figure 2 shows the time series of daily squared returns and Figure 17 shows the time–series of annualised volatility(expressed in percent), of continuously compounded returns on the Nifty using rolling windows of 250 days at a time. This roughly corresponds to a window width of one calendar year. Hence at each date, this graph reports the annualised volatility of continuously compounded returns over the last one year.

The summary statistics about the daily returns time–series are as follows:

- Mean daily return of -0.0275 percent per day
- Standard deviation 1.5715. Annualised this works out to around 25%.
- Skewness = -0.1334 and Kurtosis = 5.6902.
- The 95th percentiles are -2.5014 and 2.4131.
- The 99th percentiles are -4.8848 and 4.1379.
- The smallest value was -7.2022% and the largest value was 7.277%. Apart

from this extreme value, the next worst return was -6.3095%.

A variety of tests all strongly reject normality. That is also evident with the extreme values for skewness and kurtosis seen here. Figure 18 shows the autocorrelation function for the daily returns series. There is some evidence of mean-reversion. Figure 19 shows the autocorrelation function of squared daily returns on the Nifty. This shows strong short–dated volatility dynamics. The Box-Ljung Q statistic works out to 294, which strongly rejects the null of normality. This is seen visually in Figure 20, where the deviation from the best-fit normal distribution is sharply visible.

A time–series model that could control for the short–dated mean–reversion and short–dated volatility clustering, as seen above, would yield improved forecasts of volatility. We find that the Nifty returns series is well–modelled by the AR(1)–GARCH(1,1) model. The GARCH coefficients add up to near 1, showing very strong volatility persistence(Table 8). Figure 16 shows variance estimates from this model. We focus on the time–series of standardised residuals, $\epsilon_t = e_t/\sqrt{H_t}$. Figure 21 shows the kernel density plot of the standardised residuals. This shows a much lower peak when compared with that in Figure 20. The Box-Ljung Q statistic works out to 57, where the null of i.i.d normal cannot be rejected. Figure 22 shows the ACF of the standardised residuals and Figure 23 shows the ACF of the squared standardised residuals. Both of them seem to suggest that time dependence in the returns equation and the volatility appear to have been contained. This diagnostics suggests that we do have a plausible model of volatility dynamics of Nifty returns.

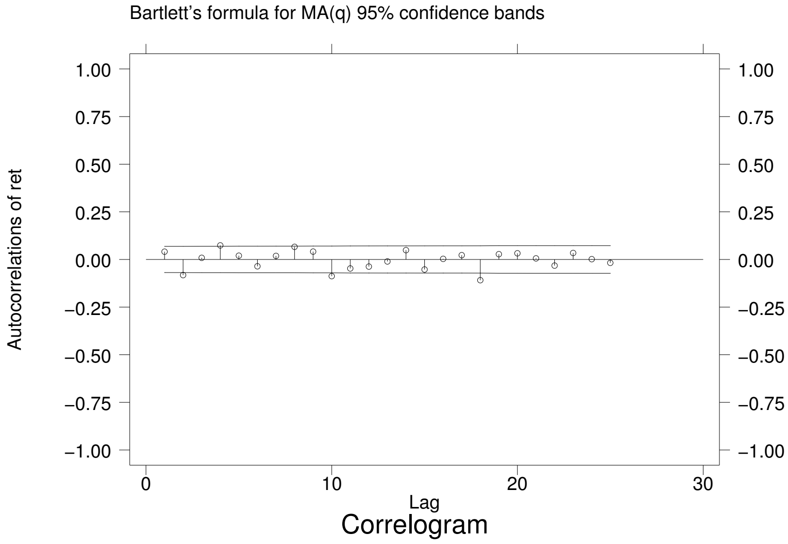

Figure 18: Autocorrelation function of daily returns

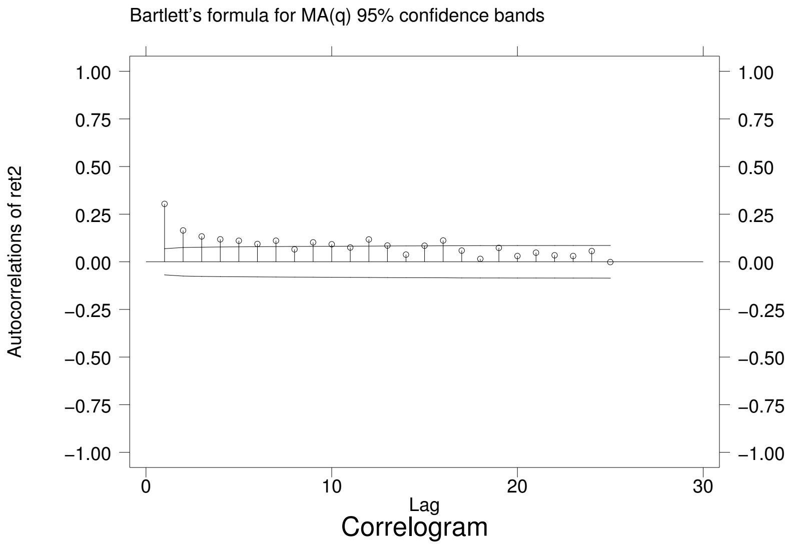

Figure 19: Autocorrelation function of squared daily returns

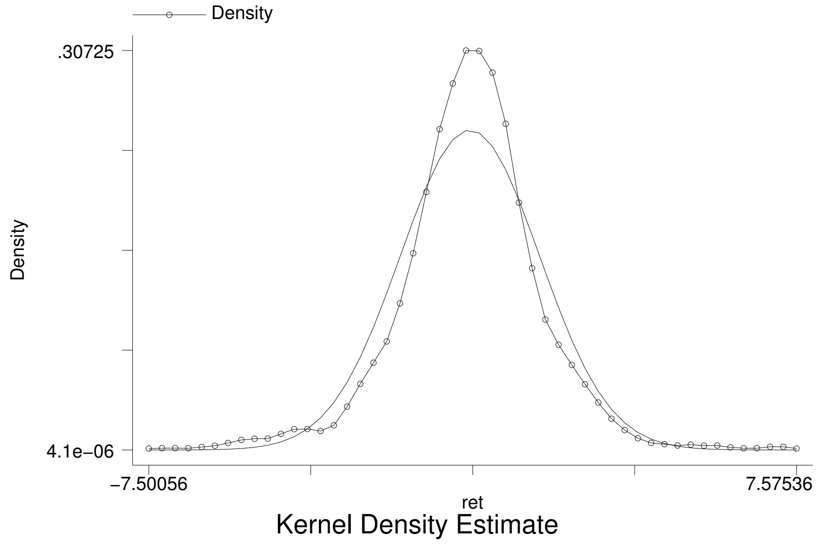

Figure 20: Kernel density plot of daily returns

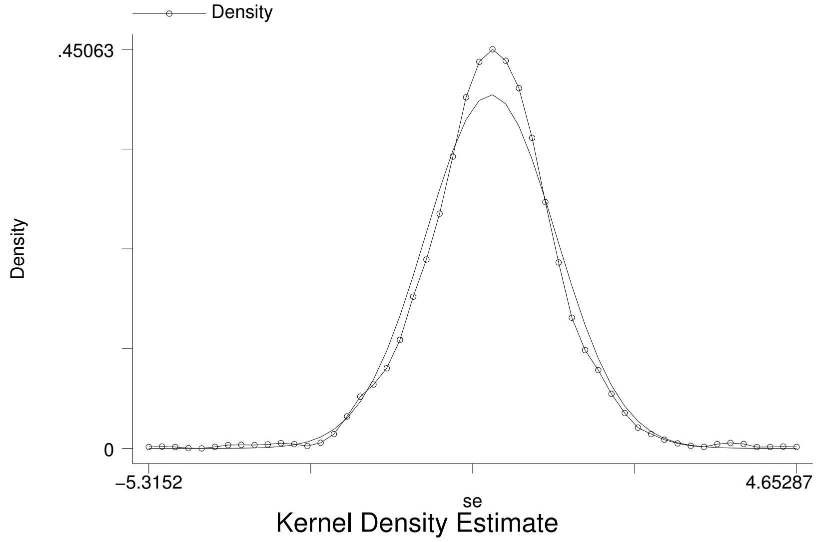

Figure 21: Kernel density plot of standardised residuals

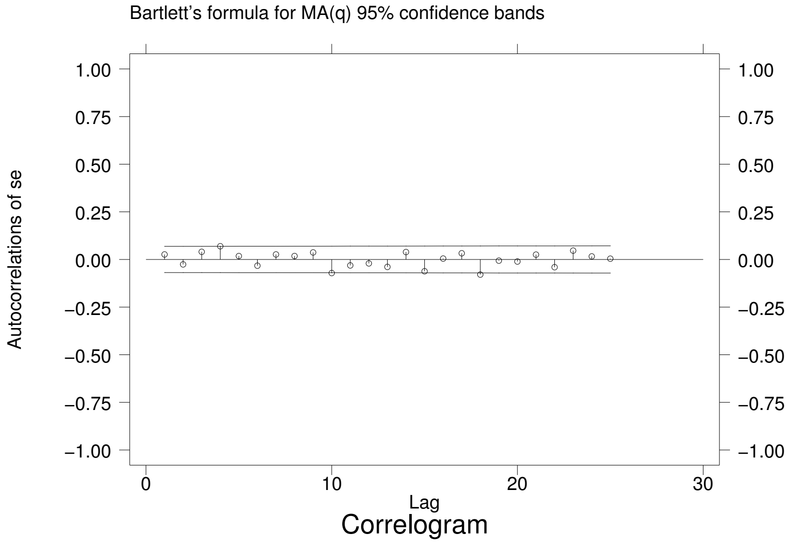

Figure 22: Autocorrelation function of standardised residuals

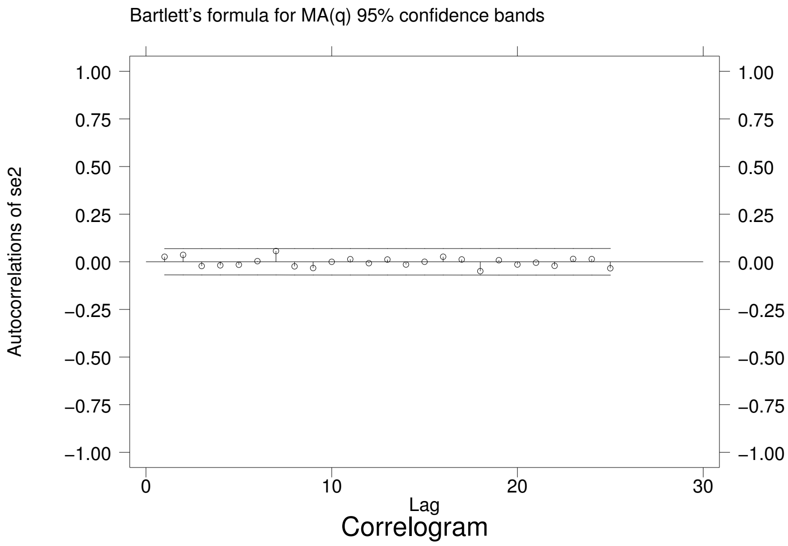

Figure 23: Autocorrelation function of squared standardised residuals

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