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Measuring Volatility Persistence and Asymmetric Effects Around Index Rebalancing of Nifty Indices

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Abstract

This paper examines the time-varying volatility behavior of the stocks that are added to or deleted from the major indices (Nifty 50 and Nifty Next 50) of the National Stock Exchange of India around the event of index rebalancing. The best fit asymmetric panel GJR-GARCH model estimates suggest that volatility persistence is relatively higher for the stocks added to a prominent benchmark index compared to the stocks deleted from such an index. On the contrary, the stocks deleted from a prominent benchmark index are exposed to a higher degree of volatility asymmetry than the stocks added. Our findings have implications on traders, asset managers, exchange managers, regulators and analysts.

Keywords: volatility model, index rebalancing

JEL Classification: C31, G12, G14.

1. Introduction

Index rebalancing is a periodic process of realigning underlying constituents of indices by adding new market representative stocks and deleting stocks that fall below threshold liquidity, delisted, acquired, or any other rules determined by index companies. Previous studies showed a direct impact of index rebalancing events on underlying stocks that are added to or deleted from an index. The price pressure hypothesis documents a temporary increase (decrease) in stock price due to buy (sell) pressure in the market (Harris & Gurel, 1986; Wurgler & Zhuravskaya, 2002). Further, the downward-sloping demand curve hypothesis suggests thata permanent price effects on stocks after addition to major benchmark indices (Shleifer, 1986; Morck & Yang, 2001).

Increase in volatility caused a decline in the equity price and return (Black, 1976; Malkiel, 1979; Pindyck, 1984). It is observed that the stock market volatility increases during recessions and periods of high business failures and financial leverage resulting from market uncertainties (Schwert, 1989). The regulatory changes also induce volatility in the market (Roll, 1989). The asymmetric conditional volatility due to the event shows the effect of bad news on underlying assets (Nelson, 1991; Goldstein, Jagannathan, & Runkle, 1993). Further, it is observed that that change in expected returns due to news affects asymmetric volatility return behaviour; a series of negative returns caused by the market, or asset-specific shocks may lead to an increase in beta (De Bondt & Thaler, 1989; Cho & Engel, 1999).

Studies also show a long term and positive price impact for stocks that are either added to or deleted from the major indices as asset managers may continue to hold the deleted stocks for diversification benefits (Chan, Kot, & Tang, 2013). Poterba and Summers (1986) observed that index rebalancing events induce a long period of shocks to the return but do not find persistence in return volatility. Index rebalancing is an information weighted event that triggered stock return volatility (Corrado, 1989; Boehmer, Masumeci, & Poulsen, 1991). Dhillon and Johnson (1991) foundthat the prices of call options written on the included stocks increase in the event of index rebalancing announcement, and this increase in prices may not be the cause of the increase in volatility. Vijh

(1994) observed that systematic risk increased for the added stocks after their inclusion into the S&P500 index. On the contrary, Kot, Leung, and Tang (2015) showed that added stocks (deleted stocks) decrease (increase) in beta is caused due to the increase (decrease) in covariance between stocks and market return of Hangseng index.

Moreover, Cho and Engle (1999) affirmed that stocks abnormal returns can be explained by the expected changes in stocks' beta. The asymmetric volatility phenomenon refers to the stylized fact that negative return shocks tend to imply higher future volatility than do positive return shocks of the same magnitude (Engel & Patton, 2001). Hilliard and Savickas (2002) studied corporate spin-offs events and reveal an enduring positive and significant effect on the volatility of the parent company's unsystematic returns. Generally, asset managers continued to hold stocks deleted from a major index either they are unaware of recent index rebalancing events or to gain the advantage of portfolio diversification (Chen, Noronha, & Singal, 2004).

Our motivation for this study emanates majorly from the existing gap in the literature, where there is no unanimity in the understanding of the pattern of time-varying volatile behaviour for the added and deleted stocks owing to index rebalancing. The index rebalancing in the emerging market is intriguing not only to academicians but also to asset managers (Note 1). Further, we have not come across any study on the Indian market that examines the volatility persistence and volatility asymmetry of stocks that are added to or deleted from the benchmark indices due to the events of index rebalancing. Our findings suggest that volatility persistence is relatively higher for stocks added to a prominent market index compared to stocks deleted from such an index, which supports the evidence that investors increase their position in added stocks. The stocks deleted from a prominent benchmark index are relatively more exposed to volatility asymmetry than the added stocks, demonstrating deleted stock's loss of recognition by investors. Hence, the result support theory that index rebalancing is an information event, and idiosyncratic risk of deleted stock remains higher than added stocks. Thus, in this paper, we contribute to the earlier work of risk dynamics of addition and deletion stock constituents of the major benchmark indices around the events of index rebalancing, especially in a major emerging market.

The rest of the paper is structured as follows. Section 2 delineates the data and methodology applied in this study. Section 3 presents and discusses the empirical findings; lastly, section 4 presents the conclusions and implications of this study.

2. Data and Methodology

2.1 Data and Event Selection

The data used are from three major sources, i.e. NSE website for events details on Index rebalancing, the stock price data from the Centre for Monitoring Indian Economy Prowess database. Last, the risk-free rate gathered from J. R.Verma's website maintained at IIM Ahmadabad (Note 2). The stock price and market data set is used from 2001 to 2021. The data is segregated into two parts, the pre-event window contains 252 days before the event day, i.e., -252 to 0 day, while post-event windows (0 days to 252 days). Index rebalancing events are segmented into two event windows, created around the effective day (i.e., 0th day). The index rebalancing events span 2002 to 2020.

2.2 Econometric Model Framework

The return series for such stocks are computed using following formula is $R_{i,t} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$, where P_t indicates the observed daily closing stock price 'i' at time 't', P_{t-1} indicates the observed daily closing stock price 'i' at time '$t-1$' and $R_{i,t}$ is the corresponding daily return for the addition and deletion categories. The abnormal return variables (AR) is calculated as the difference between stock return ($R_{i,}$) and risk free rate (Note 3) (Rf) for the period t:

$$AR_{i,t} = R_{i,t} - Rf_{i,t} \tag{1}$$

Cermeño and Grier (2001), we deploy a family of pooled-panel linear and nonlinear GARCH models to study the issue of volatility persistence and pattern of dynamic volatility behaviour of the addition and deletion category stocks owing to index rebalancing under the study. Based on the Engel (1982) ARCH modeling framework, Bollerslev (1986) demonstrates that the lower order GARCH specification fits well in most applied situations than the higher-order ARCH for modeling the time-varying volatility (Note 4). We initially fit pooled panel linear GARCH models with t-distribution to capture the **fat-tailed** distribution of the addition and deletion returns series under investigation. We also include market risk premium (mrp) computed as daily returns of Nifty 500 index less risk-free rate in conditional mean equation.

$$AR_{i,t} = \mu + \beta_{i,t} mrp_{m,t} + \varepsilon_{i,t} \tag{1}$$

Where, $i = 1,2 \ldots N,\ t = 1,2 \ldots .T,\ m = 1,2 \ldots .M,\ \varepsilon_{i,t} \sim N(0, h_{i,t})$

GARCH(1,1): The pooled panel GARCH (1, 1) model deployed for Abnormal returns of daily addition and deletion category as follows:

$$h_{i,t} = \lambda_0 + \sum_{j=1}^{q} \gamma_j \varepsilon^2{}_{t-j} + \sum_{i=1}^{p} \delta_j h_{t-i} + \nu_{i,t} \tag{2}$$

To ensure stationary of each cross-section in the panel, it is assumed that $\gamma + \delta < 1$. Where, λ_0 (mean variance) is a constant in the pooled mean equation. ϑ is the disturbance term with time dependent variance $h_{i,t}$. The $\lambda_0 \gamma$ and δ parameters associated with the time dependent conditional variance terms of ARCH and GARCH variables, where N and T are the number of cross-sections and time periods in the panel respectively. The persistence is computed as $\gamma + \delta$. The p and q represent number of lags on the ARCH and GARCH terms respectively. The GARCH models enforce the symmetric response of volatility to positive and negative shocks. This is due to the fact that the conditional variance in the GARCH equation is dependent upon the magnitude of the lagged square residuals but not on their signs.

The next two models capture the persistence and asymmetric effect on stock abnormal returns for additions and deletions stock categories. EGARCH model explains the asymmetric time varying risk premium by size and sign effect of shocks Nelson (1991). The variance equation employed for pooled panel EGARCH (p,q) estimation is given by:

$$\ln(h_{i,t}) = \lambda_0 + \sum_{j=1}^{q} \gamma_j \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} + \sum_{j=1}^{q} \theta_j \left| \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{i=1}^{p} \delta_j h_{t-i} + \nu_{i,t} \tag{3}$$

The persistence is computed as coefficient of δ. The sign effect is given by γ and impact of news on conditional variance is asymmetric if γ is significantly different from zero. Good news arrival has an impact of $\gamma + \theta$, while the bad news has impact of: $\gamma - \theta$. The asymmetric effect is calculated by in

GARCH-Exponential is calculated as $(|1 - \theta|)/(1 + \theta)$ (Malik, 2011; Dutta, 2014).

GARCH-GJR The GJR model developed by Goldstein, Jagannathan and Runkle (1993) captured the potential larger impact of negative shocks on return volatility, which is usually named as asymmetric leverage volatility effect. Specification for the pooled panel conditional variance equation for GJR GARCH (p,q) model is given by:

$$h_{i,t} = \lambda_0 + \sum_{j=1}^{q} \gamma_j\, \varepsilon^2{}_{t-j} + \sum_{j=1}^{q} \theta_j\, \varepsilon^2{}_{t-j} d_{t-1} + \sum_{i=1}^{p} \delta_j h_{t-i} + \nu_{i,t} \tag{4}$$

Next, we augment model (6) with a dummy variable dPost (i.e. dummy post which takes value 1 for post event and 0 otherwise for pre-event). The mean equation remains same as Equation 2.

$$\mathrm{h}_{\mathrm{i,t}} = \lambda_0 + \sum_{\mathrm{j=1}}^{\mathrm{q}} \gamma_{\mathrm{j}}\, \varepsilon^2{}_{\mathrm{t-j}} + \sum_{\mathrm{j=1}}^{\mathrm{q}} \theta_{\mathrm{j}}\, \varepsilon^2{}_{\mathrm{t-j}} \mathrm{d}_{\mathrm{t-1}} + \sum_{\mathrm{i=1}}^{\mathrm{p}} \delta_{\mathrm{j}} \mathrm{h}_{\mathrm{t-i}} + \mathrm{dPost} + \nu_{\mathrm{i,t}} \tag{6}$$

Where d_t takes the value of 1 for $\varepsilon_t<0$ and 0 otherwise. So bad news and good news have a different impact. In pooled panel GARCH GJR Model the asymmetric component, θ has a positive impact of $\gamma$and level of persistence (k) is measured by $k = \gamma + \delta + \theta/2$. While the impact of news on conditional variance is asymmetric if θ is significantly different from zero. The closer this value is to unity higher the persistence of stock abnormal return series. Asymmetric effect of good news and bad news for pooled panel GARCH- GJR models is calculated as which captures variation in the conditional variance $(\gamma + \delta)/\gamma$ (Malik, 2011; Dutta, 2014).

Table 1. Computation of persistence and asymmetry from GARCH models

Model	P*ersistence (κ)*	*Asymmetry* (χ)
GARCH (1,1)	$\gamma + \delta$	Symmetrical Model
E-GARCH	δ	$(\lvert 1 - \theta \rvert)/(1 + \theta)$
GARCH-GJR	$\gamma + \delta + \theta/2$	$(\gamma + \delta)/\gamma$

Following Engel and Patton (2001), we compute volatility half-life for the addition and deletion stocks as follows:

$$\tau = \log(0.5)/\log(k)$$

Where 'τ' represents volatility half-life in number of days and 'k' represents volatility persistence

3. Results and Analysis

3.1 Preliminary Results

Figure 2 shows the cumulative abnormal positive (negative) returns (CAAR) for the addition (deletion) stocks owing to Nifty 50 and Next Nifty 50 indices rebalancing. Table 2 summarizes the descriptive statistics of stocks that are added too deleted from the Nifty 50 and Nifty Next 50 indices from period 2002-2019. The mean return statistics are observed to be relatively very small compared to the unconditional volatility as indicated by the standard deviation. The series displays positive skewness and leptokurtic behavior, symptomatic of a heavier tailed distribution than the Normal. Jarque–Bera test results for all the series further confirm departure from normality. As a result, an alternative distribution that incorporates these features of the data should be adopted, such as at least student-t distribution.

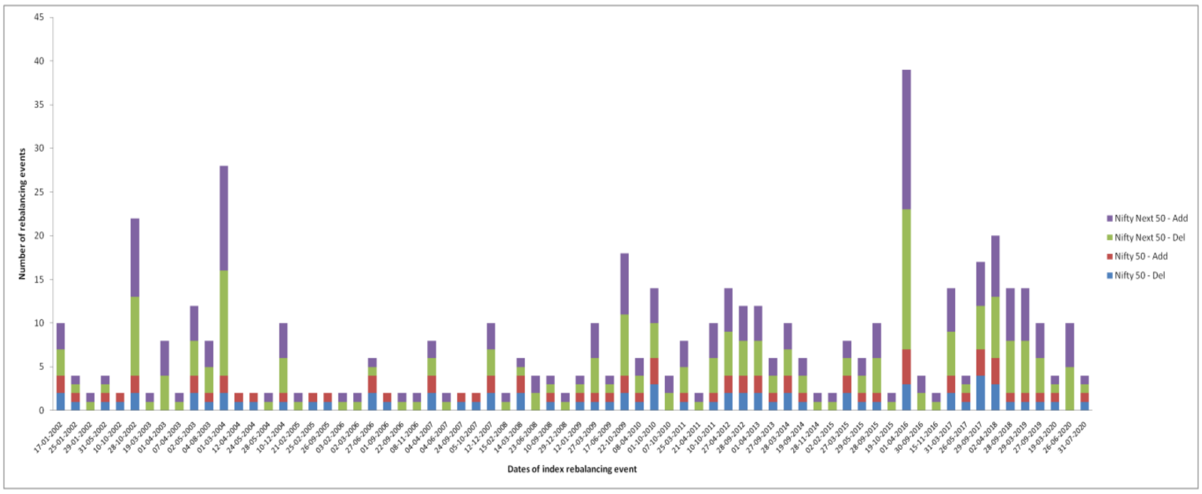

Figure 1. Number of additions and deletions across nifty indices

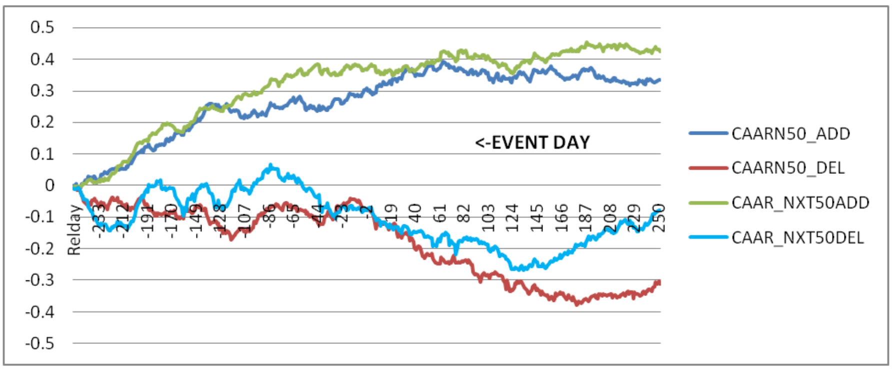

Figure 2. Cumulative Returns for Nifty Indices for additions and deletions

Note. x –axis returns in percentage and y –axis show relay day between 0^{th} effective day (-252 and 252 days)

Table 2. Descriptive statistic of the series under investigation

	Nifty 50			
	Additions		***Deletions***	
	Post Event	***Pre Event***	***Post Event***	***Pre Event***
Mean	0.0001	0.0010	-0.0005	-0.0005
Median	0.0002	0.0004	-0.0003	-0.0003
Maximum	0.3237	0.3479	0.1685	0.2738
Minimum	-0.2704	-0.3913	-0.2298	-0.3366
Std. Dev.	0.0272	0.0285	0.0273	0.0287
Skewness	0.4069	-0.1658	-0.2856	0.0611
Kurtosis	13.3943	16.3867	8.9636	12.6551
Jarque-Bera	37457	61789	7853	20399
Probability	0.000	0.000	0.000	0.000
Sum	1.0368	8.1970	-2.3652	-2.4169
Sum Square Deviation	6.1065	6.7128	3.9238	4.3368
Observations	8270	8270	5251	5251

	Nifty Next 50			
	Additions		***Deletions***	
	Post Event	***Pre Event***	***Post Event***	***Pre Event***
Mean	0.0002	0.0011	-0.0001	-0.0003
Median	-0.0002	-0.0002	-0.0007	-0.0007
Maximum	0.2902	0.2473	0.2408	0.2035
Minimum	-0.2857	-0.3116	-0.7197	-0.7197
Std. Dev.	0.0265	0.0273	0.0266	0.0280
Skewness	0.2252	0.1936	-1.7242	-1.3008
Kurtosis	13.0816	11.4127	62.5435	50.6823
Jarque-Bera	69438	48358	1516310	972009
Probability	0.000	0.000	0.000	0.000
Sum	3.9553	18.4279	-1.1150	-3.1275
Sum Square Deviation	11.5165	12.1904	7.2144	8.0037
Observations	16364	16364	10230	10230

Table 3 presents diagnostic tests results for the stationarity of time series, heteroscedasticity and serial correlation for the series under investigation. The results of the ADF test suggest that all the stock abnormal return series are stationary. Further, the ARCH-LM test results with lag up to 1, 5 and 10 show evidence of time-varying conditional distribution across the stock additions and deletions both for the Nifty 50 and Nifty Next 50. The Breusch-Godfrey Lagrange multiplier test results suggest the presence of serial correlation for all the series under investigation. The diagnostic test results suggest proceeding with the volatility analysis.

Table 3. Diagnostic results: ADF test, hetroskedacity test and serial correlation test

	Nifty 50			
	Additions		**Deletions**	
Test Statistics	**Post**	**Pre**	**Post**	**Pre**
ADF Test	-81.023†	-72.832†	-62.773†	-51.926†
ARCH Test	55.932†	2254.431†	55.867†	29.224†
Breusch-Godfrey Correlation Test	1.998†	1.9328†	2.201†	2.0172†
	Nifty Next 50			
	Additions		**Deletions**	
Test Statistics	**Post**	**Pre**	**Post**	**Pre**
ADF Test	-98.130†	-78.002†	-76.043†	-75.970†
ARCH Test	422.970†	853.27†	522.252†	526.592†
Breusch-Godfrey Correlation Test	8.311†	2.0122†	3.248†	3.557†
Test Critical Values for ADF† 1% -3.4338 -3.4330.7390				
*5%-2.8629 -2.86290.4630				
ADF Test: H_0 Unit Root Exist,				
ARCH LM: H_0 ARCH LM Root Exist				
Breusch-Godfrey LM test: H_0No serial correlation upto specified order.				

† denotes significance at 1% level, * denotes significance at 5% level and Δ denotes significance at 10% level.

3.2 Empirical Results

We conducted tests including pooled-panel GARCH (1,1), pooled-panel GARCH-GJR and pooled-panel E-GARCH models across additions and deletions for pre and post event windows. We started analysis after the determined the optimal GARCH class of models based on Likelihood ratio (LR)criteria, Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBC). The pooled-panel GARCH-GJR (1,1) shows the highest LR test statistic and the least AIC and SBC values across the stock categories. Thus,these estimates are in favor the pooled-panel GARCH-GJR specification (Note 5) Irrespective of the stock categories and event windows considered in this study.

Table 4 reports the results of the best-fit pooled panel GARCH GJR (1, 1) with *dPost* dummy (Eq. 6) volatility estimates for additions and deletion categories of stocks for Nifty 50 and Next Nifty 50 for the whole sample period. We find that the ARCH effect (γ) is statistically significant irrespective of the additions and deletion stock categories for both the indices. The volatility persistence indicators are the highest for the additions to Nifty 50 (0.9933) followed by Nifty 50 deletions stocks (0.9749) and least with the Nifty next 50 deletions stocks**.** The Nifty 50 additions and Nifty Next 50 additions *dPost* coefficients are positive and statistically significant across the stock categories, implying that the volatility has significantly increased in the post index rebalancing period. However, it is interesting to note that the Nifty 50 and Nifty next 50 deletion category stocks volatility persistence remains indifferent in the pre and post index rebalancing windows.

Table 4. Volatility model on stock abnormal returns using pooled panel GARCH-GJR with dPost variable

	Nifty 50		***Nifty Next 50***	
Coefficients	Additions	Deletions	Additions	Deletions
		Mean Equation		
μ	0.00022	-0.001213	-0.0004†	-0.000847†
	(0.7770)	(0.0002)	(0.0001)	(0.0001)
β	0.777021†	0.869751†	0.750534	0.867627†
	(0.0087)	(0.0138)	(0.0079)	(0.0089)
		Variance Equation		
$\boldsymbol{\lambda_0}$	0.0000048†	0.0000188†	0.00003†	0.0000227†
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{\gamma}$	0.093205†	0.07585†	0.128363†	0.082994†
	(0.003531)	(0.003652)	(0.006835)	(0.004366)
$\boldsymbol{\delta}$	0.898978	0.883913†	0.827955†	0.082994†
	(0.002821)	(0.008192)	(0.006483)	(0.004366)
$\boldsymbol{\theta}$	0.002249†	0.037192†	0.00859†	0.020507†
	(0.004608)	(0.005379)	(0.008839)	(0.006151)
dPost	-0.000000679*	0.000000181	-0.00000252 Δ	0.000002
	(0.000000381)	(0.00000186)	(0.00000137)	(0.000002)
Persistence(k)	0.993308	0.974904	0.960613	0.940959
Vol. Half (τ)	103.2238	27.27179	17.24948	11.38991
Asymmetry (χ)	1.0241	1.6129	1.0669	1.2471
$\mathbf{R^2}$	0.319332	0.20962	0.20146	0.201397
Log Likelihood	42098.76	24329.11	80917.39	50570.79
AIC	-5.05	-4.6319	-4.94435	-4.9427
SBC	-5.04735	-4.62706	-4.9423	-4.93999
Obs.	16540	10502	32728	20460

† denotes significance at 1% level, * denotes significance at 5% level and Δ denotes significance at 10% level. The parenthesis presents standard error of estimates.

Note. The table represents mean equation (model-2) and variance equation (model-6) for additions and deletions category.

Further, a closer look at the volatility half-life suggests that the Nifty 50 additions are exposed to the highest level of volatility persistence, where volatility half-life persists up to103.22 days. Whereas, the Nifty Next 50 deletions have the lowest level of volatility shock, the volatility half-life persists up to 11.38 days. The volatility asymmetric indicator value for Nifty 50 deletions (Nifty 50 additions) is found to be highest (lowest) with 1.61 (1.02). However, the Nifty 50 deletions stocks volatility half-life shocks remain approximately 27.27 days but its conditional volatility (Figure 3) remains more susceptible to bad news that that of the good news of the same magnitude compared to any other stock categories.

Figure 1. Plot of Conditional variance computation during Post and pre-event

Table 5 presents the volatility estimates across the stock categories in the pre and post index rebalancing windows for both the indices considered in this study. The volatility persistence for the best-fit pooled panel GARCH GJR model measured by $(\gamma + \delta + \theta/2)$ reveals that the Nifty 50 addition stocks show that in the post event and pre event windows shock to volatility decays at the rate of 0.9903and 0.7751per day respectively. However, after a month (Note 6), the proportion of shock remains at 0.814 (0.9903^{21}) and 0.0047 (0.7751^{21}), after six months the proportion of shock remains at 0.2936 (0.9903^{126}) and 0.00 (0.7751^{126}) respectively. That means the conditional volatility shocks are highly persistent with the additions stock categories stocks; even after six months, about 1/3rd of initial shocks remain in effect. Further, the volatility half-life indicators for the Nifty 50 addition stocks affirm that the half- life of a shock becomes approximately 71.27 days post event and 2.71 days pre-event. While for the Nifty 50 deletions stocks in post event and pre event windows shock to volatility decays at the rate of 0.9671 and 0.9750per day, after a month the proportion of shock remains at 0.4957 (0.9671^{21}) and 0.5876(0.9750^{21}), after a six months the proportion of shock remains at 0.01481(0.9671^{126}) and 0.0411(0.9750^{126}) respectively. Though the conditional volatility shocks are highly persistent with the deletions categories stocks, but after six months, initial shocks to volatility decays to almost zero. Further, the volatility half-life estimates for Nifty 50 addition stocks suggest that the volatility half- life of a shock becomes approximately *20.74* days post event and 27.45 days pre-event windows respectively.

Table 5. Volatility model on stock abnormal returns using pooled Panel GARCH-GJR

Nifty 50 Additions and Deletions returns around index rebalancing post event and pre-event				
	Additions		***Deletions***	
	Post	***Pre***	***Post***	*Pre*
		Mean Equation		
μ	-0.000228	*0.000718†*	0.001698	-0.000777*
	(0.000172)	(0.000000)	(0.000291)	(0.000312)
β	0.866238 †	*1.137393†*	0.866673†	0.918228†
	(0.012496)	(0.000000)	(0.015117)	(0.019746)
		Variance Equation		
λ_0	0.000003†	0.00035†	0.0000833†	0.0000219†
	(0.000000)	(0.000000)	(0.000003)	(0.00000)
γ	0.072333†	0.15†	0.191942†	0.074686†
	(0.005696)	(0.000001)	(0.00825)	(0.005117)
δ	0.006043	0.049998†	0.088857†	0.048056†
	(0.008331)	(0.000001)	(0.008821)	(0.007593)
θ	0.914967†	0.600001†	0.730768†	0.876358†
	(0.004917)	(0.000001)	(0.007066)	(0.007593)
Persistence (k)	0.9903	0.7751	0.9671	0.9750
Vol. Half (τ)	71.27	2.71	20.74	27.45
Asymmetry (χ)	1.08	1.33	1.46	1.64
$\mathbf{R^2}$	0.353769	0.254352	0.22378	0.2095
Log Likelihood	21349.52	20854.57	12350.46	12166.8
AIC	-5.20673	-5.05198	-4.70176	-4.806611
SBC	-5.20658	-5.05688	-4.7142	-4.797858
Obs.	8270	8270	5251	5251
Nifty 50 Additions and Deletions returns around index rebalancing post event and pre-event				
	Additions		***Deletions***	
	Post	***Pre***	***Post***	***Pre***
		Mean Equation		
μ	0.0000488	0.000321*	-0.00119†	-0.001343†
	(0.000158)	(0.000157)	(0.000168)	(0.00017)
β	0.864861†	0.745051†	0.826439 †	0.867808†
	(0.010552)	(0.01147)	(0.012685	(0.012533)
		Variance Equation		
λ_0	0.000025†	0.000022†	0.0000323†	0.0000284†
	(0.00000)	(0.000001)	(0.000003)	(0.000003)
γ	0.080929†	0.103672†	0.092939†	0.11958†
	0.002891)	(0.005243)	(0.010305)	(0.011303)
δ	0.031508*	0.001068†	0.045595†	0.013583†
	(0.004161)	(0.007069)	(0.015391)	(0.015219)
θ	0.858836†	0.844271†	0.835958†	0.836604†
	(0.003292)	(0.00597)	(0.012489)	(0.011073)
Persistence (k)	0.9555	0.9484	0.9516	0.962976
Vol. Half (τ)	15.23	13.10	13.99	18.37
Asymmetry (χ)	1.38	1.01	1.49	1.11
$\mathbf{R^2}$	0.22682	0.18792	0.19229	0.207361
Log Likelihood	39760.99	39566.75	25643.3	25301.68
AIC	-5.00954	-4.84084	-5.01497	-4.94679
SBC	-5.00672	-4.83802	-5.01003	-4.94184
Obs.	16364	16364	10230	10230

† denotes significance at 1% level, * denotes significance at 5% level and Δ denotes significance at 10% level. The parenthesis presents standard error of estimates

Note. The mean equation (model -2) and variance equation (model-5) of stock addition and deletion abnormal returns.

While examining the volatility persistence for the Nifty Next 50 additions post event and pre-index rebalancing windows, we find a shock to volatility decays at the rate of 0.9555 per day and 0.9484 per day respectively. However, after a month the proportion of shock remains at 0.3846 (0.9555^{21}) and 0.3292 (0.9484^{21}), after six months the proportion of shock remains at 0.0032 (0.9555^{126}) and 0.0012 (0.9484^{126}) respectively. However, the volatility half-life result implies that shock in volatility remains is13.10 days for pre-event compared to 15.23 days in the post event. Whereas, for the Nifty Next 50 deletion categories stocks, we find a shock to volatility decays at the rate of 0.9516per day and 0.9629 per day, after a month the proportion of shock remains at 0.3535 (0.9516^{21}) and 0.45281 (0.9629^{21}), after six months the proportion of shock remains at 0.0019 (0.9622^{126}) and 0.0086(0.9669^{126}) in post and pre index rebalancing windows respectively. Whereas, the volatility half-life result implies that half-life of volatility shocks remains up to 13.99 days for post-event compared to 18.37 days in the pre event. The Figure 4 represents the computation of volatility impact plotted on for six months.

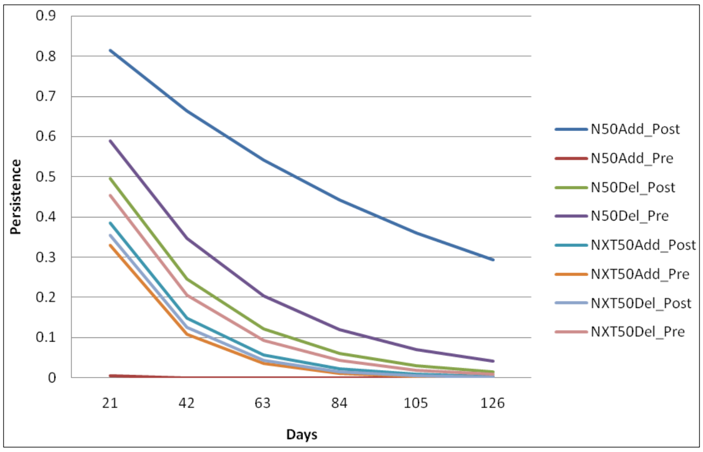

Figure 4. Volatility per day impact plotted in days

Irrespective of the indices, the asymmetric volatility indicators (θ) across most of the stock categories exhibit a higher degree of asymmetric volatility in the post-event windows than the pre-event windows of the index rebalancing. Further, deleted stocks demonstrate a higher degree of asymmetric conditional volatility effects (Note 7) irrespective of the indices under consideration. Thus, deleted stocks volatility shocks are relatively more prone to “bad news” than the added stocks, especially in the post index rebalancing windows (Table 5).

Table 6. Comparison of Persistence Post and Pre Event (Wald’s test)

	Nifty 50		**Nifty Next 50**	
	Additions	**Deletions**	**Additions**	**Deletions**
	Persistence (Wald’s test H_0=Parameter is 0)			
Post Event	-0.38642†	-0.02874†	-0.05912	-0.04293†
	(0.004022)	(0.00264)	(0.003763)	(0.009478)
Pre-Event	-0.03822†	-0.01788*	-0.03282†	-0.03422†
	(0.00682)	(0.005285)	(0.07220)	(0.00438)

† denotes significance at 1% level, * denotes significance at 5% level and Δ denotes significance at 10% level.

The parenthesis presents standard error of estimates.

Note. The table presents the Wald test parameters for Nifty 50 and Nifty Next 50 Indices.

Further, Table 6 presents Wald test result with null hypothesis that persistence calculated by coefficients $(\gamma + \delta + \theta/2)$ is equal to zero for both the pre and post event across Nifty50 and Nifty Next 50 additions and deletions categories. All the post event categories (Nifty 50additions, Nifty 50 deletions, Nifty Next 50 Deletions) except Nifty Next 50 additions show the volatility persistence is significantly different from zero, suggesting that the volatility is persisting and decaying at a very slower rate for these stock categories in the post index rebalancing windows. Keeping academic brevity in mind, we have not presented the results here. However, the testing for equality between pre and post index rebalancing periods of the volatility persistence indicators $(\gamma + \delta + \theta/2)$ in most of the cases found to be statistically different, implying that the volatility persistence is observed to be relatively higher in post event window compared to the pre-event window for both the indices.

4. Conclusion

In this paper, we examined the pattern of pre and post index rebalancing time-varying volatility behaviour of stocks that are added to or deleted from the two major indices, Nifty 50 and Nifty Next 50; of the National Stock Exchange of India Ltd. (NSE). The best fit pooled-panel GJR GARCH (1, 1) model estimates reveals that Nifty 50 additions volatility persistence increases by 28 percent in the post index rebalancing period than the pre event period. Further, we do not observe any significant shift in volatility persistence for the Nifty Next 50 additions and deletions in the pre and post-index rebalancing windows. The volatility half-life estimates confirm that shock persistence decays relatively at a slower rate for the Nifty 50 additions than the Nifty 50 deletions. It can be inferred that the Nifty 50 additions draw greater attention of the investors and asset managers' in the post index rebalancing period and thus; these stocks have greater recognition and discharge higher stabilization effects**.** Further, the abnormal returns for Nifty 50 deletions in particular, are exposed to a higher degree of volatility asymmetry than its additions in the pre- and post-index rebalancing windows. The deleted stocks volatility is relatively more prone to "bad news" than added stocks. The market participants actions might have a bearing on the volatility asymmetry for the deletions and more so with the Nifty 50 deletions.

This study makes two contributions to the existing stock of literature. This is the first study in the Indian market, which explores the conditional volatility persistence and asymmetric behaviour of the addition and deletion stocks around the events of index rebalancing events. The volatility persistence result supports the view that prominent index addition stocks earn more considerable market attention compared to deletion stocks. Further, the conditional asymmetry results provide evidence that deletions stocks are riskier compared to addition stocks. We believe that the contribution of our study not only adds to the existing stock of literature but also exert its implication to the exchange manager, index fund managers, individual traders, analysts and regulators. First, as index rebalancing is a highly anticipated market event, the exchange should take enough of care to ensure that the indexes are rebalanced appropriately and the market changes that occurred in the preceding period should just be captured. Second, index fund managers may benchmark against broader market indices like Nifty 500 or Nifty 100. Like other empirical studies; this study is also not free from limitations. One may argue around the event windows, periods of the study and the reasons for the non-inclusion of the other prominent indices in the Indian market.

Compliance with Ethical Standards:

1) No funding was provided for this research.

2) This article does not contain any studies with human participants performed by any of the authors.

   (Or) Ethical approval: This article does not contain any studies with animals performed by any of the authors.

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Notes

Note 1. Number of ETFs benchmarking Nifty Indices has grown from 4 in 2010 to 18 in 2020.

Note 2. Refer to the website http://faculty.iima.ac.in/~jrvarma/blog/index.cgi

Note 3. The risk-free returns are taken from the annualized yields of new issuances of 91-day Treasury Bills, provided by the Reserve Bank of India (RBI). The risk free daily returns are calculated from the annual yields, by assuming 250 trading days in the one year forward period. Refer to weblink: http://faculty.iima.ac.in/~iffm/Indian-Fama-French-Momentum/FAQ.php

Note 4. Hansen and Lunde (2005a) the compare the forecasting performance of 330 ARCH-type models to GARCH (1,1) model. They found no evidence that more sophisticated models outperform the GARCH (1,1) model in forecasting the volatility of daily currency returns.

Note 5. E-GARCH and GARCH (1,1) results are added in appendix in Table-7 and Table-8 respectively.

Note 6. 21 days trading for 1 month and 126 days trading for 6 months is computed with persistence indexed with a number of days.

Note 7. The average θ = (1.462937+1.6434)/2= 1.553189 for Nifty 50 and average θ = (1.4906+1.1136)/2=1.3021 for Nifty Next 50] compared to the addition categories stock [average θ = (1.0835+1.33332)/2=1.208432 for Nifty 50 and average θ = (1.3893+1.0103)/2=1.1998 for Nifty Next 50

Appendix

Table 7. Volatility model on stock abnormal returns using pooled panel E-GARCH model

Nifty 50 Additions and Deletions returns around index rebalancing post event and pre-event				
	Additions		*Deletions*	
	Post	*Pre*	*Post*	*Pre*
	Mean Equation			
μ	-0.000247	0.000557†	-0.000006†	-0.001235
	(0.000163)	(0.000162)	(0.000306)	(0.000255)
β	0.851132†	0.566892†	0.865053†	0.86952†
	(0.012681)	(0.013661)	(0.01724)	(0.01969)
	Variance Equation			
λ_0	-0.2671	-0.29742†	-0.594977†	-0.34743†
	(0.02529)	(0.017887)	(0.041552)	(0.047003)
γ	0.183684†	0.22636†	0.219503†	0.187224†
	(0.011708)	(0.008392)	(0.010193)	(0.01722)
δ	0.00021†	0.005272†	0.004642†	0.02597†
	(0.00796)	(0.005486)	(0.004745)	(0.010477)
θ	0.983711†	0.9844†	0.94225†	0.97156†
	(0.002653)	(0.001899)	(0.004942)	(0.005382)
Persistence(k)	0.9837	0.98443	0.94225	0.97156
Vol. Half (τ)	42.20	44.19	10.54	24.03
Asymmetry (χ)	0.99	0.98	1.02	1.05
R^2	0.35	0.25	0.22	0.20
Log Likelihood	21421.5	20885.29	12376.93	12626.76
AIC	-5.1788	-5.049	-4.711	-4.63
SBC	-5.1788	-5.0443	-4.704	-4.62
Obs.	8270	8270	5251	5251
Nifty Next -50 Additions and Deletions returns around index rebalancing post event and pre-event				
	Additions		*Deletions*	
	Post	*Pre*	*Post*	*Pre*
	Mean Equation			
μ	-0.000539†	0.000335	-0.001162*	-0.001299*
	0.000134	(0.000153	(0.000167)	0.000169)
β	0.796429†	0.740062†	0.830263†	0.868888†
	(0.01118)	(0.01133)	(0.012745)	(0.012622)

	Variance Equation			
λ_0	-0.2671	-0.29742†	-0.594977†	-0.34743†
	(0.02529)	(0.017887)	(0.041552)	(0.047003)
γ	0.183684†	0.22636†	0.219503†	0.187224†
	(0.011708)	(0.008392)	(0.010193)	(0.01722)
δ	0.00021†	0.005272†	0.004642†	0.02597†
	(0.00796)	(0.005486)	(0.004745)	(0.010477)
θ	0.983711†	0.9844†	0.94225†	0.97156†
	(0.002653)	(0.001899)	(0.004942)	(0.005382)
Persistence(k)	0.9837	0.98443	0.94225	0.97156
Vol. Half (τ)	42.20	44.19	10.54	24.03
Asymmetry (χ)	0.99	0.98	1.02	1.05
R^2	0.35	0.25	0.22	0.20
Log Likelihood	21421.5	20885.29	12376.93	12626.76
AIC	-5.1788	-5.049	-4.711	-4.63
SBC	-5.1788	-5.0443	-4.704	-4.62
Obs.	8270	8270	5251	5251

† denotes significance at 1% level, * denotes significance at 5% level and Δ denotes significance at 10% level.

The parenthesis presents standard error of estimates.

Note. The mean equation (model -2) and variance equation (model-4) of stock addition and deletion abnormal returns.

Table 8. Volatility model on stock abnormal returns using pooled panel GARCH (1, 1) Model

Nifty 50 Additions and Deletions returns around index rebalancing post event and pre-event				
	Additions		***Deletions***	
	Post	***Pre***	***Post***	***Pre***
μ	0.000003	0.000509†	-0.00006†	-0.001156*
	(0.00000)	(0.00017)	(0.0003)	(0.000256)
β	0.0748†	0.57688†	0.8875†	0.875†
	(0.01248)	(0.01364)	(0.018536)	0.019599
λ_0	0.000003†	0.000003†	0.00004†	0.00002†
	(0.00000)	(0.00000)	(0.0000)	(0.00000)
γ	0.074802†	0.113184†	0.125232†	0.097857†
	(0.00476)	(0.007029)	(0.007358)	0.011275)
δ	0.9153†	0.8835†	0.807225†	0.877902†
	(0.004851)	(0.004937)	(0.010566)	(0.012092)
θ	0.000003†	0.000003†	0.00004†	0.00002†
	(0.00000)	(0.00000)	(0.0000)	(0.00000)
Persistence(k)	0.9901	0.9925	0.93245	0.9757
Vol. Half (τ)	70.36	92.14	9.911	28.24
R^2	0.35	0.25	0.22	0.207
Log Likelihood	21349.3	20854.06	12350.43	12600.08
AIC	-5.1618	-5.042	-4.702	-4.7968
SBC	-5.1576	-5.037	-4.695	-4.789
Obs.	8270	8270	5251	5251
Persistence (k)	0.9901	0.9925	0.93245	0.9757
Nifty Next 50 Additions and Deletions returns around index rebalancing post event and pre-event				
	Additions		***Deletions***	
	Post	***Pre***	***Post***	***Pre***
	Mean Equation			
μ	0.000163	0.000323	-0.00112	-0.00132†
	0.000155	(0.000155)	(0.000167)	(0.00017)
β	0.8650†	0.745106†	0.8303†	0.86868†
	(0.010381)	(0.011466)	0.012702	(0.012541)

		Variance Equation		
λ_0	0.000026†	0.00002†	0.000031†	0.00002†
	(0.0000)	(0.000001)	(0.000003)	(0.000003)
γ	0.095841†	0.104013†	0.10608†	0.122424†
	(0.002519)	(0.0044)	(0.00966)	(0.010079)
δ	0.856694†	0.844435†	0.843422†	0.840148†
	(0.003422)	(0.005963)	(0.012013	(0.010822)
θ	0.000026†	0.00002†	0.000031†	0.00002†
	(0.0000)	(0.000001)	(0.000003)	(0.000003)
Persistence(k)	0.8566	0.8444	0.8434	0.8401
Vol. Half (τ)	4.481	4.099	4.070	3.979
R^2	0.22	0.18	0.19	0.20
Log Likelihood	39751.9	39566.74	25638.8	25301.29
AIC	-4.8578	-4.835	-5.011	-4.9453
SBC	-4.855	-4.8328	-5.008	-4.9410
Obs.	16364	16364	10230	10230
Persistence (k)	0.8566	0.8444	0.8434	0.8401

† denotes significance at 1% level, * denotes significance at 5% level and Δ denotes significance at 10% level.

The parenthesis presents standard error of estimates.

Note. The mean equation (model -2) and variance equation (model-3) of stock addition and deletion abnormal returns.