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EXAMINING THE LONG MEMORY IN STOCK RETURNS AND LIQUIDITY IN INDIA

Keywords: emerging market, long memory, persistence and market efficiency.

JEL Classifications: C1, C5, G1, G14.

Abstract: The present study examines the long memory in stock liquidity and returns in Indian equity market by using data for broad indices from January, 1997 to December, 2019 by applying the hurst exponent (1951) rescaled range analysis. It is observed that time varying degree of persistence nature in individual and full series analysis of returns. Moreover, liquidity series exhibit long memory process in Nifty-100, Nifty-200 and Nifty MidCap-50. Findings are consistent with Sadique and Silvapulle (2001), Henry (2002), Cavalcante (2002) and Baum, Barkoulas and Caglayan (1999).

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Introduction

The presence of long memory supports the notion of market inefficiency in securities market (Onour, 2010). Market inefficiency refers to the fact that it does not immediately absorb the new information flow but it responds gradually and takes a substantial time for relevant information to disseminate across the market (Fama, 1970, 1991) and (Peters, 1994). There is trend to either understate or overstate the effect of such information in stock prices (Barkoulas & Baum, 1996). If returns series demonstrate the presence of persistence behavior, previous returns can be utilized to estimate the upcoming returns (Hiremath & Kamaiah, 2010). Therefore, presence of long memory property provides support for framing portfolio strategy, which may also help to generate abnormal profits from the financial investment (Cevik & Emec, 2013). The investigation on persistence behavior in asset prices, liquidity is essential for the practitioners, since, its presence can have an impact on investment decision, portfolio selection and trading strategies (Balcilar, Ozdemir & Cakan, 2015; Badhani, 2008).

The seminal research on long memory in capital market was initiated by Hurst (1951). Furthermore, Greene and Fietlitz (1977) and Aydogan and Booth (1988) demonstrated that US stock returns exhibit long memory. However, Lo (1991) did not find significant long memory in US stock returns. Nonetheless, Mandelbrot (1971) confronted that the arbitrage may not be negotiable when long memory is exhibited. Thereafter, Lo (1991) observed that the dynamic behavior in financial markets may be a considerable reason for long memory dynamics.

Furthermore, Hiremath and Kamaiah (2010) and Badhani (2012) found that high volatility, anomalous behavior and market trend are the characteristics of developing economies, which affirms that due to presence of market imperfections, long memory behavior might arise in the developing markets.

Moreover, Badhani (2006; 2008) explored the persistence behavior in India and found that stock returns do not report the presence of long memory, whereas absolute returns and squared returns (proxy of volatility) exhibit persistence behavior. On the other hand, subsample covering the duration from March, 2001 to December, 2007 affirms that volatility does not exhibit persistence behavior.

In addition, Goudarzi (2010) observed persistence behavior in BSE-500 returns, which suggests that BSE 500 returns and volatility are more significant with leverage. Moreover, Ma, Li, Zou and Wu (2006) found significant serial correlation in returns of Chinese stock market. Likewise, Verma (2008) affirms that only three companies out of sixty entail the persistence behavior in returns. Kilic (2004) reported significant serial correlation in the volatility process in Turkey. Furthermore Souza, Tabak and Cajueiro (2008) observed the moderate long memory in European Monetary System using the Hurst Exponent, which suggests that being inside the EMS increases predictability. In addition, Bala and Gupta (2018) reported considerable long-term persistence in Sensex and Nifty returns series. However, volatility series does not contain any persistence behavior but exhibits clustering.

Similarly, Nath and Reddy (2002) examined the persistence behavior in Rupee-Dollar exchange rates and found that there are chances of random walk in three month, while for other time period, it may have mean reverting or persistence tendency. Furthermore, Mahalingam and Selvam (2014) observed high degree of persistence behavior in Indian stock market.

Furthermore, Bhattacharya and Bhattacharya (2012) found persistence behavior in absolute returns along with volatility in international markets. However, evidence did not support the Taylor effect. Moreover, Chen and Diaz (2013) observed significant persistence behavior in green exchange traded funds. Whereas, non-green exchange traded funds did not advocate serial correlation in volatility. Henry (2002) tested the long range dependence in Taiwanese, German and South Korean stock markets and found that persistence behavior is real and not occurred due to shift enhancement and structural breaks of Africa (MENA) vicinity and Middle East in variance. On the contrary, Jayasuriya (2009) advocate that structural changes and persistence behavior in volatility does not show any significant relationship. Similarly, Chung, Lin and Wu (2000) found that Asia-pacific markets hold spurious serial correlation due to shift enhancement in variance series. However, Cevik and Emec (2013) observed persistence behavior in returns series of Turkish stock market.

Moreover, Turkyilmaz and Balibey (2014) examined Pakistan security exchange and found that it is inefficient in weak form and contain serial correlation structure in volatility series also. Cavalcante and Assaf (2004) found significant serial correlation in volatility and return series in Brazilian financial markets. Likewise, Danilenko (2009) found that industrial sector report significant long memory whereas, healthcare and utilities sector entail the weak long range dependence.

In the Indian context, liquidity patterns were studied by Krishnan and Mishra (2013) and Kumar and Misra (2018) for the equity indices and they found that individual stock liquidity co-moves to a high degree with market liquidity and industry liquidity.

Bhattacharya, Sengupta, Bhattacharya and Roychoudhury (2016) found significant degrees of positive association between liquidity and return and noted the order of importance of selected liquidity dimensions in explaining stock market returns.

Cajueiro and Tabak (2008) observed strong long memory in Asian markets than in Latin America. There is considerable support for long memory in stochastic volatility in stock returns. Bhattacharya and Bhattacharya (2012; 2013) and Hull and Mc Groarty (2014) found strong evidence of long memory persistence in volatility over the time. Bariviera (2011) observed that long memory parameter is positively correlated with market capitalization but negatively with an average daily turnover.

In nutshell, a plethora of literature is available in emerging as well as developed markets, however, there is a dearth of empirical research on examining the presence of long memory in India, which is one of the most liquid capital market of the world (Soofi, Wang & Zhang, 2006), (Krishnan & Mishra, 2013) and (Goudarzi & Ramanarayanan, 2011).

The study also tries to pursuit to check whether liquidity and returns both have long memory effect. There is a paucity of literature to study the persistence behavior of Indian Stock Market. Therefore, this paper is an attempt to plug the research gap.

Paper is further organized in four sections. Second section describes the database and research methodology. The results and analysis of the study are discussed in the third section. Discussion and implication of the study presented in fourth section and the conclusion of the study has been presented in the five sections.

Research methodology and the courses of the research process

This study makes an attempt to study the presence of long-memory in returns and liquidity of Nifty-50, Nifty-100, Nifty-200, Nifty-500, Nifty Next -50, Nifty

Small Cap 50, Nifty Large MidCap-250, Nifty Full MidCap-100, Nifty Mid Cap-150, and Nifty Mid Cap -50 indices using rescale range analysis (hurst exponent). The present study uses daily data from the National Stock Exchange of India (NSE) from January, 1997 to December, 2019 as presented in table 1. The study has also calculated long memory components for each year and full period from January, 1997 to December, 2019 to check whether the presence of long memory is due to structural breaks, regime shift, market friction, political changes and market microstructure etc. that have taken place during the sample period in India.

Table 1. Description of sample size (returns and liquidity)

Index	No. of Observations (N)(Returns)	Sample Period (Returns)	No. of Observations (N) (Liquidity)	Sample Period (Liquidity)
Nifty-50	5682	1-1-1997 to 31-12-2019	5682	1-1-1997 to 31-12-2019
Nifty-100	4323	1-1-2003 to 31-12-2019	3636	20-9-2005 to 31-12-2019
Nifty-200	3972	1-1-2004 to 31-12-2019	2090	20-7-2011 to 31-12-2019
Nifty-500	5219	8-6-1999 to 31-12-2019	5219	8-6-1999 to 31-12-2019
Nifty Next -50	5721	1-1-1997 to 31-12-2019	5721	1-1-1997 to 31-12- 2019
Nifty SmallCap-50	3715	1-1-2005 to 31-12-2019	923	1-4-2016 to 31-12-2019
Nifty Large MidCap-250	3655	1-4-2005 to 31-12-2019	681	28-3-2017 to 31-12-2019
Nifty Full MidCap-100	3547	1-4-2005 to 20-2-2019	716	4-4-2016 to 20-2-2019
Nifty MidCap-150	3651	1-4-2005 to 31-12-2019	924	1-4-2016 to 31-12-2019
Nifty Midcap-50	3968	1-1-2004 to 31-12-2019	3968	1-1-2004 to 31-12-2019

Sources: compiled by author on the basis of data downloaded from official website of NSE.

Methodology

Daily returns are computed as the difference in the natural logarithm of the closing index value for the two consecutive trading days. It can be presented is equation 1:

$$Rt = \ln(Pt/ Pt{-}1) \text{ or } Rt = \ln(Pt) - \ln(Pt{-}1) \quad (1)$$

Where Rt is natural logarithmic daily return at time t. Pt–1 and Pt are daily prices of stock index at two successive days t-1 and t respectively.

Hurst exponent

To examine long memory, 'Hurst' exponent is computed. The origin of long memory test can be attributed to Hurst exponent 'H', which was developed in 1951 by Hurst to measure water related process. The Hurst exponent (or the self-similarity parameter) is a dimensionless parameter and diverse methodologies exist to estimate it. The concept of Hurst exponent finds its applications in many research fields including the field of financial studies due to the path-breaking works of Mandelbrot, (1963; 1997) and Peters (1994; 1996). The Hurst exponent lies in the range $0 \leq H \leq 1$. If the Hurst exponent is 0.5 then the process is said to follow a random walk. When the Hurst exponent is more than 0.5, it suggests positive long-range autocorrelation or persistence in the series. On the other hand, when the Hurst exponent is smaller than 0.5, it suggests the presence of negative autocorrelation or means reversion in the series (Kumar, 2004), (Chen & Huang, 2014), (Gayathri, Murugesan & Gayathri, 2012) and (Kumar, 2014).

Table 2. Hurst exponent coefficient

The values of Hurst exponent range between 0 and 1:	
$0 < H < 0.5$	Anti-persistence
$H = 0.5$	Random walk
$0.5 < H < 1$	Persistence

Sources: presented by author to show the range of hurst exponent (Kumar, 2004).

Hurst Exponent and Rescaled Range (R/S) Analysis

Qian and Rasheed (2004) and Cajueiro and Tabak (2005) suggested that the Hurst exponent can be calculated by rescaled range analysis (R/S analysis). For a time series, X = X1, X2, … Xn, R/S analysis method is as follows:

n
(1) Calculate mean value m.= 1/n ∑ Xi i=1
(2) Calculate mean adjusted series Y: Yt = Xt − m, t = 1, 2, …, n t
(3) Calculate cumulative deviate series Z: ∑Yi , t = 1, 2, …, n i=1
(4) Calculate range series R: Rt=max(Z1, Z2, …, Zt)− min(Z1, Z2, …, Zt) t = 1, 2, .., n t 2
(5) Calculate standard deviation series St= √1/n∑(Xi-u)
t=1,2,……,n i=1
Here, u is the mean value from X1 to Xt.
(6) Calculation of Rescaled Range Series(R/S): (R/S)t = Rt/St where, t = 1, 2, …, n

Note: (R/S) it is averaged over the regions [X1, Xt], [Xt+1, X2t] until [X(m-1) t+1, Xmt] where m=floor(n/t). In practice, to use all data for calculation, a value of t is chosen that is divisible by n.

Results and analysis

Before discussing the long memory estimation results through Hurst exponent procedure proposed in third section and comparing the efficiency in reducing the portfolio risk, it is important to discuss the series properties of under examination. Results in table 3 indicate the information relating to the summary of full sample period for returns and liquidity in Nifty Small-Cap 50, Nifty LargeMidCap-250, Nifty MidCap-150, Nifty-50, Nifty-100, Nifty-200, Nifty-500, Nifty Next -50, Nifty Full MidCap-100, and Nifty Mid Cap -50 (Barkoulas, Baum & Travlos, 2000). Table 3 provides that returns series of all indices reports significantly persistent behavior. The estimated coefficient of H exponent suggests that all indices exhibit long memory in returns series, which implies that past returns could forecast the upcoming returns (Chow, Denning, Ferris & Noronha, 1995) and (Baillie, 1996). These findings would be helpful to understand the behavior of the market for an investor, policymakers and portfolio managers to decide where they would get abnormal profits by using long memory insights data Henry (2002), Lillo and Farmer (2004), Garvey and Gallagher (2009), Cavalcante and Assaf (2004). However, finding in liquidity series shows that only Nifty MidCap-50 exhibits long memory component (Ozun & Cifter, 2007; Barkoulas, Baum & Travlos, 2000).

Table 3. Long Memory in NSE Indices during Full Sample Period (Returns and Liquidity)

Index	Nifty- 50	Nifty- 100	Nifty- 200	Nifty- 500	Nifty Next - 50	Nifty Small Cap 50	Nifty Large Mid Cap-250	Nifty Full Mid Cap-100	Nifty Mid Cap- 150	Nifty Mid Cap - 50
Hurst Exponent Coefficient (Returns)	0.5610	0.5741	0.5705	0.5826	0.5875	0.6402	0.6059	0.5637	0.6045	0.5806
Hurst Exponent Coefficient (Liquidity)	0.4882	0.5002	0.5061	0.4657	0.4743	0.4815	0.4347	0.4680	0.4232	0.5812

Sources: calculated by author using secondary data downloaded from official website of NSE.

Table 4. Year Wise Estimation of Long Memory in All Indices (Returns Series)

Time Period	Nifty- 50	Nifty- 100	Nifty- 200	Nifty- 500	Nifty Next - 50	Nifty small Cap 50	Nifty Large Mid Cap-250	Nifty Full Mid Cap-100	Nifty Mid Cap 150	Nifty Mid Cap 50
1997	**0.5527**	NA	NA	NA	**0.5766**	NA	NA	NA	NA	NA
1998	**0.5607**	NA	NA	NA	**0.6023**	NA	NA	NA	NA	NA
1999	0.4906	NA	NA	**0.5804**	**0.5263**	NA	NA	NA	NA	NA
2000	**0.5103**	NA	NA	**0.6532**	**0.6672**	NA	NA	NA	NA	NA
2001	**0.6046**	NA	NA	**0.6295**	**0.6452**	NA	NA	NA	NA	NA
2002	**0.5915**	NA	NA	**0.5385**	**0.6358**	NA	NA	NA	NA	NA
2003	**0.6521**	**0.6501**	NA	**0.6407**	**0.6156**	NA	NA	NA	NA	NA
2004	**0.5819**	**0.5748**	**0.5670**	**0.5697**	**0.5391**	NA	NA	NA	NA	**0.5330**
2005	**0.5815**	**0.5863**	**0.5790**	**0.5753**	**0.5444**	**0.6305**	**0.6271**	**0.6301**	**0.6259**	**0.5238**
2006	**0.6741**	**0.6813**	**0.6955**	**0.7006**	**0.6789**	**0.7085**	**0.7139**	**0.7062**	**0.7102**	**0.6871**
2007	**0.5775**	**0.5629**	**0.5740**	**0.5777**	**0.5091**	**0.5798**	**0.5957**	0.3956	**0.6105**	**0.5858**
2008	**0.5529**	**0.5493**	**0.5578**	**0.5608**	**0.5278**	**0.6371**	**0.6329**	**0.5681**	**0.5858**	**0.5618**
2009	**0.6118**	**0.6289**	**0.6487**	**0.6554**	**0.6893**	**0.7244**	**0.6775**	**0.6828**	**0.6886**	**0.6832**
2010	**0.5844**	**0.5900**	**0.6199**	**0.6235**	**0.5829**	**0.6396**	**0.6163**	**0.5998**	**0.6017**	**0.5635**
2011	0.4728	0.4534	0.4928	0.5022	**0.5505**	**0.5875**	**0.5732**	**0.5507**	**0.5723**	**0.5386**
2012	**0.6182**	**0.6233**	**0.6265**	**0.6261**	**0.6468**	**0.6320**	**0.6229**	**0.4928**	**0.6393**	**0.6347**
2013	0.4976	**0.5183**	**0.5359**	0.4451	**0.6010**	**0.7002**	**0.6696**	**0.6293**	**0.6414**	**0.6024**

Table 4. Year Wise...

Time Period	Nifty- 50	Nifty- 100	Nifty- 200	Nifty- 500	Nifty Next - 50	Nifty small Cap 50	Nifty Large Mid Cap-250	Nifty Full Mid Cap-100	Nifty Mid Cap 150	Nifty Mid Cap 50
2014	**0.5383**	**0.5594**	**0.5800**	**0.5951**	**0.5923**	**0.6801**	**0.6595**	**0.6269**	**0.6241**	**0.6563**
2015	0.4328	0.4232	0.4248	0.4257	0.4360	0.4749	0.4335	0.4082	0.4053	0.4324
2016	**0.6311**	**0.6413**	**0.6422**	**0.6450**	**0.6350**	**0.6767**	**0.6399**	**0.6382**	**0.6519**	**0.6352**
2017	0.4733	0.4511	0.4457	0.4582	0.4312	**0.5765**	**0.5479**	**0.5241**	**0.5259**	0.5060
2018	0.5076	**0.6343**	0.5056	**0.6156**	**0.5662**	**0.5955**	0.5067	0.5054	**0.5767**	**0.5120**
2019	**0.6014**	**0.6326**	**0.6326**	**0.6144**	**0.7131**	**0.7607**	**0.5722**	0.4977	**0.6085**	**0.6441**

S o u r c e s : calculated by author using secondary data downloaded from official website of NSE.

Table 4 presents estimated long memory during year wise analysis of Nifty-50, Nifty-100, Nifty- 200, Nifty-500, Nifty Next -50, Nifty small Cap 50, Nifty Large Mid Cap-250, Nifty Full Mid Cap-100, Nifty Mid Cap 150 and Nifty Mid Cap 50 using Rescaled Range Statistics. The estimated H coefficient suggests that from 1997 to 2019 almost all indices in each year show significant persistence behavior with the exception of Nifty full Mid Cap-100 in year 2007, Nifty- 50, Nifty-100, Nifty-200, and Nifty-500 in year 2011, Nifty-50, Nifty-200, Nifty-500, Nifty Next-50 and Nifty Mid Cap -50 in year 2017, Nifty-50, Nifty-500, Nifty Large Mid Cap-250, and Nifty Full Mid Cap-100 in year 2018 and Nifty Full Mid Cap-100 in year 2019. However, 2015 was the year when all indices exhibit anti-persistence behavior. It is pertinent to note that year 2014 observed significant political change from the Congress Lead Government to the NDA lead Government, which brought significant changes in the political, regulatory and governance environment in India. Moreover, on November 8, 2016 a major announcement was made by Prime Minister Mr. Narender Modi regarding demonetization of Rs. 1,000 and Rs. 500 currency notes, which amounted to nearly 86% of the total currency in circulation. This announcement brought a revolution in the Indian economy and there was major shift in the mode of transactions from cash to digital modes of transactions and change in the outlook of Indian capital market for foreign investors[1] (Booth & Tse, 1995), (Cheung & Lai, 1995) and (Cont, 2005).

Table 5 presents the each year analysis of long memory of all indices in liquidity series. Results indicate that Nifty-50 showing significant long memory in the years 1998, 1999, 2001, 2009, 2010, 2011, 2014, 2016, 2017, 2018, and 2019. Furthermore, Nifty 100 displays persistence behavior in 2009, 2010, 2014, 2015, 2016, 2017, and 2018. Nifty-200 shows long memory in 2011, 2014, and 2018. This indicates possibility of predictable component of past liquidity (Huang & Yang, 1999) and (Hiremath & Kamaiah, 2010). Nifty-500 exhibits persistence behavior in 2001, 2009 and 2010and Nifty Next -50 advocate's long memory in 1998, 1999, 2000, 2001, 2009, 2014, 2015, 2016, and 2017. Moreover, Nifty small Cap 50, Nifty full Mid Cap-100 and Nifty Mid Cap 150 shows serial correlation behavior only in the year 2019.

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1 "TheriseofsmalltowninvestorsinIndianequitymarket" (https://economictimes.indiatimes.com/markets/stocks/news/the-rise-of-small-town-investors-in- indian-equity-markets/articleshow/71270423.cms?from=mdr).

Table5. Year Wise Estimates of Long Memory in All Indices (Liquidity Series) (Inferences of Coefficient of Liquidity) (Calculated value of Hurst Exponent)

Time Period	Nifty- 50	Nifty- 100	Nifty- 200	Nifty- 500	Nifty Next - 50	Nifty small Cap 50	Nifty LargeMid Cap-250	Nifty Full Mid Cap-100	Nifty Mid Cap 150	Nifty Mid Cap 50
1997	0.4301	NA	NA	NA	0.3872	NA	NA	NA	NA	NA
1998	**0.5128**	NA	NA	NA	**0.5741**	NA	NA	NA	NA	NA
1999	**0.5144**	NA	NA	0.4944	**0.5211**	NA	NA	NA	NA	NA
2000	0.4211	NA	NA	0.4435	**0.5956**	NA	NA	NA	NA	NA
2001	**0.5369**	NA	NA	**0.5370**	**0.5306**	NA	NA	NA	NA	NA
2002	0.3456	NA	NA	0.4196	0.3830	NA	NA	NA	NA	NA
2003	0.4517	NA	NA	0.4852	0.4405	NA	NA	NA	NA	NA
2004	0.4405	NA	NA	0.4372	0.4381	NA	NA	NA	NA	0.3761
2005	0.4676	0.4411	NA	0.4834	0.4177	NA	NA	NA	NA	0.3349
2006	0.4606	0.4779	NA	0.4748	0.4557	NA	NA	NA	NA	0.3664
2007	**0.5230**	0.4979	NA	0.4939	0.4708	NA	NA	NA	NA	0.3621
2008	0.5041	0.4921	NA	0.4939	0.4484	NA	NA	NA	NA	0.3978
2009	**0.5195**	**0.5194**	NA	**0.5193**	**0.5196**	NA	NA	NA	NA	0.4543
2010	**0.5566**	**0.5576**	NA	**0.5373**	0.5042	NA	NA	NA	NA	0.4473
2011	**0.5111**	0.4897	**0.5384**	0.4929	0.4885	NA	NA	NA	NA	0.3337
2012	0.4606	0.4525	0.4640	0.4483	0.4506	NA	NA	NA	NA	0.3867
2013	0.5023	0.4872	0.5020	**0.5109**	0.4653	NA	NA	NA	NA	0.4223

Table5. Year Wise...

Time Period	Nifty- 50	Nifty- 100	Nifty- 200	Nifty- 500	Nifty Next - 50	Nifty small Cap 50	Nifty LargeMid Cap-250	Nifty Full Mid Cap-100	Nifty Mid Cap 150	Nifty Mid Cap 50
2014	**0.5239**	**0.5195**	**0.5169**	0.5099	**0.5284**	NA	NA	NA	NA	0.4555
2015	0.4741	**0.5337**	0.4985	0.4940	**0.5240**	NA	NA	NA	NA	0.4125
2016	**0.5166**	**0.5174**	0.5060	0.5135	**0.5125**	0.4383	NA	0.3540	0.3540	0.3600
2017	**0.5140**	**0.5252**	0.5116	0.4943	**0.5330**	0.4763	0.4758	0.4602	0.4011	0.4012
2018	**0.5206**	**0.5203**	**0.5257**	0.4910	0.3144	0.3752	0.3555	0.4782	0.3743	0.2872
2019	**0.5312**	0.4921	0.4921	0.4999	0.4065	**0.6363**	0.4729	**0.5967**	**0.5635**	0.4884

S o u r c e s : calculated by author using secondary data downloaded from official website of NSE.

Furthermore, Nifty large Mid Cap-250 and Nifty Mid Cap 50 did not show the significant long memory, which may arise due to micro and macro factors i.e. changes in interest rates, inflation or deflation and happenings in global markets (Kang & Yoon, 2007), (Asian crisis, IT bubbles, Indo-Pak political crisis and Real estate bubbles) are counted as the significant ones (Gurgul & Wojtowicz, 2006), (Christodoulou-Volos & Siokis, 2006), and (Pandy, April14, 2018)[2].

Discussion and implecation

Result of present study focuses on measurement of the portfolio management for retail investors and first time investors who are going to invest their money into the market, where they could consider the effect of all micro and macro factors on their investment strategy. Moreover, findings would be beneficial for the academician, practitioners, policy makers, portfolio manager and investors, whose decision depend upon the market predictability, therefore, present study provide insights for better understanding and is useful for forecasting to take financial decision. Findings are consistent with (Hiremath & Kamaiah, 2011), (Sadique & Silvapulle, 2001), (Henry, 2002), (Cavalcante & Assaf, 2004; Booth & Tse, 1995; Turkyilmaz & Balibey, 2014).

Conclusion

The present study is an attempt to examine the presence of long memory in broad stock Indices at National Stock Exchange of India. Using daily log returns and liquidity of Nifty-50, Nifty-100, Nifty-200, Nifty-500, Nifty Next -50, Nifty Small Cap 50, Nifty Large Mid Cap-250, Nifty Full Mid Cap-100, Nifty Mid Cap-150 and Nifty Mid Cap-50 index in India Hurst Exponent in Rescaled Range Analysis has been estimated. The results of the study confirm presence of long memory in returns of all indices during full sample period. However, in case of liquidity series, it shows persistent nature in Nifty Mid Cap 50 only. Moreover, for year-wise analysis of long memory has been estimated for all indices. Findings suggest significant long memory in returns series across all indices except

[2] See Source: https://www.financialexpress.com/market/three-key-economic-factors-which-affect-sensex-nifty/1132894/ (Pandy, April ,14, 2018, “Three key economic factors which affect Sensex, Nifty” Financial Express).

for the years 2015 and 2017 whereas, in case of liquidity, all indices show anti-persistence behavior. An important observation from the year-wise analysis is that nonetheless various regulatory, technological, structural changes have taken place in the Indian equity market during last two decades but the price discovery in Indian equity market is yet not efficient (Mukherjee, Sen & Sarkar, 2011), (Verma, 2008), (Hassler & Wolters, 1995), (Baillie & Morana, 2009), (Caporale & Gil-Alana, 2008) and (Limam, 2003).

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