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ATTENTION TO THE ELECTION-ECONOMICS-POLITICS (EEP) NEXUS IN THE INDIAN STOCK MARKETS

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Abstract. Do investors pay attention to the election-economics-politics (EEP) nexus in the stock markets? In examining this research problem during the 17th Lok Sabha Election in India, this study explores the cointegrating relationships of its' stock markets' returns and realised trade volumes with investors' selective attention to keywords in Google searches. The article uses the autoregressive distributed lag (ARDL) model. It reveals ingenious findings that investors' attention dynamics at EEP nexus cointegrate either with the stock-markets' returns or realised trade-volumes. It also identifies investors' attention myopia, where the cointegration twists once the nexus pulls off its election or economic factor/s.

1. Introduction

Investors pay focused (selective) attention to the general (task) environments of business. They pay focused attention to the political and economic issues like sovereign debt crisis, countries' credit worthiness, bilateral bailouts, nations' political democratic advantages, and country's political referendums as well (Paudyn, 2014; Schneider & Tobin, 2020; Glaurdić, Lesschaeve, & Vizek, 2019; Fakhry, 2019; Cucinelli, Farina, Schwizer, & Soana, 2020; and Malik, 2018). They also pay selective attention to the economic information related to their portfolio formations, computing markets' volatility index, and buy or sell recommendations of stocks, etc. (Sicherman, Loewenstein, Seppi, & Utkus, 2015; Madsen & Niessner, 2019). Even if they show the ostrich effect and remain inactive to new information at the worse times, their behavioral utility is conditioned to their selective attention distributions of risk aversion (Karlsson, Loewenstein, & Seppi, 2009; Blajer-Gołębiewska, Wach, & Kos, 2018; and Aharon, & Qadan, 2020). Do investors pay selective attention to the elections and politics or political economy as well?

On a mostly related query, Santa-Clara & Valkanov (2003) showed that the abnormal return in the US stock markets is higher (lower) during its Democratic (Republican) presidents. They have called this as the US presidential puzzle, a bizarre unexplained phenomenon. Novy-Marx (2014) finds that bizarre factors like market failure probability, the political party of the US president, the US weather, the global temperature anomaly, and the natural phenomena can predict the US stock market returns. Are these factors relevant at investors' decision choices? On the plausibility of such hypothesis, Kim (2019) argues that researchers' statistical thinking should rely on the size-effects of the data, the model's explanatory power, and the confidence intervals rather than the p-value criterion only. Wagner, Zeckhauser, and Ziegler (2018) show that the bizarre surprise element in Donald Trump's election campaign has shifted investors' expectations. Marshall, Nguyen, Nguyen, and Visaltanachoti (2018) find that the US equity

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market/s is more liquid during democratic presidencies than republican presidencies while its liquidity is influenced by information asymmetry and volatility or economic policy uncertainty. Li, Li, and Xu (2018) find that stock market crashes are less (more) likely to appear at the pre (post)-election times and these are consistent with the suppression (release) of negative information about political uncertainty if these are boldened (reduced) around the pre (post)-election periods. At the presence of information bursts all through the internet of things, the aforementioned bizarre political factors cease to turn up that so bizarre presently (Grover, Kar, Dwivedi, & Janssen, 2019 read with Carlisle & Patton, 2013).

Now, why do investors pay selective attention to the nations' elections, politics, or political economies? Such a research query leads us towards exploring the role of investors' behavioral psychology in decision choices, in general, and the role of attention economics, in particular. In behavioral political economy, the research on investors' attention to the election-economics-politics (EEP) nexus has begun recently. Besides attention to recession, gold prices, GDP, and bankruptcy, Da, Engelberg, and Gao (2015) show that investors pay attention to aspects that are mainly in the domain of the nations' politics viz., "unemployment" (a general political agenda), "unemployed" (a task-environment agency factor), "social security office" (to influence the public affairs), "social security card" (to reach the public at large), "donation" (to fund by the public), "charity" (to gain popularity), and "poverty" (to touch the human face of politics), etc. In that direction of exploring investors' search attention impacts on the markets, this study proposes that investors pay selective attention to the nexus of EEP and it finds that their online search attention to keywords for election, economics, and politics are interlinked at providing the economic impacts of such nexus on the Indian stock markets.

This study specifically explores if investors' attention to the EEP nexus is cointegrated with the NSE Nifty and BSE Sensex market returns as well as with their trade-volumes. In organizing the flow, it reviews the literature in Section 2. This is followed by the data and methodology in Section 3, and the results and findings in Section 4. It concludes in Section 5.

2. Literature Review

Investors' attention to the EEP nexus can be viewed from three different perspectives – the political business cycle theory, standard finance theories, and behavioral finance theories. These theories link the triad of noises - popularity politics, corrupt politicians, and noisy economics, that exist within the governments' economic control measures (Dubois, 2016; Nordhaus, 1975; Park, 2011). This review specifically concentrates on the scope and nature of the triad of noises and identifies its basic threads.

The said triad locked noisy business politics is observed in the post-crisis scenario of the European Union, EU's sovereign debt crisis (Keller, 2018), Greece's sovereign debt crisis (Lavdas, 2016; Goodhart, 2018), Brexit referendum (Bohn, 2019), Vietnam Conflict and Gulf war (Fox & Phillips, 2003; Nickelsburg & Norpoth, 2000; Wisniewski, 2009), Trump election (Yates, 2019), and the currency demonetization in India in 2016 (Sathyanarayana & Gargesha, 2017) as well. It also exists in Thailand and Myanmar (James, 2010), in Pakistan's politics (Tabassam, Hashmi, & Rehman, 2016), and Egypt (Ahmed, 2017). Angelini, Foglia, Ortolano, and Leone (2018) show that the "Trump sentiments index" causes both short-term and long-term effects on the US stock market, the S&P 500.

On the origin of such noisy triad, Shaikh (2017) finds that the global financial markets are inefficient to Trump shocks at the bull or bear-effects during the election times. The BRICS markets are also exposed to the turmoil of Trump's election agenda (Bouoiyour & Selmi, 2018). The Brexit of the UK and Donald Trump's wining in the US election in 2016 show attention effects amongst the voters at their campaign bases, rhetoric pitches, and social consolidations (Wilson, 2017). Investors utilize "peer country effect" as a heuristic measure in assessing the sovereign risk of a country (Brooks, Cunha, & Mosley, 2015). Qadan and Nama (2018) have showed that investors' short-run and long-run sentiment-shocks influence the returns and volatility in the oil markets. Economic sentiments attract investors' attention (Baker & Wurgler, 2007). In brief, investors' selective attention to issues in election-economics-politics influence their behaviors in the stock markets.

Now, how do such bizarre noisy attention manifest investors' behaviors in the capital markets? Investors' decision psychology and the notion of rationality influence their choices of stocks and the microstructure noise in the stock markets (Sinha, 2019a; 2018). With election-economics-politics search attention data, Sinha (2019b) shows that in India investors are more attentive to the political news than that to the economic news. Their sentiments link some sort of psychological unit representing expectation (frustration) leading to hope (despair) and these relate individual's or groups' optimism and pessimism in the stock markets (Brown & Cliff, 2005). In contrast to the standard finance theories, the behavioral finance theories propose that investors' irrational exuberances and their attention to forces like their hope, fear, uncertainty, despair, doubt, expectation, etc. influence their investment motives and information access as well (Shiller, 2000; Daniel, Hirshleifer, & Subrahmanyam, 1998; Da, Engelberg, & Gao, 2011; Da, Engelberg, & Gao, 2015; Akerlof & Shiller, 2010).

On possible cointegration of the perceptions of the larger society with the performances of the stock markets, Yan and Wooi (2016) show that during the election periods in Indonesia, Malaysia, and Thailand, the CAARs for stocks' returns are higher for the Government banks than the private banks. Prechter, Goel, Parker, and Lampert (2012) find that during re-election times, the general social mood can explain the mood of the stock markets more robustly than the known economic variables. Readers may find the theoretical foundations of social mood in financial economics and erratic market behaviors in Nofsinger (2005), Irannezhad, et al (2019), and Rapp (2019). Moreover, Addoum and Kumar (2016) have showed that the changes in political parties at the incumbent government in the US induce systematic changes in portfolio formation and such political effects reduce the information arbitrage effects and form patterns. The presence of such cointegrations is also observed in the experimental studies (Li, et al, 2019) as well as empirical studies (Zhang, Xu, and Xue, 2017).

On the aforementioned triad of noises viz., popularity politics, corrupt politicians, and noisy economics, there is little study on the Indian contexts. Do investors pay attention to the influences of election, economics, and politics (EEP) nexus in the Indian stock markets? This study proposes the following theoretical proposition P1 and explores it empirically.

P1: Investors' selective attention to the economic, election and political attributes has short-run dynamics along with the presence of their long-run references, and these influence the pricing dynamics in the stock markets.

3. Data and Methodology

In identifying the relevant variables for the proposed election-economics-politics (EEP) nexus, this study defines "election" from the institutional contexts, "economics" from investors' perspectives about the capital markets, and "politics" from public perceptions about the political leaders in India. In Indian democracy, both the intra-party and constitutional elections vary from one political party to another at the state-levels and country-level as well. The institutional presence of political parties is also different from their leaders' political personalities at the public. They both do not perfectly substitute their election symbols as well. Nonetheless, election issues very often tend to show fads and fashions over the time periods but political personalities persist over the public attention. Therefore, keeping the trio in three different attention segments fundamentally helps us to explore the nexus in this present empirical study and it avoids variable selection myopia.

The study now considers a time range from 10.03.2019 to 23.05.2019 covering the last general parliamentary elections of 2019 in India. The study uses the *search volume index* (SVI) data collected from the Google Trends database. It uses keywords for seven election ($E1$) attention attributes, seven economic ($E2$) attention attributes, and six political (P) attention attributes in the Indian politics. The search keywords and their acronyms are given in Table 1. It has used keywords that have consistent SVI data over the stated periods. It generates the first differences of the daily SVI data ($DSVI$) at selective attention presence that proxy for surprise attention. The variables $DSVIE_{1\ x,it}$, $DSVIE_{2\ x,it}$, and $DSVIP_{\ x,it}$ respectively at the $E1$ attributes, $E2$ attributes, and P attributes provide for the selective surprise attention effects.

Table 1: Google search keywords, their acronyms, data periods, and attention Variables

DSVI Dara Time Range	Election (E1) Attributes (Acronyms)	Economic (E2) Attributes (Acronyms)	Political (P) Attributes (Acronyms)
Acronyms	DSVIE1	DSVIE2	DSVIP
Daily data, time range: 1.3.2019 ti 23.5.2019	Electronic Voting Machine (D_EVM), Lok Sabha Election (D_LSE), Next PM (D_NXPM), United Progressive Alliance (D_UPA), National Democratic Alliance (D_NDA), Bharatiya Janata Party (D_BJP), Indian National Congress (D_INC)	BSE SENSEX Index (D_BSE), NSE NIFTY 50 Index (D_NSE), risk-free rate (D_RFR), Risk-free interest rate (D_RFIR), Internal rate of return (D_IRR), Stock market index (D_SMI), Stok market return (D_SMR).	Sonia Gandhi (D_SG), Manmohan Singh (D_MS), Rahul Gandhi (D_RG), Atal Bihari Vajpayee (D_ABV), Lal Krishna Advani (D_LKA), Narendra Modi (D_NM)
Note: RBSE (VBSE) and RNSE (VNSE) refer to BSE Sensex and NSE Nifty market returns (realised volume traded).			

We have collected the stock market-related data viz., the low indices and realised trade-volumes for the NSE Nifty and BSE Sensex markets at *www.investing.com.* The data for daily NSE Nifty and BSE Sensex market return, at notation of MR_t in general, are derived at the Log-transformed Index Relative method $[MR_t = Log_{10}(LI_t)/Log_{10}(LI_{t-1})]$ where LI is the daily Low Index data. To get the relevant data for the investors' realized presence i.e., the realized trade-volumes in the markets, at notation of RP_t in general, the daily trade-volume (V_t) data are also log-transformed $[RP_t = Log_{10}(V_t)]$. To make it reader friendly, we use the notation MR_t (RP_t) in the regression models while at reporting the same in the texts and tables as well, we use the acronyms $RBSE$ ($VBSE$) and $RNSE$ ($VNSE$) respectively for the BSE Sensex and NSE Nifty stock market returns (realized volume traded).

Now, to provide the space for long-run adjustments due to the cointegrating relationship along with short-run dynamics in the pricing system, as proposed in the theoretical proposition, this study specifies the static long-run linear relationship form in equation (1) and equation (2) respectively for the market returns and trade-volumes. It follows the Autoregressive Distributed Lag i.e., $ARDL(r \geq 1, q \geq 1)$ model setups of Pesaran, Shin, and Smith (2001). Here, r and q are their respective lag-lengths viz., for the endogenous dependent variable and independent variable/s. It specifies the unrestricted short-run forms ($SRFs$) of dynamic relationships in the unrestricted versions of the ARDL model respectively in the equations (3) and (4), and their conditional long-run forms ($LRFs$) in the equations (5) and (6). Nonetheless, it specifies their respective conditional error correction forms ($ECFs$) in the equations (7) and (8). In the respective $LRFs$ viz., equations (5) and (6) and $ECFs$ viz., equations (7) and (8) of the $ARDL$ models, the first differences of these search attention variables are prefixed with a dell symbol, Δ in the notations and these suggest for short-run impacts while their respective long-run impacts are specified at one period lag of the variables and/or that of the error correction terms ($ECTs$) viz., ηZ_{t-1} and φE_{t-1}. The coefficients η and φ with the respective $ECTs$ show their speeds of adjustment towards their long-run relationships in the $ARDL$ models. These three forms – $SRFs$, $LRFs$, and $ECFs$ of the $ARDL$ models, are free from autocorrelation bias once the variables are of either $I(0)$ or $I(1)$ or a mixture of $I(0)$ and $I(1)$ but not $I(2)$ or higher. To be specific to the research objectives stated earlier, this study ventures into all the three versions of the $ARDL$ models and concisely reveals the short-run impacts, speed of adjustments, and long-run overall impacts of investors' attention searches on the stock markets as well.

Static Long-Run Relationships:

$$MR_t = \alpha_0 + \sum_{i,\ \ t=1}^{E1,n} \alpha_{1i} DSVIE_{1it} + \sum_{j,t=1}^{E2,n} \alpha_{2j} DSVIE_{2jt} + \sum_{k=1}^{P,n} \alpha_{3k}\ DSVIP_{kt} +\ \epsilon_t \tag{1}$$

$$RP_t = \beta_0 + \sum_{i,\ \ t=1}^{E1,n} \beta_{1i} DSVIE_{1it} + \sum_{j,t=1}^{E2,n} \beta_{2j}\ DSVIE_{2jt} + \sum_{k=1}^{P,n} \beta_{3k}\ DSVIP_{kt} +\ \xi_t \tag{2}$$

Unrestricted Short-Run Forms (SRF) of the $ARDL$ Models:

$$\begin{aligned} MR_t \quad &= \quad \gamma_0 + T_t + \sum_{r=1}^{r}\sum_{t=1}^{n} \gamma_{1r}\ MR_{t-r}\ + \sum_{A=i}^{E1,E2,\ P}\ \sum_{q=1}^{q}\sum_{i,\ \ t=1}^{A,n} \gamma_{Aqi} DSVIA_{it-q} \\ &\quad + \sum_{A=i}^{E1,E2,\ P}\ \sum_{t=1}^{A,n} \gamma_{Ai} DSVIA_{it}\ + \varepsilon_t \end{aligned} \tag{3}$$

$$\begin{aligned} RP_t \quad &= \quad \delta_0 + T_t + \sum_{r=1}^{r}\sum_{t=1}^{n} \delta_{1r}\ RP_{t-r}\ + \sum_{A=i}^{E1,E2,\ P}\ \sum_{q=1}^{q}\sum_{i,\ \ t=1}^{A,n} \delta_{Aqi} \Delta DSVIA_{it-q} \\ &\quad + \sum_{A=i}^{E1,E2,\ P}\ \sum_{t=1}^{A,n} \delta_{Ai} DSVIA_{it}\ + \varsigma_t \end{aligned} \tag{4}$$

Conditional Long-Run Forms (LRF) of the $ARDL$ Models:

$$\begin{aligned} \Delta MR_t \quad &= \quad \rho_0 + T_t + \sum_{r=1}^{r}\sum_{t=1}^{n} \rho_{1r}\ \Delta MR_{t-r}\ + \sum_{A=i}^{E1,E2,\ P}\ \sum_{q=1}^{q}\sum_{i,\ \ t=1}^{A,n} \rho_{Ai} \Delta DSVIA_{it-q} \\ &\quad + \sum_{r=1}^{r}\sum_{t=1}^{n} \rho_{1r}\ MR_{t-r}\ + \sum_{A=i}^{E1,E2,\ P}\ \sum_{q=1}^{q}\sum_{i,\ \ t=1}^{A,n} \rho_{Ai} DSVIA_{it-q} + \eta_t \end{aligned} \tag{5}$$

$$\begin{aligned} \Delta RP_t \quad &= \quad \sigma_0 + T_t + \sum_{r=1}^{r}\sum_{t=1}^{n} \sigma_{1r}\ \Delta RP_{t-r}\ + \sum_{A=i}^{E1,E2,\ P}\ \sum_{q=1}^{q}\sum_{i,\ \ t=1}^{A,n} \sigma_{Ai} \Delta DSVIA_{it-q} \\ &\quad + \sum_{r=1}^{r}\sum_{t=1}^{n} \sigma_{1r}\ RP_{t-r}\ + \sum_{A=i}^{E1,E2,\ P}\ \sum_{q=1}^{q}\sum_{i,\ \ t=1}^{A,n} \sigma_{Ai} DSVIA_{it-q} + \vartheta_t \end{aligned} \tag{6}$$

Conditional Error Correction Forms (ECF) of the $ARDL$ Models:

$$\Delta MR_t = \theta_0 + T_t + \sum_{r=1}^{r}\sum_{t=1}^{n} \theta_{1r}\ \Delta MR_{t-r}\ + \sum_{A=i}^{E1,E2,\ P}\ \sum_{q=1}^{q}\sum_{i,\ \ t=1}^{A,n} \theta_{Ai} \Delta DSVIA_{it-q} + \eta Z_{t-1} + \eta_t \tag{7}$$

$$\Delta RP_t = \omega_0+T_t+\sum_{r=1}^{r}\sum_{t=1}^{n}\omega_{1r}\ \Delta RP_{t-r}\ +\sum_{A=i}^{E1,E2,\ P}\ \sum_{q=1}^{q}\ \sum_{i,\ \ t=1}^{A,n}\omega_{Ai}\Delta DSVIA_{it-q}+\varphi E_{t-1}+\vartheta_t \quad (8)$$

Hence, with the methodology of the three versions of the unrestricted short-run form, conditional long-run form, and conditional error correction form of the respective $ARDL$ regression model, this study explores the impacts of the three sets of selective attention variables on the NSE Nifty and BSE Sensex market returns and that on their respective volume-traded as well. It tests the dynamic models in equations (3), (4), (5), (6), (7) and (8) separately for the two stock markets' returns as well as for their respective traded-volumes. The study has the null hypotheses H_{01} and H_{02} against the alternative hypotheses H_{11} and H_{12} respectively. It performs the F-bound tests to examine the stability of the stated cointegrating relationship/s of the selective attention variables with the dependent variable/s.

H01: Investors' selective attention to the stated E1-attributes, E2-attributes, and P-attributes has no impact on the NSE Nifty and BSE Sensex stock market returns.

H11: Investors' selective attention to the stated E1-attributes, E2-attributes, and P-attributes has long-run and short-run attention impacts on the NSE Nifty and BSE Sensex stock market returns.

H02: Investors' selective attention to the said E1-attributes, E2-attributes, and P-attributes has no impact on the volume traded in the NSE Nifty and BSE Sensex stock markets.

H12: Investors' selective attention to the said E1-attributes, E2-attributes, and P-attributes has long-run and short-run attention impacts on the volume-traded in the NSE Nifty and BSE Sensex stock markets.

This study performs the ADF Unit Root Test of the data series and identifies if these are stationary in $I(0)$, $I(1)$, or $I(2)$. It performs the Breakpoint Unit Root Test as well to explore if there is any breakpoint unit root in the data series. In Table 2 and Table 3, respectively, the study depicts the observations for the ADH Unit Root tests and Breakpoint Unit Root tests for the data series. Table 2 shows that the data series of DBSE, $DNSE$, $DBJP$, $DNXPM$, DRG, DNM and $DLSE$ are $I(1)$ in nature, i.e., these variables are stationary at their first-order differences, and the rest data series are $I(0)$, i.e., those variables are stationary at their level data. That is, the study has mixed types of data - $I(0)$ and $I(1)$.

Table 2: T-Statistics (prob.) at ADF Unit Root tests for Dependent and Independent Variables

DSVIA$_i$	ADF Unit Root Test Statistics		
	t-statistic (prob.)		
	I(0)	I(1)	I(2)
Dependent Variables' Set:			
RBSE	**-3.757** (0.005)	**-15.18** (0.001)	**-9.932** (0.001)
RNSE	**-6.072** (0.001)	**-11.21** (0.001)	**-7.544** (0.001)
VBSE	**-4.629** (0.001)	**-10.26** (0.001)	**-7.333** (0.001)
VNSE	**-4.401** (0.001)	**-8.072** (0.001)	**-7.305** (0.001)
Independent Election Variables (E1 - Attributes):			
DUPA	**-12.12** (0.001)	**-8.491** (0.001)	**-6.672** (0.001)
DNDA	**-7.084** (0.001)	**-6.855** (0.001)	**-7.151** (0.001)
DINC	**-3.70** (0.006)	**-7.987** (0.001)	**-6.647** (0.001)
DBJP	-2.09 (0.258)	**-4.878** (0.001)	**-10.49** (0.001)
DLSE	-0.951 (0.766)	**-3.221** (0.023)	**-6.427** (0.001)
DEVM	**-8.19** (0.001)	**-8.741** (0.001)	**-7.080** (0.001)
D$NXPM$	-2.015 (0.99)	**-5.678** (0.001)	**-6.856** (0.001)

Independent Economic Variables (E2 - Attributes):			
D*BSE*	-0.82 (0.994)	**-8.703** (0.001)	**-8.652** (0.001)
D*NSE*	-2.026 (0.275)	**-12.33** (0.001)	**-8.119** (0.001)
D*RFR*	**-9.662** (0.001)	**-7.364** (0.001)	**-6.608** (0.001)
D*RFIR*	**-7.992** (0.001)	**-8.052** (0.001)	**-8.171** (0.001)
D*IRR*	**-13.96** (0.001)	-7.182 (0.001)	**-6.443** (0.001)
D*SMI*	**-6.942** (0.001)	**-7.81**5 (0.001)	**-6.286** (0.001)
D*SMR*	**-9.916** (0.001)	**-7.898** (0.001)	**-8.167** (0.001)
Independent Political Variables (P - Attributes):			
DSG	**-3.446** (0.012)	**-6.731** (0.001)	**-5.589** (0.001)
DMS	**-6.866** (0.001)	**-6.543** (0.001)	**-6.796** (0.001)
DRG	-1.547 (0.504)	**-3.825** (0.005)	**-8.029** (0.001)
DABV	**-5.36** (0.001)	**-10.85** (0.001)	**-8.49** (0.001)
DLKA	**-10.67** (0.001)	**-8.897** (0.001)	**-6.783** (0.001)
DNM	-0.027 (0.958)	**-3.208** (0.024)	**-8.902** (0.001)
Note: For the variables' acronyms please refer to Table 1.			

The results in Table 3 also show that none of the variables has any breakpoint unit root in their time series.

Table 3: Statistics at ADF Breakpoint Unit Root tests for Dependent and Independent Variables			
DSVIA$_i$	Breakpoint ADF Unit Root Test Statistics		
	t-statistic (prob.)		
	I(0)	I(1)	I(2)
Dependent Variables' Set:			
R*BSE*	**-6.628** ($<$ 0.01)	**-15.85** ($<$ 0.01)	**-21.2**9 ($<$ 0.01)
R*NSE*	**-7.576** ($<$ 0.01)	**-12.92** ($<$ 0.01)	**-14.12** ($<$ 0.01)
V*BSE*	**-5.527** ($<$ 0.01)	**-11.2**4 ($<$ 0.01)	**-13.92** ($<$ 0.01)
V*NSE*	**-4.852** ($<$ 0.015)	**-9.26** ($<$ 0.01)	**-13.04** ($<$ 0.01)
Independent Election Variables (E1 - Attributes):			
D*UPA*	**-13.324** ($<$ 0.01)	**-13.76** ($<$ 0.01)	**-17.79** ($<$ 0.01)
D*NDA*	**-10.136** ($<$ 0.01)	**-8.802** ($<$ 0.01)	**-13.679** ($<$ 0.01)
D*INC*	**-9.31** ($<$ 0.01)	**-10.54** ($<$ 0.01)	**-14.80** ($<$ 0.01)
D*BJP*	**-11.24** ($<$ 0.01)	**-7.536** ($<$ 0.01)	**-15.03** ($<$ 0.01)
D*LSE*	**-6.985** ($<$ 0.01)	**-7.593** ($<$ 0.01)	**-10.244** ($<$ 0.01)
D*EVM*	**-11.45** ($<$ 0.01)	**-15.19** ($<$ 0.01)	**-18.07** ($<$ 0.01)
D*NXPM*	**-9.88** ($<$ 0.01)	**-17.29** ($<$ 0.01)	**-19.60** ($<$ 0.01)
Independent Economic Variables (E2 - Attributes):			
D*BSE*	**-12.01** ($<$ 0.01)	**-12.08** ($<$ 0.01)	**-13.13** ($<$ 0.01)
D*NSE*	**-13.5**9 ($<$ 0.01)	**-13.04** ($<$ 0.01)	**-15.72** ($<$ 0.01)
D*RFR*	**-13.01** ($<$ 0.01)	**-16.74** ($<$ 0.01)	**-20.06** ($<$ 0.01)
D*RFIR*	**-17.74** ($<$ 0.01)	**-22.15** ($<$ 0.01)	**-25.57** ($<$ 0.01)
D*IRR*	**-14.25** ($<$ 0.01)	-19.24 ($<$ 0.01)	**-23.07** ($<$ 0.01)
D*SMI*	**-12.39** ($<$ 0.01)	**-17.49** ($<$ 0.01)	**-21.93** ($<$ 0.01)
D*SMR*	**-16.02** ($<$ 0.01)	**-18.74** ($<$ 0.01)	**-22.49** ($<$ 0.01)
Independent Political Variables (P - Attributes):			
DSG	**-8.248** ($<$ 0.01)	**-8.929** ($<$ 0.01)	**-11.705** ($<$ 0.01)
DMS	**-9.357** ($<$ 0.01)	**-12.93** ($<$ 0.01)	**-19.426** ($<$ 0.01)
DRG	**-10.96** ($<$ 0.01)	**-8.056** ($<$ 0.01)	**-11.49** ($<$ 0.01)
DABV	**-11.19** ($<$ 0.01)	**-11.93** ($<$ 0.01)	**-17.52** ($<$ 0.01)

DLKA	**-12.66** (< 0.01)	**-19.09** (< 0.01)	**-18.06** (< 0.01)
DNM	**-11.83** (< 0.01)	**-8.533** (< 0.01)	**-13.957** (< 0.01)
Note: For the variables' acronyms please refer to Table 1.			

In Table 4, the study also demonstrates the statistics for the VAR lag-order selection criteria with the respective endogenous variables. However, it follows the AIC method for using the lags'-length in the regression models. The study now presents the results for the $ECFs$ of the $ARDL$ models.

Table 4: VAR Lag Order Selection Criteria for the Regression Models						
Endogenous Variable	LogL	LR	FPE	AIC	SC	HQ
RBSE	ND^	2nd Lag	3rd Lag	3rd Lag	2nd Lag	2nd Lag
RNSE	ND^	1st Lag	1st Lag	1st Lag	1st Lag	1st Lag
VBSE	ND^	1st Lag	1st Lag	2nd Lag	1st Lag	1st Lag
VNSE	ND^	2nd Lag	2nd Lag	2nd Lag	2nd Lag	2nd Lag
ND refers not defined. Note: For the variables' acronyms please refer to Table 1.						

4. Results and Findings

The study depicts the results on the $ECFs$, $SRFs$, and $LRFs$ of the $ARDL$ models respectively in Table 5 (Table 6), Table 7 (Table 8), and Table 9 (Table 10) for the BSE Sensex (NSE Nifty) stock-market returns. Accordingly, it presents the same on the respective $ARDL$ models in Table 11 (Table 12), Table 13 (Table 14), and Table 15 (Table 16) for the BSE Sensex (NSE Nifty) stock-markets' realized trade-volumes. With the explained variables of BSE and NSE market-returns viz., $RBSE$ and $RNSE$ (and traded-volumes viz., $VBSE$ and $VNSE$) respectively, the study shows the $CUSUM$ of the recursive residuals in Figure 1 and Figure 2 (Figure 3 and Figure 4), and the $CUSUM$ of the recursive squared-residuals in Figure 5 and Figure 6 (Figure 7 and Figure 8). The study now analyses the results.

EEP nexus and Market returns: In Table 5 and Table 6, with the $ECFs$ of the $ARDL$ models, the study finds that the different proxies as used for the selective attention variables suggesting for the presence of possible election-economics-politics (i.e., EEP) nexus are found significant in explaining the market returns of both the stock markets. In particular (please refer to Table 5), besides the short-term effect of the endogenous variable, the BSE Sensex market returns can be explained by investors' dynamic short-run selective attention impacts for search keywords viz., "National Democratic Alliance" i.e., NDA, "Next PM" i.e., $NXPM$, "Sonia Gandhi" i.e., SG, and "United Progressive Alliance" i.e., UPA.

Table 5: Effects of election- economics-politics (EEP) nexus on the BSE stock-markets' returns				
Variables	Coef.	Std. Error	t-Stat	Prob.
Constant	**0.4075**	0.0371	10.97	0.001
Δ (R_BSE(-1))	**-0.199563**	0.06205	-3.216	0.003
Δ (D_EVM)	0.0000019	0.0000018	1.077	0.287
Δ (D_INC)	0.0000037	0.0000110	0.334	0.740
Δ (D_NDA)	**0.0000339**	0.0000057	5.912	0.001
Δ (D_NXPM)	**-0.0000140**	0.0000052	-2.708	0.010
Δ (D_SG)	**0.0000597**	0.0000141	4.226	0.001
Δ (D_SMI)	-0.0000006	0.0000010	-0.621	0.538
Δ (D_UPA)	**-0.0000078**	0.0000022	-3.641	0.001
CointEq(-1)*	**-0.4074560**	0.0371400	-10.971	0.001
ECM Summary Statistics:				
R2	0.8297	MDV	-0.000024	
Adj. R2	0.8054	S.D.D.V.	0.000937	

S.E.R.	0.000413	AIC	-12.6185
S.S.R.	0.000011	SIC	-12.3048
Log Likelihood	470.58	HQIC	-12.4935
F-stat.	**34.102**	DW stat.	2.222
P(F-stat.)	0.001	BGSCLM (1)	1.065 (0.308)
B-P-G HT (prob)	0.985 (0.51)	BGSCLM (2)	0.768 (0.470)
Skewness	0.3715	Kurtosis	3.277
Resid. J.B. Normality (prob.)			
F-Bound Test (n =73, k = 20)		F-Bound F-stat Value	**3.912**
F-Bound Table Value (α = 0.01)		I(0) = 2.54, I(1) = 3.86	

*Results on the regression model in equation (7) with the BSE Sensex returns data as the dependent variable. The trend effect (T_t,) in the regression model is significant only at probability of 81.95% for R_BSE and the same is omitted in the final results here to avoid over-estimation problem in the error correction form (ECF) of the ARDL model. An * marked p-value is compatible with the F-Bounds distribution. Please refer to Table 1 for variable acronyms. In residual analysis, $B-P-GHT$ suggests for Breusch-Pagan-Godfrey heteroskedasticity test and $BGSCLM$ suggests for Breusch-Godfrey serial correlation test. Resid. J.B. Normality refers to Jarque-Bera Normality Test.*

In Table 6, the NSE market return does not show any endogenous short-term effect but the same can be explained by investors' selective attention to NDA, "Narendra Modi" i.e., NM, "Risk-Free Return" i.e., RFR, "Rahul Gandhi" i.e., RG, and "Lok Sabha Election" i.e., LSE. These two tables also categorically show that the positive impact of NDA is higher on the BSE market returns than that on the NSE market returns while the rest attention variables have significant market-specific attention impacts but these are at isolations – that is, the search keywords except NDA are not effective as usual in both the stock markets. The size or number of the variables with significant coefficients also confirms that a presence of short-run attention cointegration relationship with the stock market returns in tune to the EEP nexus is more at NSE Nifty market returns than that at BSE Sensex market returns. Nonetheless, the long-run impact of attention cointegration, in terms of coefficient of the lagged $CointEq$ variable, also shows that it is higher for the NSE Nifty market returns (viz., 46.97%) than that for the BSE Sensex market returns (viz., 40.75%).

Table 6: Effects of election- economics-politics (EEP) nexus on the NSE stock-markets' returns				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	**0.4698**	0.0313	15.014	0.001
Δ (D_NDA)	**0.0000260**	0.0000051	5.126	0.001
Δ (D_NM)	**0.0000385**	0.0000133	2.892	0.006
Δ (D_RFR)	**0.0000071**	0.0000012	5.774	0.001
Δ (D_RG)	**-0.000069**	0.0000156	-4.386	0.001
Δ (D_SG)	-0.0000076	0.0000180	-0.420	0.677
Δ (D_UPA)	0.0000029	0.0000019	1.527	0.134
Δ (D_LSE)	**-0.000398**	0.0000469	-8.486	0.001
CointEq(-1)*	**-0.469717**	0.0312850	-15.014	0.001
ECM Summary Statistics:				
R2	0.8241	MDV	0.000014	
Adj. R2	0.8021	S.D.D.V.	0.000958	
S.E.R.	0.000426	AIC	-12.5685	
S.S.R.	0.000012	SIC	-12.2861	
Log Likelihood	467.75	HQIC	-12.456	
F-stat.	**37.482**	DW stat.	2.059	

P(F-stat.)	0.001	BGSCLM (1)	0.091 (0.76)
B-P-G HT (prob)	0.871 (0.65)	BGSCLM (2)	1.221 (0.31)
Skewness	-0.2965	Kurtosis	2.7685
Resid. J.B. Normality (prob.)		1.232 (0.540)	
F-Bound Test (n =73, k = 20)		F-Bound F-statistic Value	**7.379**
F-Bound Table Value (α = 0.01)		I(0) = 2.54, I(1) = 3.86	

Results on the regression model in equation (7) with the NSE Nifty returns data as the dependent variable. The trend effect (T_t,) *in the regression model is significant only at probability of 80.53% for* R_NSE *and the same is omitted in the final regression model to avoid over-estimation problem in the error correction form* (ECF) *of the* $ARDL$ *model. An * marked p-value is compatible with the F-Bounds distribution. Please refer to Table 1 for variable acronyms. In residual analysis,* $B-P-GHT$ *suggests for Breusch-Pagan-Godfrey heteroskedasticity test and* $BGSCLM$ *suggests for Breusch-Godfrey serial correlation test. Resid. J.B. Normality refers to Jarque-Bera Normality Test.*

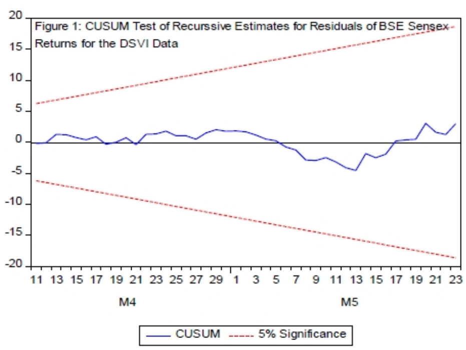

Figure 1: CUSUM Test of Recurssive Estimates for Residuals of BSE Sensex Returns for the DSVI Data

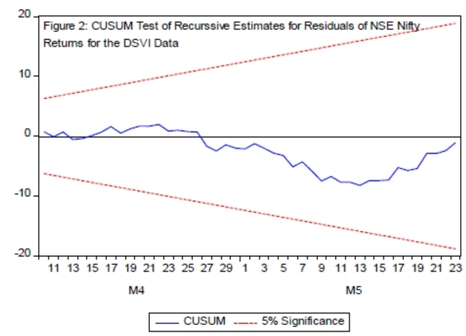

Figure 2: CUSUM Test of Recurssive Estimates for Residuals of NSE Nifty Returns for the DSVI Data

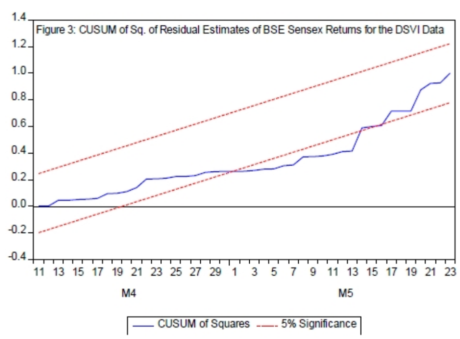

Figure 3: CUSUM of Sq. of Residual Estimates of BSE Sensex Returns for the DSVI Data

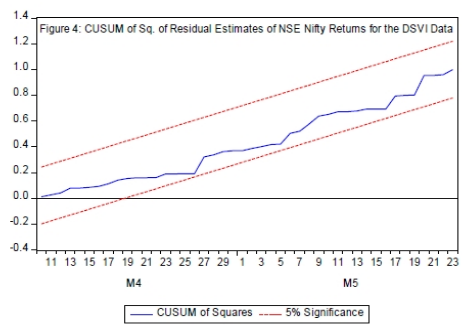

Figure 4: CUSUM of Sq. of Residual Estimates of NSE Nifty Returns for the DSVI Data

Before we explain the above differential impacts of NDA vis-à-vis the disjoint impacts of $NXPM$, SG, UPA, NM, RFR, RG, and LSE on the returns of the two markets, let us examine the power of the respective models. The concerned $ARDL$ models for both the market returns have mostly equivalent and good explanatory powers in terms of their Adj. R2 values. These have good-fits of the models in terms of their significant F-statistic values. Again, their robust magnitudes for the F-bound F-statistic values confirm the respective models' soundness at their cointegrating relationships. Apart from the above, the residuals of ECFs of the $ARDL$ models with these two stock markets' returns are free from the problems of serial correlations and that of heteroskedasticity as well. Their respective $ARDL$ regression residuals are normal in their distributions as well. Apart from the above observations, the results for $CUSUM$ tests for stability analysis, as demonstrated in Figure 1 and Figure 2, show that both the market returns are stable at their $CUSUM$ of recursive residuals. Nonetheless, at a robustness check of stability with the market returns, the $CUSUM$ test with the square of recursive residuals (read with Figure 3 and Figure 4) finds that the respective $ARDL$ model is persistently stable with the NSE market returns but that is kinked-instable at BSE market returns and stretched along the middle of the study period. This shows the presence of some larger swings in investors' mood to attend new information through keyword searches in the BSE than those in the NSE. The coefficients of the regression models are of the best linear unbiased and efficient i.e., $BLUE$ in nature but they are persistent with the NSE returns and not with the BSE returns.

But why there is a rift about the stability of the attention impacts and investors' moods to attend new information in the two stock markets? At a glance, it is apprehensible that the aforementioned differential and disjoint attention impacts contribute to such difference in the nature of the two models' coefficients. Besides, we find lesser long-run adjustments of about 40.75% for the BSE market returns than that of about 46.97% for the NSE market returns. The BSE market returns are more exposed to short-run dynamics and such exposures lead to kinked-instability of the model for attention dynamics (please read with Table 5). Hence, a presence of general but stretched attention impetus of NDA, in the form of investors' differential attention impacts suggesting for a presence of their sustained attention interests towards their attention cointegration, is a valid explanation for such asymmetric dynamics in the EEP nexus. Its triads are visible in attention cointegrations for the NSE market returns (please refer to Table 6) while the economic impetus is missing for the BSE market returns except of its lagged impacts as depicted in Table 5. It infers that investors in the BSE market attend more information impetus related to the election and politics than those related to economics.

The study now explains the differential and disjoint or isolated attention impacts on the BSE Sensex and NSE Nifty stock-markets' returns with their results for the unrestricted short-run $ARDL$ models in Table 7 and Table 8 respectively. It shows that both differential and disjoint attention impacts are very common phenomena across the attention searches of investors and these are contributed neither by the presence of attention heterogeneity nor by any attention bias rather these constitute their fundamental features. Since investor's learning and trading activity are behaviorally conditioned to their levels of selective attention and such attention brings in the effects of new information, the observed differential impacts suggest for presence of differing volatility in attention searches in the two stock markets. The BSE market returns are experiencing more volatility caused by attention impacts than that on the NSE market. The differential attention impacts of BSE also confirm the said proposition (please refer to Table 7). Furthermore, since the investors vis-à-vis the number of listed stocks in the BSE Sensex and NSE Nifty are different and exploring the attention searches across the scripts is at a too distant limit at hand, we view the disjoint effects with the isolation effect in Kahneman and Tversky (1979) and Tversky and Kahneman (1992). An isolation effect suggests for investors' decision framing with unique and unfamiliar factors. The results in the table identify that investors' attention impacts show search keyword-specific isolation effects. The presence of isolation effects across attention searches also emboldens the empirical plausibility of the election-economics-politics (EEP) nexus in the stock markets.

Table 7: EEP nexus on the BSE stock-markets' returns with the Unrestricted Short-Run ARDL Model

Variables	Coef.	Std. Error	t-Stat	Prob.
R_BSE(-1)	**0.3929810**	0.1136430	3.458	0.001
R_BSE(-2)	0.1995630	0.1007490	1.981	0.054
D_ABV	**0.0000312**	0.0000134	2.325	0.025
D_BJP	0.0000320	0.0000300	1.066	0.292
D_BSE	**0.0000912**	0.0000230	3.959	0.001
D_EVM	0.0000019	0.0000043	0.443	0.660
D_EVM(-1)	**0.0000101**	0.0000035	2.878	0.006
D_INC	0.0000037	0.0000208	0.177	0.861
D_INC(-1)	**-0.0000521**	0.0000213	-2.443	0.019
D_IRR	0.0000004	0.0000033	0.133	0.895
D_LKA	0.0000017	0.0000063	0.268	0.790

D_LSE	**-0.0002330**	0.0001150	-2.022	0.050
D_MS	-0.0000122	0.0000069	-1.757	0.086
D_NDA	**0.0000339**	0.0000153	2.217	0.032
D_NDA(-1)	**0.0000271**	0.0000110	2.470	0.018
D_NM	-0.0000429	0.0000300	-1.430	0.160
D_NSE	**-0.0000665**	0.0000157	-4.226	0.001
D_NXPM	-0.0000140	0.0000108	-1.304	0.199
D_NXPM(-1)	**0.0000379**	0.0000156	2.435	0.019
D_RFIR	0.0000044	0.0000024	1.825	0.075
D_RFR	**0.0000104**	0.0000037	2.809	0.008
D_RG	**-0.0000666**	0.0000309	-2.157	0.037
D_SG	0.0000597	0.0000371	1.608	0.115
D_SG(-1)	-0.0000607	0.0000494	-1.229	0.226
D_SMI	-0.0000006	0.0000019	-0.339	0.736
D_SMI(-1)	**-0.0000056**	0.0000025	-2.223	0.032
D_SMR	**-0.0000069**	0.0000020	-3.442	0.001
D_UPA	-0.0000078	0.0000068	-1.150	0.257
D_UPA(-1)	**-0.0000155**	0.0000044	-3.528	0.001
C	**0.4075280**	0.1204170	3.384	0.002
ECM Summary Statistics:				
R2	0.75874	MDV	1.00019	
Adj. R2	0.59603	S.D.D.V.	0.000787	
S.E.R.	0.0005	AIC	-12.0706	
S.S.R.	0.000011	SIC	-11.1293	
Log Likelihood	470.5766	HQIC	-11.6955	
F-stat.	**4.663**	DW stat.	2.222	
P(F-stat.)	0.001	BGSCLM (1)	1.065 (0.308)	
B-P-G HT (prob)	0.985 (0.51)	BGSCLM (2)	0.768 (0.470)	
Skewness	0.3715	Kurtosis	3.277	
Resid. J.B. Normality (prob.)		1.913 (0.384)		
F-Bound Test (n=73, k = 20)		F-Bound F-stat Value		**3.912**
F-Bound Table Value ($\alpha = 0.01$)		I(0) = 2.54, I(1) = 3.86		

Results on the regression model in equation(3)\ with the BSE Sensex returns data as the dependent variable. The trend effect (T_t,) in the regression model is significant only at probability of 86.07% for R_BSE and the same is omitted in the final results here to avoid over-estimation problem. Please refer to Table 1 for variable acronyms. In residual analysis, $B-P-GHT$ suggests for Breusch-Pagan-Godfrey heteroskedasticity test and $BGSCLM$ suggests for Breusch-Godfrey serial correlation test. Resid. J.B. Normality refers to Jarque-Bera Normality Test.

Table 8: EEP nexus on the NSE stock-markets' returns with the Unrestricted Short-Run ARDL Model				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
R_NSE(-1)	**0.530283**	0.105707	5.017	0.001
D_ABV	-0.000005	0.000017	-0.314	0.755
D_BJP	**0.000115**	0.000033	3.458	0.001
D_BSE	**0.000056**	0.000023	2.411	0.020
D_EVM	-0.000008	0.000005	-1.672	0.102
D_INC	0.000031	0.000026	1.205	0.235
D_IRR	0.000003	0.000004	0.819	0.417
D_LKA	-0.000009	0.000007	-1.342	0.186

D_MS	-0.000010	0.000009	-1.139	0.261
D_NDA	**0.000026**	0.000013	1.981	0.054
D_NDA(-1)	**0.000031**	0.000012	2.685	0.010
D_NM	0.000039	0.000037	1.048	0.301
D_NM(-1)	0.000048	0.000035	1.369	0.178
D_NSE	**-0.000039**	0.000017	-2.383	0.022
D_NXPM	-0.000016	0.000014	-1.146	0.258
D_RFIR	0.000004	0.000002	1.774	0.083
D_RFR	**0.000007**	0.000003	2.329	0.025
D_RFR(-1)	**0.000007**	0.000003	2.517	0.016
D_RG	-0.000069	0.000039	-1.769	0.084
D_RG(-1)	0.000073	0.000050	1.457	0.152
D_SG	-0.000008	0.000045	-0.170	0.866
D_SG(-1)	**-0.000122**	0.000048	-2.565	0.014
D_SMI	-0.000003	0.000002	-1.239	0.222
D_SMR	**-0.000005**	0.000002	-2.276	0.028
D_UPA	0.000003	0.000005	0.604	0.549
D_UPA(-1)	-0.000008	0.000005	-1.688	0.099
D_LSE	**-0.000398**	0.000139	-2.857	0.007
D_LSE(-1)	**0.000223**	0.000096	2.337	0.024
C	**0.469787**	0.105720	4.444	0.001
ECM Summary Statistics				
R2	0.757541	MDV	1.000218	
Adj. R2	0.603249	S.D.D.V.	0.000816	
S.E.R.	0.000514	AIC	-12.0206	
S.S.R.	0.000012	SIC	-11.1107	
Log Likelihood	467.7504	HQIC	-11.6579	
F-stat.	**4.909**	DW stat.	2.059	
P(F-stat.)	0.001	BGSCLM (1)	0.091 (0.76)	
B-P-G HT (prob)	0.871 (0.65)	BGSCLM (2)	1.221 (0.31)	
Skewness	-0.2965	Kurtosis	2.7685	
Resid. J.B. Normality (prob.)		1.232 (0.540)		
F-Bound Test (n =73, k = 20)		F-Bound F-statistic Value		**7.379**
F-Bound Table Value ($\alpha = 0.01$)		I(0) = 2.54, I(1) = 3.86		

Results on the regression model in equation (3) with the NSE Nifty returns data as the dependent variable. The trend effect (T_t,) in the regression model is significant only at probability of 84.97% for R_NSE and the same is omitted in the final regression model to avoid over-estimation problem. Please refer to Table 1 for variable acronyms. In residual analysis, $B-P-GHT$ suggests for Breusch-Pagan-Godfrey heteroskedasticity test and $BGSCLM$ suggests for Breusch-Godfrey serial correlation test. Resid. J.B. Normality refers to Jarque-Bera Normality Test.

In Table 9 and Table 10, respectively for the BSE Sensex and NSE Nifty market returns, let us now locate the overall long-run attention impacts with the conditional LRF of $ARDL$ models. These show that investors' aggregate attention to the Indian political leaders has moderately weak impacts while the election attributes and economic issues perform strongly. Investors' attention to BSE (NSE and SMR) has positive (negative) attention impacts on the both stock-markets' returns suggesting for the presence of positive (dampening) mood of investors about the market movements. Besides the presence of both differential attention impacts and isolation effects of the search keywords across the attention attributes and the markets, the study demonstrates investors' precautionary attention motive with RFR as well.

In brief, the study documents an overall intriguing but moderate presence of the EEP nexus active in investors' attention decision choice in the two premier Indian stock markets.

Table 9: EEP nexus on the BSE stock-markets' returns with the Conditional LRF of ARDL Model				
Variables	Coef.	Std. Error	t-Stat	Prob.
C	**0.4075280**	0.1072100	3.801	0.000
R_BSE(-1)	**-0.4074560**	0.1071920	-3.801	0.000
D_ABV**	0.0000312	0.0000162	1.933	0.060
D_BJP**	0.0000320	0.0000324	0.988	0.329
D_BSE**	**0.0000912**	0.0000223	4.090	0.000
D_EVM(-1)	0.0000120	0.0000072	1.674	0.101
D_INC(-1)	-0.0000484	0.0000371	-1.305	0.199
D_IRR**	0.0000004	0.0000035	0.126	0.900
D_LKA**	0.0000017	0.0000065	0.262	0.795
D_LSE**	-0.0002330	0.0001300	-1.790	0.081
D_MS**	-0.0000122	0.0000081	-1.499	0.141
D_NDA(-1)	**0.0000610**	0.0000168	3.629	0.001
D_NM**	-0.0000429	0.0000372	-1.153	0.255
D_NSE**	**-0.0000665**	0.0000160	-4.149	0.000
D_NXPM(-1)	0.0000239	0.0000222	1.074	0.289
D_RFIR**	0.0000044	0.0000024	1.830	0.074
D_RFR**	**0.0000104**	0.0000031	3.408	0.001
D_RG**	-0.0000666	0.0000376	-1.769	0.084
D_SG(-1)	-0.0000011	0.0000703	-0.015	0.988
D_SMI(-1)	-0.0000062	0.0000042	-1.488	0.144
D_SMR**	**-0.0000069**	0.0000022	-3.204	0.003
D_UPA(-1)	**-0.0000234**	0.0000081	-2.893	0.006
D(RTN_BSE(-1))	-0.1995630	0.1089480	-1.832	0.074
D(D_EVM)	0.0000019	0.0000046	0.420	0.677
D(D_INC)	0.0000037	0.0000265	0.139	0.890
D(D_NDA)	**0.0000339**	0.0000123	2.768	0.008
D(D_NXPM)	-0.0000140	0.0000132	-1.068	0.292
D(D_SG)	0.0000597	0.0000424	1.407	0.167
D(D_SMI)	-0.0000006	0.0000025	-0.250	0.804
D(D_UPA)	-0.0000078	0.0000049	-1.581	0.121
* F-Bound Test (n=73, k = 20)		F-Bound F-stat Value		**3.912**
F-Bound Table Value ($\alpha = 0.01$)		I(0) = 2.54, I(1) = 3.86		

Error Correction:

$EC = R\_BSE - (0.000077 * D\_ABV + 0.000079 * D\_BJP + 0.000224 * D\_BSE + 0.000030 * D\_EVM - 0.000119 * D\_INC + 0.000001 * D\_IRR + 0.000004 * D\_LKA - 0.000572 * D\_LSE - 0.000030 * D\_MS + 0.000150 * D\_NDA - 0.000105 * D\_NM - 0.000163 * D\_NSE + 0.000059 * D\_NXPM + 0.000011 * D\_RFIR + 0.000026 * D\_RFR - 0.000163 * D\_RG - 0.000003 * D\_SG - 0.000015 * D\_SMI - 0.000017 * D\_SMR - 0.000057 * D\_UPA)$

*Results on the regression model in equation (5) with the BSE Sensex returns data as the dependent variable. The trend effect (T_t,) in the regression model is significant only at probability of 86.07% for R_BSE and the same is omitted in the final results here to avoid over-estimation problem. An * marked p-value is compatible with F-Bounds distribution. The ** marked Variables are interpreted as $Z = Z(-1) + D(Z)$.*

Table 10: EEP nexus on the NSE stock-markets' returns with the Conditional LRF of ARDL Model				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
C	**0.4697870**	0.1057200	4.444	0.000
R_NSE(-1)	**-0.4697170**	0.1057070	-4.444	0.000
D_ABV**	-0.0000054	0.0000172	-0.314	0.755
D_BJP**	**0.0001150**	0.0000333	3.458	0.001
D_BSE**	**0.0000556**	0.0000230	2.411	0.020
D_EVM**	-0.0000077	0.0000046	-1.672	0.102
D_INC**	0.0000312	0.0000259	1.205	0.235
D_IRR**	0.0000033	0.0000040	0.819	0.417
D_LKA**	-0.0000087	0.0000065	-1.342	0.186
D_MS**	-0.0000101	0.0000089	-1.139	0.261
D_NDA(-1)	**0.0000572**	0.0000196	2.912	0.006
D_NM(-1)	0.0000868	0.0000593	1.465	0.150
D_NSE**	**-0.0000394**	0.0000165	-2.383	0.022
D_NXPM**	-0.0000157	0.0000137	-1.146	0.258
D_RFIR**	0.0000043	0.0000024	1.774	0.083
D_RFR(-1)	**0.0000145**	0.0000046	3.158	0.003
D_RG(-1)	0.0000048	0.0000663	0.072	0.943
D_SG(-1)	-0.0001300	0.0000736	-1.766	0.084
D_SMI**	-0.0000028	0.0000023	-1.239	0.222
D_SMR**	**-0.0000054**	0.0000024	-2.276	0.028
D_UPA(-1)	-0.0000052	0.0000083	-0.631	0.532
D_LSE(-1)	-0.0001740	0.0001610	-1.083	0.285
D(D_NDA)	0.0000260	0.0000131	1.981	0.054
D(D_NM)	0.0000385	0.0000368	1.048	0.301
D(D_RFR)	**0.0000071**	0.0000031	2.329	0.025
D(D_RG)	-0.0000685	0.0000387	-1.769	0.084
D(D_SG)	-0.0000076	0.0000445	-0.170	0.866
D(D_UPA)	0.0000029	0.0000048	0.604	0.549
D(D_LSE)	**-0.0003980**	0.0001390	-2.857	0.007
* F-Bound Test (n =73, k = 20)		F-Bound F-statistic Value		**7.379**
F-Bound Table Value ($\alpha = 0.01$)		I(0) = 2.54, I(1) = 3.86		

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Error Correction:

$EC = R\_NSE - (-0.000012 * D\_ABV + 0.000245 * D\_BJP + 0.000118 * D\_BSE - 0.000016 * D\_EVM + 0.000067 * D\_INC + 0.000007 * D\_IRR - 0.000019 * D\_LKA - 0.000022 * D\_MS + 0.000122 * D\_NDA + 0.000185 * D\_NM - 0.000084 * D\_NSE - 0.000033 * D\_NXPM + 0.000009 * D\_RFIR + 0.000031 * D\_RFR + 0.000010 * D\_RG - 0.000277 * D\_SG - 0.000006 * D\_SMI - 0.000012 * D\_SMR - 0.000011 * D\_UPA - 0.000371 * D\_LSE)$

*Results on the regression model in equation (5) with the NSE Nifty returns data as the dependent variable. The trend effect ($T_{t,}$) in the regression model is significant only at probability of 84.97% for R_NSE and the same is omitted in the final results here to avoid over-estimation problem. An * marked p-value is compatible with F-Bounds distribution. The ** marked Variables are interpreted as $Z = Z(-1) + D(Z)$.*

EEP nexus and volume traded: In Table 11 and Table 12 respectively for the realized volume traded in the BSE Sensex and NSE Nifty, with the concerned $ARDL$ models, the study also finds that the selective attention variables show the presence of EEP nexus in explaining the realized volume-traded of both the markets. In explaining investors' realized presence in the BSE Sensex (NSE Nifty) stock market, the short-term effect of the endogenous trade-volume variable is weakly (strongly) significant at an α value of 0.091 (0.028). Besides, the volume traded in the BSE Sensex can be weakly explained by "Manmohan Singh" i.e., MS but strongly explained by investors' short-run selective attention to search keywords viz., "Bharatiya Janata Party" i.e., BJP, "Indian National Congress" i.e., INC, "National Stock Exchange" i.e., NSE, and "Next PM" i.e., $NXPM$, "Risk-Free Interest Rate" i.e., $RFIR$, and "Stock Market Index" i.e., SMI as well (please refer to Table 11). In Table 12, in contrast, the volume traded in the NSE Nifty can strongly be explained by their short-run selective attention to "Bombay Stock Exchange" i.e., BSE, "Lal Krishna Advani" i.e., LKA, "Narendra Modi" i.e., NM, "Risk-Free Return" i.e., RFR, "Sonia Gandhi" i.e., SG, and "Stock Market Return" i.e., SMR.

Table 11: Effects of election- economics-politics nexus on the BSE stock-markets' trade-volume

Variables	Coef.	Std. Error	t-Stat	Prob.
Constant	**1.089927**	0.077862	13.998	0.001
Δ (V_BSE(-1))	0.125328	0.072442	1.730	0.091
Δ (D_BJP)	**-0.006761**	0.000967	-6.989	0.001
Δ (D_INC)	**0.004352**	0.001169	3.721	0.001
Δ (D_MS)	0.000558	0.000356	1.568	0.124
Δ (D_NSE)	**-0.003378**	0.000292	-11.568	0.001
Δ (D_NXPM)	**-0.002225**	0.000579	-3.846	0.001
Δ (D_RFIR)	**0.000414**	0.000106	3.927	0.001
Δ (D_SMI)	**0.000453**	0.000103	4.403	0.001
CointEq(-1)*	**-0.257995**	0.018446	-13.986	0.001
ECM Summary Statistics				
R2	0.7789	MDV	0.003977	
Adj. R2	0.7473	S.D.D.V.	0.085193	
S.E.R.	0.04282	AIC	-3.33696	
S.S.R.	0.115515	SIC	-3.0232	
Log Likelihood	131.7991	HQIC	-3.21192	
F-stat.	**24.67**	DW stat.	1.82309	
P(F-stat.)	0.001	BGSCLM (1)	0.7485 (0.39)	
B-P-G HT	1.135 (0.35)	BGSCLM (2)	0.3806 (0.686)	
Skewness	0.3783	Kurtosis	4.674	
Resid. J.B. Normality (prob.)		**10.268** (0.006)		
F-Bound Test (n=73, k = 20)		F-Bound F-stat Value		**6.358**
F-Bound Table Value (α = 0.01)		I(0) = 2.54, I(1) = 3.86		

*Results on the regression model in equation (8) with the BSE Sensex Trade-Volume data as the dependent variable. The trend effect ($T_{t,}$) in the regression model is significant only at probability of 20.01% for VOL_BSE and the same is omitted in the final results here to avoid over-estimation problem in the error correction form (ECF) of the ARDL model. An * marked p-value is compatible with the F-Bounds distribution. Please refer to Table 1 for variable acronyms. In residual analysis, $B-P-GHT$ suggests for Breusch-Pagan-Godfrey heteroskedasticity test and $BGSCLM$ suggests for Breusch-Godfrey serial correlation test. Resid. J.B. Normality refers to Jarque-Bera Normality Test.*

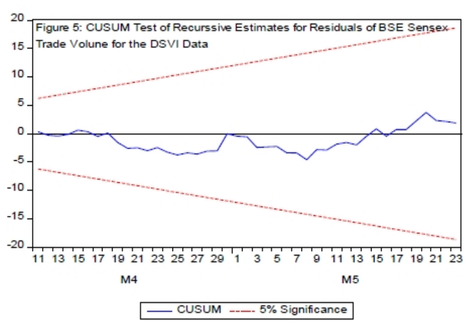
These results are interesting to interpret that there is a complete asymmetry in terms of investors' attention impacts in explaining their realized presence in the two stock markets. The search keywords in their attention consideration are different even if the magnitudes of the speed of adjustment in terms of the coefficient values of $CointEq$ are mostly at the one-fourth marks i.e., 25% only. The rest explanatory powers, mostly about to 75% dynamic adjustments, are exposed to investors' short-run attention impacts. Furthermore, it is amazing to locate that the effect of investors' attention to "National Democratic Alliance" i.e., NDA is weakly significant at an α value of 0.085 in explaining the realized presence of investors in the NSE market (read with Table 12) while that in explaining the trade-volume in the BSE Sensex, is not included by the regression system at all (please refer to Table 11). These confirm that investors' attention dynamics, concerning the attention cointegration and thereby corroborating the EEP nexus, are in effect different for the realized volume-traded from that for the stocks' market returns. Nonetheless, the presence of asymmetry impacts can further be illustrated with the market-wise general attention impetus explaining the stocks' market returns vis-a-vis their realized traded-volumes. Again, in support of the above attention-search specific isolation effects, the study identifies that the keyword $NXPM$ (RFR) is the only search keyword that explains both the BSE Sensex (NSE Nifty) stock market returns and its realized traded-volumes. Therefore, the investors' attention cointegrations are mostly asymmetric in nature and market-specific as well.

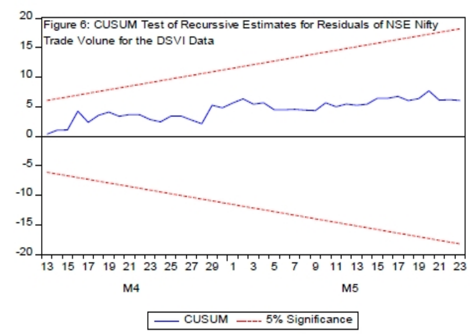
Table 12: Effects of election- economics-politics nexus on the NSE stock-markets' trade-volume				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	**2.12099**	0.2134	9.939	0.000
Δ (V_NSE(-1))	**0.193957**	0.08509	2.279	0.028
Δ (D_BSE)	**-0.0081**	0.000825	-9.823	0.000
Δ (D_LKA)	**-0.00356**	0.000512	-6.947	0.000
Δ (D_NDA)	-0.00095	0.000535	-1.767	0.085
Δ (D_NM)	**0.0085**	0.001502	5.660	0.000
Δ (D_RFIR)	0.00018	0.000118	1.527	0.134
Δ (D_RFR)	**0.000494**	0.000158	3.119	0.003
Δ (D_SG)	**-0.00793**	0.002244	-3.533	0.001
Δ (D_SMI)	0.000181	0.00012	1.505	0.140
Δ (D_SMR)	**0.000887**	0.000162	5.475	0.000
CointEq(-1)*	**-0.24852**	0.025001	-9.940	0.000
ECM Summary Statistics:				
R2	0.6705	MDV	0.002853	
Adj. R2	0.6111	S.D.D.V.	0.083011	
S.E.R.	0.051765	AIC	-2.93504	
S.S.R.	0.163455	SIC	-2.55852	
Log Likelihood	119.129	HQIC	-2.78499	
F-stat.	**11.288**	DW stat.	**2.27**	
P(F-stat.)	0.001	BGSCLM (1)	2.241 (0.14)	
B-P-G HT	0.871 (0.65)	BGSCLM (2)	1.093 (0.35)	
Skewness	0.358919	Kurtosis	3.54633	
Resid. J.B. Normality (prob.)		2.4752 (0.290)		
F-Bound Test (n =73, k = 20)		F-Bound F-statistic Value		**3.1624**
F-Bound Table Value (α = 0.10)		I(0) =1.83, I(1) = 2.94		
F-Bound Table Value (α = 0.05)		I(0) =2.06, I(1) = 3.24		

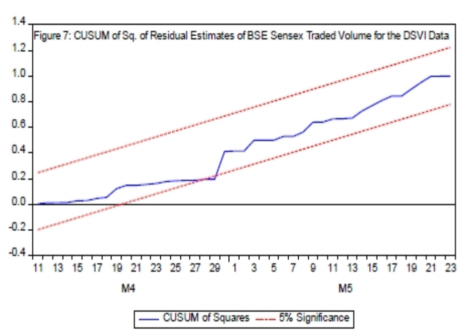
*Results on the regression model in equation (8) with the NSE Nifty Trade-Volume data as the dependent variable. The trend effect ($T_{t,}$) in the regression model is significant only at probability of 93.16% for VOL_NSE and the same is omitted in the final regression model to avoid over-estimation problem in the error correction form (ECF) of the $ARDL$ model. An * marked p-value is compatible with the F-Bounds distribution. Please refer to Table 1 for variable acronyms. In residual analysis, $B-P-GHT$ suggests for Breusch-Pagan-Godfrey heteroskedasticity test and $BGSCLM$ suggests for Breusch-Godfrey serial correlation test. Resid. J.B. Normality refers to Jarque-Bera Normality Test.*

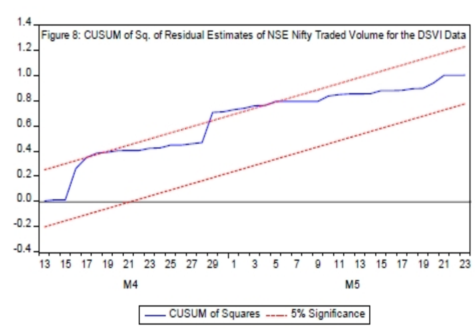
A deeper analysis of the above results shows that the models explaining the realized trade volumes of the BSE Sensex (NSE Nifty) markets have their explanatory powers of about 74.73% (61.11%) in terms of the Adj. R2 value. The $ECFs$ of the $ARDL$ models also have good-fits in terms of their significant F-statistic values. The results at the F-bound test statistic value for the $ARDL$ models also confirm their cointegrating relationships while the same is strongly (weakly) significant at the 1% (10%) level of significance for the BSE (NSE) market [readers are requested to refer to Table 11 (Table 12)]. These results primarily suggest for the presence of an unsustainable attention cointegration at investors' realized presence in the NSE market. At a strict 0.1 percent level, the regression residuals are neither serially correlated nor there are presence of heteroskedastic effects and these are also normal in their statistical distributions. Their $CUSUM$ tests for the recursive residuals towards the stability analysis (read with Figure 5 and Figure 6) of the cointegration relationship show that both the $ARDL$ models for market returns are stable at their $CUSUM$ of the recursive residuals. These results apparently find no distinctions in terms of models' stability between the two markets.

But there are gloomy areas about the stated stability of the models. With both markets' realized trade volumes, the $CUSUM$ of squared residuals for the regression models (read with Figure7 and Figure 8) are not persistently stable. In the BSE market, these have a downside V-shaped kink while in the NSE market, these have an M-shaped upside twin kinks. That is, even if the coefficients of the models are of $BLUE$ in nature but the models are kinked-stable at both markets' realized trade volumes' data suggesting that investors show repetitive attention checks and these are reflected on their realized presence in both the stock markets. Such a sort of kinked-stability can also be substantiated with the low magnitudes of their speeds of adjustment to their long-run relationships. Their realized trade volumes show higher responsiveness to their short-term selective attention impacts while their long-run relationships have lesser weights. Investors' realized presence shows the dynamics of the EEP nexus in both the markets but weak at the BSE (please refer to Table 11) and strong at the NSE (also see Table 12).









The said difference in short-run attention impacts on investors' realized presence in the two markets are reviewed in details with their respective unrestricted short-run $ARDL$ models and the results are given in Table 13 and Table 14 respectively for the BSE Sensex and NSE Nifty stock markets. Here, the study finds the presence of two different cases of EEP nexus – investors realized presence at the BSE (NSE) market is exposed to their attention to BJP, LSE, MS, $NXPM$, and SMI (BSE, LKA, NDA, NSE, RFR, SMR).

Table 13: EEP nexus on the BSE stock markets' trading-volume with the Unrestricted Short-Run ARDL Model				
Variables	Coef.	Std. Error	t-Stat	Prob.
V_BSE(-1)	**0.867333**	0.116541	7.442	0.000
V_BSE(-2)	-0.125328	0.107111	-1.170	0.248
D_ABV	0.001785	0.001644	1.086	0.284
D_BJP	-0.006761	0.003715	-1.820	0.076
D_BJP(-1)	**0.011352**	0.003993	2.843	0.007
D_EVM	0.000009	0.000446	0.019	0.985
D_INC	0.004352	0.002662	1.635	0.109
D_INC(-1)	-0.004606	0.002725	-1.691	0.098
D_IRR	-0.000020	0.000363	-0.056	0.956
D_LKA	-0.001035	0.000880	-1.176	0.246
D_LSE	**-0.028289**	0.013242	-2.136	0.038
D_MS	0.000558	0.000983	0.568	0.573
D_MS(-1)	**0.002601**	0.000933	2.789	0.008
D_NDA	0.001361	0.001325	1.027	0.310
D_NM	0.005742	0.003434	1.672	0.102
D_NSE	-0.003378	0.001702	-1.985	0.054
D_NSE(-1)	-0.000520	0.000321	-1.621	0.112
D_NXPM	-0.002225	0.001403	-1.586	0.120
D_NXPM(-1)	**-0.003460**	0.001424	-2.430	0.019
D_RFIR	0.000414	0.000344	1.204	0.235
D_RFIR(-1)	0.000534	0.000353	1.513	0.138
D_RFR	-0.000132	0.000316	-0.419	0.678
D_RG	0.004623	0.003653	1.266	0.213
D_SG	0.003266	0.004127	0.791	0.433
D_SMI	0.000453	0.000264	1.718	0.093
D_SMI(-1)	**0.000884**	0.000282	3.136	0.003
D_SMR	0.000286	0.000234	1.222	0.229
D_UPA	0.000733	0.000453	1.619	0.113
D_BSE	0.004493	0.002300	1.953	0.057
C	**1.089927**	0.428624	2.543	0.015
ECM Summary Statistics				
R2	0.775866	MDV	4.229305	
Adj. R2	0.624705	S.D.D.V.	0.084606	
S.E.R.	0.051831	AIC	-2.78902	
S.S.R.	0.115515	SIC	-1.84773	
Log Likelihood	131.7991	HQIC	-2.4139	
F-stat.	**5.133**	DW stat.	**1.823**	
P(F-stat.)	0.001	BGSCLM (1)	0.7485 (0.39)	
B-P-G HT	1.135 (0.35)	BGSCLM (2)	0.3806 (0.686)	
Skewness	0.3783	Kurtosis	4.674	
Resid. J.B. Normality (prob.)		**10.268** (0.006)		
F-Bound Test (n=73, k = 20)		F-Bound F-stat Value		**6.358**
F-Bound Table Value ($\alpha = 0.01$)		I(0) = 2.54, I(1) = 3.86		

Results on the regression model in equation (4) with the BSE Sensex Trade-Volume data as the dependent variable. The trend effect ($T_{t,}$) in the regression model is significant only at probability of 32.46% for VOL_BSE and the same is omitted in the final results here to avoid over-estimation problem. Please refer to Table 1 for variable acronyms. In residual analysis,

$B-P-GHT$ suggests for Breusch-Pagan-Godfrey heteroskedasticity test and $BGSCLM$ suggests for Breusch-Godfrey serial correlation test. Resid. J.B. Normality refers to Jarque-Bera Normality Test.

These results confirm the aforesaid presence of isolation effects contributing to EEP nexus and their extents in terms of investors' realized presence in the two stock markets. Besides, the respective stock market's endogenous realized presence at their 1st lags has lesser impacts at the BSE stock market (see in Table 13) than that at the NSE stock market (see in Table 14) and this substantiates the higher explanatory power with the former stock market. In brief, the realized trade-volume shows the comparative nature of attention impacts contributing to the EEP nexus across the two markets.

Table 14: EEP nexus on the NSE stock markets' trading-volume with the Unrestricted Short-Run ARDL Model				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
V_NSE(-1)	**0.945441**	0.136244	6.939	0.000
V_NSE(-2)	-0.19396	0.134548	-1.442	0.157
D_ABV	4.44E-05	0.002112	0.021	0.983
D_BJP	0.005329	0.004242	1.256	0.216
D_BSE	**-0.0081**	0.003405	-2.379	0.022
D_BSE(-1)	**0.001648**	0.000638	2.583	0.014
D_EVM	-0.00122	0.000632	-1.936	0.060
D_INC	0.002801	0.003168	0.884	0.382
D_IRR	-0.00037	0.000507	-0.733	0.468
D_LKA	**-0.00356**	0.001104	-3.224	0.003
D_LKA(-1)	0.001304	0.00086	1.517	0.137
D_LSE	0.006743	0.018201	0.370	0.713
D_MS	0.001257	0.001105	1.138	0.262
D_NDA	-0.00095	0.001636	-0.577	0.567
D_NDA(-1)	**0.004425**	0.0015	2.950	0.005
D_NM	0.0085	0.004473	1.900	0.064
D_NM(-1)	0.007546	0.004483	1.683	0.100
D_NSE	**0.005859**	0.002488	2.355	0.023
D_NXPM	-0.00092	0.001628	-0.566	0.575
D_RFIR	0.00018	0.000434	0.416	0.680
D_RFIR(-1)	0.000751	0.000461	1.629	0.111
D_RFR	0.000494	0.00038	1.300	0.201
D_RFR(-1)	**0.000938**	0.000412	2.274	0.028
D_RG	-0.00788	0.005151	-1.530	0.134
D_SG	-0.00793	0.005647	-1.404	0.168
D_SG(-1)	-0.00728	0.006224	-1.170	0.249
D_SMI	0.000181	0.000345	0.525	0.603
D_SMI(-1)	0.000548	0.000344	1.593	0.119
D_SMR	**0.000887**	0.000377	2.353	0.024
D_SMR(-1)	**0.001418**	0.000417	3.403	0.002
D_UPA	**0.001212**	0.000541	2.238	0.031
C	**2.120987**	1.051847	2.016	0.050
ECM Summary Statistics:				
R2	0.694229	MDV	8.551424	
Adj. R2	0.463037	S.D.D.V.	0.086166	
S.E.R.	0.06314	AIC	-2.38709	
S.S.R.	0.163455	SIC	-1.38305	
Log Likelihood	119.1288	HQIC	-1.98696	

F-stat.	**3.003**	DW stat.	**2.273**	
P(F-stat.)	0.001	BGSCLM (1)	2.241 (0.14)	
B-P-G HT	0.871 (0.65)	BGSCLM (2)	1.093 (0.35)	
Skewness	0.358919	Kurtosis	3.54633	
Resid. J.B. Normality (prob.)		2.4752 (0.290)		
F-Bound Test (n =73, k = 20)		F-Bound F-statistic Value		**3.1624**
F-Bound Table Value ($\alpha = 0.10$)		I(0) =1.83, I(1) = 2.94		
F-Bound Table Value ($\alpha = 0.05$)		I(0) =2.06, I(1) = 3.24		

Results on the regression model in equation (4) with the NSE Nifty Trade-Volume data as the dependent variable. The trend effect ($T_{t,}$) in the regression model is significant only at probability of 94.67% for VOL_NSE and the same is omitted in the final regression model to avoid over-estimation problem Please refer to Table 1 for variable acronyms. In residual analysis, $B-P-GHT$ suggests for Breusch-Pagan-Godfrey heteroskedasticity test and $BGSCLM$ suggests for Breusch-Godfrey serial correlation test. Resid. J.B. Normality refers to Jarque-Bera Normality Test.

Table 15: EEP nexus on the BSE stock markets' trade-volume with the Conditional LRF of ARDL Model				
Variables	Coef.	Std. Error	t-Stat	Prob.
C	**1.089927**	0.428624	2.543	0.015
V_BSE(-1)	**-0.257995**	0.101511	-2.542	0.015
D_ABV**	0.001785	0.001644	1.086	0.284
D_BJP(-1)	0.004591	0.006501	0.706	0.484
D_EVM**	0.000009	0.000446	0.019	0.985
D_INC(-1)	-0.000254	0.003877	-0.065	0.948
D_IRR**	-0.000020	0.000363	-0.056	0.956
D_LKA**	-0.001035	0.000880	-1.176	0.246
D_LSE**	**-0.028289**	0.013242	-2.136	0.038
D_MS(-1)	0.003160	0.001624	1.945	0.058
D_NDA**	0.001361	0.001325	1.027	0.310
D_NM**	0.005742	0.003434	1.672	0.102
D_NSE(-1)	**-0.003898**	0.001848	-2.110	0.041
D_NXPM(-1)	**-0.005685**	0.002294	-2.478	0.017
D_RFIR(-1)	0.000948	0.000628	1.509	0.139
D_RFR**	-0.000132	0.000316	-0.419	0.678
D_RG**	0.004623	0.003653	1.266	0.213
D_SG**	0.003266	0.004127	0.791	0.433
D_SMI(-1)	**0.001337**	0.000470	2.843	0.007
D_SMR**	0.000286	0.000234	1.222	0.229
D_UPA**	0.000733	0.000453	1.619	0.113
D_BSE**	0.004493	0.002300	1.953	0.057
D(V_BSE(-1))	0.125328	0.107111	1.170	0.248
D(D_BJP)	-0.006761	0.003715	-1.820	0.076
D(D_INC)	0.004352	0.002662	1.635	0.109
D(D_MS)	0.000558	0.000983	0.568	0.573
D(D_NSE)	-0.003378	0.001702	-1.985	0.054
D(D_NXPM)	-0.002225	0.001403	-1.586	0.120
D(D_RFIR)	0.000414	0.000344	1.204	0.235
D(D_SMI)	0.000453	0.000264	1.718	0.093
* F-Bound Test (n=73, k = 20)		F-Bound F-stat Value		**6.358**
F-Bound Table Value ($\alpha = 0.01$)		I(0) = 2.54, I(1) = 3.86		

Error Correction:

$EC = V\_BSE-(0.00692*D\_ABV+0.017797*D\_BJP+0.000034*D\_EVM-0.000984*D\_INC-0.000078*D\_IRR-0.004010*D\_LKA-0.109648*D\_LSE+0.012247*D\_MS+0.005276*D\_NDA+0.022256*D\_NM-0.015110*D\_NSE-0.022036*D\_NXPM+0.003674*D\_RFIR-0.000513*D\_RFR+0.017918*D\_RG+0.012660*D\_SG+0.005182*D\_SMI+0.001108*D\_SMR+0.002842*D\_UPA+0.017414*D\_BSE)$

*Results on the regression model in equation (6) with the BSE Sensex Trade-Volume data as the dependent variable. The trend effect ($T_{t,}$) in the regression model is significant only at probability of 32.46% for VOL_BSE and the same is omitted in the final results here to avoid over-estimation problem. * marked p-value is compatible with F-Bounds distribution. ** marked Variables are interpreted as $Z = Z(-1) + D(Z)$.*

Table 16: EEP nexus on the NSE stock markets' trade-volume with the Conditional LRF of ARDL Model				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
C	**2.120987**	1.051847	2.016	0.050
V_NSE(-1)	**-0.248516**	0.123062	-2.019	0.050
D_ABV**	0.000044	0.002112	0.021	0.983
D_BJP**	0.005329	0.004242	1.256	0.216
D_BSE(-1)	**-0.006452**	0.003079	-2.096	0.042
D_EVM**	-0.001224	0.000632	-1.936	0.060
D_INC**	0.002801	0.003168	0.884	0.382
D_IRR**	-0.000372	0.000507	-0.733	0.468
D_LKA(-1)	-0.002255	0.001157	-1.949	0.058
D_LSE**	0.006743	0.018201	0.370	0.713
D_MS**	0.001257	0.001105	1.138	0.262
D_NDA(-1)	0.003480	0.002328	1.495	0.143
D_NM(-1)	**0.016046**	0.007262	2.210	0.033
D_NSE**	**0.005859**	0.002488	2.355	0.023
D_NXPM**	-0.000921	0.001628	-0.566	0.575
D_RFIR(-1)	0.000931	0.000831	1.120	0.269
D_RFR(-1)	**0.001431**	0.000602	2.378	0.022
D_RG**	-0.007879	0.005151	-1.530	0.134
D_SG(-1)	-0.015211	0.009276	-1.640	0.109
D_SMI(-1)	0.000729	0.000598	1.219	0.230
D_SMR(-1)	**0.002305**	0.000708	3.256	0.002
D_UPA**	**0.001212**	0.000541	2.238	0.031
D(V_NSE(-1))	0.193957	0.134548	1.442	0.157
D(D_BSE)	**-0.008100**	0.003405	-2.379	0.022
D(D_LKA)	**-0.003559**	0.001104	-3.224	0.003
D(D_NDA)	-0.000945	0.001636	-0.577	0.567
D(D_NM)	0.008500	0.004473	1.900	0.064
D(D_RFIR)	0.000180	0.000434	0.416	0.680
D(D_RFR)	0.000494	0.000380	1.300	0.201
D(D_SG)	-0.007928	0.005647	-1.404	0.168
D(D_SMI)	0.000181	0.000345	0.525	0.603
D(D_SMR)	**0.000887**	0.000377	2.353	0.024
* F-Bound Test (n =73, k = 20)		F-Bound F-statistic Value		**3.1624**
F-Bound Table Value ($\alpha = 0.10$)		I(0) =1.83, I(1) = 2.94		
F-Bound Table Value ($\alpha = 0.05$)		I(0) =2.06, I(1) = 3.24		

Error Correction:

$EC = V\_NSE - (0.000179*D\_ABV + 0.021442*D\_BJP - 0.025961*D\_BSE - 0.004924*D\_EVM + 0.011272*D\_INC - 0.001496*D\_IRR - 0.009073*D\_LKA + 0.027133*D\_LSE + 0.005058*D\_MS + 0.014003*D\_NDA + 0.064567*D\_NM + 0.023577*D\_NSE - 0.003706*D\_NXPM + 0.003747*D\_RFIR + 0.005760*D\_RFR - 0.031704*D\_RG - 0.061207*D\_SG + 0.002932*D\_SMI + 0.009275*D\_SMR + 0.004876*D\_UPA)$

*Results on the regression model in equation (6) with the NSE Nifty Trade-Volume data as the dependent variable. The trend effect ($T_{t,}$) in the regression model is significant only at probability of 94.67% for VOL_NSE and the same is omitted in the final results here to avoid over-estimation problem. * marked p-value is compatible with F-Bounds distribution. ** marked Variables are interpreted as $Z = Z(-1) + D(Z)$.*

Nonetheless, the study locates the overall attention impacts on the realized trade-volume across the two stock markets with the conditional LRF of the concerned $ARDL$ models in Table 15 and Table 16 respectively with the BSE and NSE markets. It shows the presence of EEP nexus at presence of significant attention impacts of LKA along with the election and economic attributes in the NSE market (see in Table 16) while the same in the BSE market is moderately weak at presence of NM and MS (please find in Table 15). Investors also show familiarity driven positive attention effects of BSE (NSE) on their realized presence in the BSE (NSE) stock markets. These results also confirm the stated differential and disjoint attention impacts on the realized presence in both the markets leading to presence of EEP nexus.

5. Conclusion

This study has theoretically hypothesized that stock-markets' pricing dynamics in terms of the markets' returns and realized trade-volumes could be explained by investors' attention dynamics at attention cointegration of election-economics-politics nexus. It has used both short-run and long-run proxy variables within the $ARDL$ setup. With the use of the Google SVI daily data for the EEP nexus variables during the 17th Lok Sabha Elections in 2019 in India, the study has empirically revealed different depictions of attention cointegrations for the NSE Nifty and BSE Sensex stock markets' returns and their realised trade volumes with the speeds of adjustment, their short-run attention impacts (unrestricted as well as conditional), and their overall conditional long-run impacts as well.

With reference to market returns, the NSE market presents a prominent presence of EEP nexus while the BSE market offers that the nexus pulls off the economic factor. With reference to the volume traded i.e., investors' realised presence in the market, the BSE market shows the EEP nexus while in the NSE market, the nexus pulls off the election factor. In the other words, the NSE (BSE) stock market returns (traded-volumes) are subject to investors' attention to the EEP nexus. Besides the EEP nexus, the overall observations at large show the presence of either differential or disjoint attention effects across attention searches vis-à-vis speeds of adjustments over the two stock markets. The study attributes the two effects as caused by investors' mood driven attention searches and their differential volatility in attention searches during the election season in India. Therefore, this study originally contributes to the literature with the presence of attention dynamics leading to the effects of EEP nexus in the NSE and BSE stock markets and investors' attention myopia at isolation effects as well.

The stated overall attention effects on the two stock markets open up a new window of knowledge about the market dynamics that our attention searches on the internet of things (IoT) have economic values. Nonetheless, our selective attention searches to the various aspects of nations' elections, economics, and politics all are not so bizarre phenomena as they appear at our normal understandings. The google attention searches on the IoT show predictive powers over the two stock markets and investors can identify attention trends in the public moods and their impacts on the markets, and they can measure their natures of persistency, and thereby, they may take a few profitable trading positions in the stock markets. However, a positive notion in interpreting the EEP nexus in the NSE or BSE stock markets links the same with investors' attention dynamics across their listed stocks resulting in attention coordination while its negative notion means for presence of attention cartel. At presence of EEP nexus, both the investors and the stock markets behave irrationally and inefficiently but quite normally and behaviourally and at such situations, the capital markets should be explained with investors' psychological biases rather than with available information contents only. Furthermore, the market regulators can investigate if there are such cartels manipulating the public mood, and thereby, exploiting the investors and damaging the flow of information in the stock markets. The regulators should be vigilant to make stocks' trading a fare game.

The present study limits its scope at recognizing the presence of EEP nexus only. Since investors' attention is driven by the public mood, future researches can decode the business implications of the EEP nexus on the stock markets. They can identify a general public mood and construct hypothetical attention portfolios, identify its constituents' stock-specific attention volatilities, and utilise the same in the $ARDL$ model and then augment the same in the generally autoregressive heteroskedastic ($GARCH$) models as well.

But why such attention myopia exists? Or why does it pull-off the economic or election factor in the contrary cases? Future researches may explore these research queries as well. A factor-wise or a group-wise exploration of the impacts of attention searches, rather than the EEP setup as used in this study, across the different layers of investors' attention might locate those footprints behind such pull-offs and identify their impacts on the stocks' markets vis-à-vis individual stocks as well. On managerial implication, this study can be used by the mutual fund managers to locate possible attention coordination or cartel/s in the stock markets and to take hedging positions accordingly.

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