

ARTICLE

Noise of Investors' Attention Mania in the 21st Century Indian Stock Markets

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Abstract

This paper characterises neoclassical investors as behavioral listeners rather than rational activists in their choices of attention searches online. It proposes that investors' attention search is distributed at three different attention layers – focused, selective and homogenized attention layers. It employs three sets of attention attributes on economics, politics, and political party and personality, and empirically, examines if attention search keywords at different attention layers have attention impacts on the NSE Nifty and BSE Sensex market returns. At group-wise attention attributes, the paper shows that investors' attention impacts are scattered over attributes and related to economics, politics, and political parties and personalities. With the ARDL models, at economic attributes, it finds local vis-à-vis global attention impacts and the presence of familiarity bias on both stock markets' returns and the noise of “investors' attention mania” (IAM) at the other sets of attention attributes. Furthermore, these effects vary across different attention layers.

Keywords: Noise in Financial Markets, Investors' Attention Mania, Behavioral Decision Choices, Indian Stock Markets, Google Search Volume Index.

1 Introduction

Investors are exposed to biases, irrationality, hope, frustrations and microstructure noise (Popescul et al., 2020; Sinha, 2019a; Ahmed, 2017). Noise of election mania (NOEM) exists – victory of the Democratic Party influences the US stock market/s negatively, the Republic Party has little effects and elections have transitional effects (Ejara et al., 2012; Behl and Sethi, 2016). The post-election US market movements have increasing power to predict its GDP growth rates (Chien et al., 2014). At synchronicity of stock-markets in the US and India (Bhuyan et al., 2016), the investors' attention mania (IAM), a noise in attention search, is expected to influence stock-markets' movements in India.

The Brexit referendum has significant event-day shock effects and 12th-day aftershock effects on the Indian stock markets (Sathyanarayana and Gargsha, 2016). The policies of its domestic political parties on corruption and anti-corruption mechanisms and disclosure of information to the public show serious political implications and economic effects (Sengupta, 2018; Lehne et al., 2018). Investors' aggregate sentiment index explains the volatility of stock market returns in India (Kumari and Mahakud, 2015). Vital political developments appear at specific political articulation of party agenda, media coverage of scandals about party or personal charisma of its leaders, proposal or enactment of extensive legislation, political manifesto, promises or slogans, actual or shadow-wars or war-like situations or peace between neighbouring regions, the balance of payments and terrorist attacks (Kapoor and Dwivedi, 2015; Ahmad, 2019; Newman, 2013; Chakravartty and Roy, 2015; De Leon et al., 2009).

Indian democracy shows presence of tensions and dilemmas at economic reforms and election results (Suri, 2004; Baloch and Vaishnav, 2020). Investors' perceptions at the pre- and post-election environments about foreign policy influence its domestic political development (Kronstadt, 2000). Economic issues are not too loud to attract the majority-voters' attention in India, its mass politics is different from its elite politics (Varshney, 1998; Kumar, 2004) and this may cause noise of investors' attention mania (Schaefer, 2020). (Schaefer, 2020) reviews (Grossberg, 2018) and argues that the conservative political narratives and nudge effect, pessimism and affect effect and storytelling and intervention induce the noise of investors' attention mania amongst the public. Political leaders and political chaos both represent each other. The fragility of affect effect and the affect-effect of fragile political stories both represent mania in the mass behaviors.

(Kabiru et al., 2015) find varied political risk factors in election environments in Kenya. We propose that the noise of investors' attention mania (IAM) behaviourally brings critical political risks in the stock-markets and argue that noise to economic and political changes influences stocks' performance. We hypothesize that IAM variables intervene stock-markets' performance. We explore if online attention searches for economic attributes (E-factor), political attributes (P-factor) and political parties and personalities (H-factor) have attention impacts on the NSE Nifty and BSE Sensex returns at long-term perspectives and their robustness as well.

In organizing the flow of this research, the literature is briefly reviewed in Section-II followed by its empirical foundation on the data and methodology for Noise of IAM in Section-III, the results and findings in Section-IV and the conclusion in Section-V.

2 Literature Review

On the noise of election mania (NOEM), (Grossberg, 2018) finds that socio-political manic narrative devastates economic life of the general US citizens while (Whybrow, 2006) shows that the economic-political manic narrative devastates its social life. On politics and economic developments, we review the political business cycle (PBC) theory, the efficient market (EM) theory and the behavioral finance (BF) theory.

The PBC theory suggests that the leaders and politicians of the incumbent government try to manipulate the fiscal and monetary mechanisms at contractionary or expansionary economic policies and influence the pre-election economic performance indicators and try to re-shape their prospects to win in elections (May, 1987; Park, 2011). Its early studies show the developed countries' contexts (Kramer, 1971; Drazen, 2000) and contemporary studies evidence the developing countries' contexts (Roman et al., 2009). (Lobo and Tufte, 1998) show exchange rate volatilities across the Japanese Yen, British Pound, German Mark and Canadian Dollar at the election cycle and policy of incumbent political party. Once the incumbent Indian governments come close to the general election, its economic globalization slowdowns and its state government's political determinants influence their revenue collections (Vadlamannati, 2008; Dash and Raja, 2014). (Sieg and Batool, 2012; Scholl, 2017; Lei, 2018) show the election effects on macroeconomic variables in detail.

The EM theory views the political and economic developments as event studies. The market's inefficiencies are contributed by the political risk factors. (Kabiru et al., 2015) depict that the Nairobi Stock Market reacts to volatility of election environments differently at the different general elections in Kenya. (Celis and Shen, 2015) find investors' asymmetric information effects at elections and government policy, which influence the Malaysian stock-market's volatility. Political connections of firms' officers or their elections to political positions influence the stocks' returns and firms' values (Wisniewski, 2016; Ang et al., 2013). Political connections link firms' costs of capital (Boubakri et al., 2012), governments' investments (Duchin and Sosyura, 2012) and corruption level in a country (Amore and Bennedsen, 2013).

In behavioral finance, (Bradley et al., 2016) find that bias to politically-linked stocks and investors' local bias increase costs to taxpayers and pensioners and affect the US's States' Pension Funds' equity holdings. (Iyengar et al., 2017) identify that the US election results influence the Indian stock markets and these have psychological biases in the IT sector and BFSI and logistics firms. (Behl and Sethi, 2016) depict the US elections' transitional effects on its stock markets which are unusual during election seasons. (Döpke and Pierdzioch, 2006) found weak effects of politics on the German stock-markets' movements. (Hong and Kacperczyk, 2009) showed that fund managers' political bias influences their fund-allocation to "sin stocks". (Durand et al., 2013) confirm that the pricing of sin stocks in Australia, India, Japan, South Korea, Malaysia, New Zealand and Singapore shows positive and negative herds to sin-stocks. (Mendes, 2015) and (Frot and Santiso, 2013) show cross countries' evidence of the political risk factors.

In the Indian context with the BSE stocks, (Reddy, 2015) depicts huge volatility at the 2014 general parliamentary election and positive impact at post-election periods. (Kaur, 2015) finds that the NSE listed stocks brought at that election period depict investors' "hope" and "belief" about their future prosperity. (Dash, 2016) shows crowding-out effect (supportive effect) of the public investment on private investments for the sectors which are more concerned with specific (general) goods and services and exclusive (inclusive) in nature. (Datta and Ganguli, 2014) reveal that the Indian firms' political connections also influence stock prices divergently at election results.

In exploring the Indian stock markets, (Sinha, 2021a) interprets the attention mania as repeated online search, calls the mania as attention homogeneity, and its noise as attention heterogeneity. The noise of investors' attention mania can also mean "investors' attention mania" itself as a noise element in investors' decision choices such as

the railway mania (McCartney and Arnold, 2003) and the dotcom mania [(Ofek and Richardson, 2003)]. (Sinha, 2021a) is limited within exploring the methodological foundation of the noise of investors' attention mania and has overlooked its behavioral foundations across the different categories of attention attributes revealing the noise of election mania, economic mania and political mania separately. This study addresses this exact research gap in the literature of behavioral finance in general and attention impacts in particular.

At the internet of things, attention is scarce economic resource (Falkinger, 2008) and investors are exploited psychologically, socially and economically at online searches (Bhargava and Velasquez, 2020; Popescu et al., 2020). From a welfare perspective, this study is vital for investors and marketing practitioners. We postulate the concept of the noise of investors' attention mania, IAM as follows. Its long-run relationship is given in equation 1 as well.

P₀: The Google search volume index (SVI) data for attention to economic attributes (SVIE), political attributes (SVIP) and political parties and personalities (SVIH) demonstrate the effects of investors' attention mania (IAM) on the stock markets' (NSE Nifty and BSE Sensex) returns, R_t in India.

$$R_t = \alpha_0 + \sum_{i,t=1}^{e,l} \beta_i SVIE_{it} + \sum_{j,t=1}^{p,l} \gamma_j SVIP_{jt} + \sum_{k=1}^{h,l} \delta_k SVIH_{kt} + \theta_t \quad (1)$$

3 Data and Methodology

In exploring effects of IAM on the NSE Nifty and BSE Sensex monthly returns, we assume that investors are scattered over scripts in the markets. We avoid a direct or email survey for time inconvenience and lack of target respondents. We use the online search volume index (SVI) data for searches available in the Google Trends database. It serves as a proxy for popularity attention to search keywords across the selected countries, languages and categories. It provides data for keywords at an input-driven time range and retrieves the highest SVI data as 100% and the rest accordingly. We use the time range 1.1.2004 – 11.6.2019 to cover the general parliamentary elections in 2004, 2009, 2014 and 2019 in India.

Table 1. Search Keywords, Data Periods, Attention Variables and their Acronyms

Monthly SVI Data Time Range	Economic Attributes (7 E-Factors)	Political Attributes (6 P-Factors)	Political Parties and Personalities (12 H-Factors)
Variables Acronyms	SVIE, DSVIE, RSVIE (Acronyms)	SVIP, DSVIP, RSVIP (Acronyms)	SVIH, DSVIH, RSVIH (Acronyms)
1.1.2004 – 11.6.2019	BSE SENSEX (BSE), NSE NIFTY 50 (NSE), Risk-Free Rate (RFR), Risk-Free Interest Rate (RFIR), Internal Rate of Return (IRR), Stock Market Index (SMI), and Stok Market Return (SMR).	Electronic Voting Machine (EVM), EVM (EVM_A), Lok Sabha (LS), Lok Sabha Election (LSE), LS Election (LS_E), and Next PM (NXPM).	United Progressive Alliance (UPA), UPA (UPA_A), National Democratic Alliance (NDA), NDA (NDA_A), Bharatiya Janata Party (BJP), Indian National Congress (INC), Sonia Gandhi (SG), Manmohan Singh (MS), Rahul Gandhi (RG), Atal Bihari Vajpayee (ABV), Lal Krishna Advani (LKA), and Narendra Modi (NM).

On consistency of SVI data from 2004 –2019, we use 25 search keywords as the independent variables (see Table 1) and BSE Sensex and NSE NIFTY as the dependent variables. The independent variables are grouped into the economic (E)-attribute, political (P)-attribute and political parties and personality (H)-attribute. We use the Log-transformed Index Relative method to compute the market returns R_t [as $\text{Log}_{10}(LI_t)/\text{Log}_{10}(LI_{t-1})$] where LI stands for Low Index. We get the LI data for the BSE Sensex and NSE Nifty from www.finance.yahoo.com and www.investing.com respectively. Average index, open index or high index can be used alternatively. We use the time-trend variable in EViews 10. We transform the SVI data to fit attention layers.

3.1 Cointegration Tests

Our attention variables are mixed stationary, I (0) and I (1) while the dependent return variables are stationary, I (0). We cannot perform the Johansen Cointegration test and Granger causality test to examine cointegrations amongst the variables. The bound-test approach of (Pesaran and Smith, 2001) is the desired one for the ARDL models in the following, and we modify and apply them at the different attention levels.

In the following, the first two ARDL models viz., the unrestricted ARDL model (equation 2) and the conditional long-run form of the ARDL model (equation 3) augment the behavioral autocorrelation features of the data and use the lagged dependent variables as explanatory variables. The conditional error correction form of the ARDL model

(equation 4) derives its long-run adjustment factor systematically. We use both equation 2 and equation 3 along with the ECF (r, q) of the conditional long-run ARDL model in equation 4.

$$R_t = \theta_0 + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=1}^q \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Aiq} SVIA_{it-q} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \eta_{Ai} SVIA_{it} + \eta_t \quad (2)$$

$$R_t = \theta_0 + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=0}^q \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Aiq} SVIA_{it-q} + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \eta_{Ai} SVIA_{it} + \eta_t \quad (3)$$

$$R_t = \theta_0 + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Ai} \Delta SVIA_{it-q} + \eta Z_{t-1} + \eta_t \quad (4)$$

3.2 Attention Layers and Hypotheses

We introduce focused, selective and sustained levels of attention (Sohlberg and Mateer, 1987). Focused attention involves attention to a specific task or object and it can be measured by the popularity index for keywords. Selective attention involves classifying attention interest purposefully and it shows attention surprise. Sustained attention involves continuing attention ability and it shows stressed responses to stimuli and reflects homogeneity effects. Investors' attention has focused popularity-effect, selective surprise-effect and sustained homogeneity-effect.

In the first layer, Google SVI data show the relative popularity of searches within the set time range in India. These data for E-attributes, P-attributes and H-attributes are likely to provide for their respective popularity attention effects with the variables of SVIE, SVIP and SVIH (Sinha, 2019b). In exploring investors' focused attention effects on the NSE Nifty (R_{N_t}) and BSE Sensex (R_{B_t}) monthly returns, we assume that the monthly returns R_t have long-run and short-run attention effects.

In deriving observations for the regression models equation 5, equation 6 and equation 7 with the NSE Nifty and BSE Sensex markets' returns at their respective Low Index relatives, we include the month's trend effects T_t . The explanatory variable acronyms $SVIE_{it}$, $SVIP_{jt}$ and $SVIH_{kt}$ are economic factors (E-factors), political factors (P-factors) and the political parties and personalities (H-factors) respectively. We explore individual effects at group-wise and full-length models. In the unrestricted and conditional long-run ARDL specifications at equation 5 and equation 6 respectively, the long-run focused attention effects on market returns are dynamically adjusted along with the short-run attention effects and random noise effect, η_t . In model D3.1, the long-run effects are adjusted at the dynamic error correction term (ECT), ηZ_{t-1} being the adjustment multiplier factor along with the respective short-run attention effects and the random noise effect η_t . Hence, with the SVI search variables' data, we examine investors' focused attention impacts on both NSE Nifty and BSE Sensex stock markets' returns separately with the ARDL models equation 5, equation 6 and equation 7. We test the null hypothesis H_{01} against the alternative hypothesis H_{11} .

$$R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=1}^q \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Aiq} SVIA_{it-q} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \eta_{Ai} SVIA_{it} + \eta_t \quad (5)$$

$$\Delta R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=0}^q \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Aiq} SVIA_{it-q} + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \eta_{Ai} \Delta SVIA_{it} + \eta_t \quad (6)$$

$$\Delta R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Ai} \Delta SVIA_{it-q} + \eta Z_{t-1} + \eta_t \quad (7)$$

H_{01} : Investors' focused attention at E-attributes (SVIE), P-attributes (SVIP) and H-attributes (SVIH) has no popularity effect on the NSE Nifty and BSE Sensex market returns.

H_{11} : Investors' focused attention at E-attributes, P-attributes and H-attributes has popularity effect on the NSE Nifty and BSE Sensex market returns.

In the second layer, investors' selective surprise attention data is derived at differences of SVI data, $SVI_{x,it} - SVI_{x,it-1}$. A positive (negative) surprise in SVI data surrogates for a positive (negative) herd in investors' attention and it reflects presence (absence) of confirmation bias of peer investors. The differential data $DSVIE_{x,it}$, $DSVIP_{x,it}$ and $DSVIH_{x,it}$ with E-attributes, P-attributes and H-attributes respectively provide for selective surprise effects. We explore group effects and combined effects separately on each market's monthly returns with the ARDL models in equation 8, equation 9 and equation 10 at the unrestricted version, long-run conditional form and conditional ECF respectively. We test null hypothesis H_{02} against its alternative hypothesis H_{12} .

$$R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=1}^q \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Aiq} DSVIA_{it-q} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \eta_{Ai} DSVIA_{it} + \eta_t \quad (8)$$

$$\Delta R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=1}^q \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Aiq} DSVIA_{it-q} + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \eta_{Aiq} \Delta DSVIA_{it-q} + \eta_t \quad (9)$$

$$\Delta R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Ai} \Delta DSVIA_{it} + \eta Z_{t-1} + \eta_t \quad (10)$$

H_{02} : Investors' differential attention at E-attributes, P-attributes and H-attributes has no selective surprise effect on the NSE Nifty and BSE Sensex market returns.

H_{12} : Investors' differential attention at E-attributes, P-attributes and H-attributes has selective surprise effects on the NSE Nifty and BSE Sensex market returns.

In the third layer, the ascending ranks of SVI data in descending orders for RSVIE, RSVIP and RSVIH variables are derived at E-attributes, P-attributes and H-attributes respectively. Since ranks' data are ordered, RSVIE, RSVIP and RSVIH variables are unbiased at scale and they provide sustained homogeneity effects. A high (low) degree of homogeneity refers to a presence of low (high) degree of herds in attention search. Both at groups and overall, we explore this effect on the markets' monthly returns with the unrestricted ARDL model, its restricted long run form and ECF in equation 11, equation 12 and equation 13 respectively. We test null hypothesis H_{03} against its alternative H_{13} .

$$\Delta R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=0}^q \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Aiq} RSVIA_{it-q} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \eta_{Ai} RSVIA_{it} + \eta_t \quad (11)$$

$$\Delta R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=0}^q \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Aiq} RSVIA_{it-q} + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \eta_{Ai} \Delta RSVIA_{it} + \eta_t \quad (12)$$

$$\Delta R_t = \theta_0 + T_t + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t=1}^{e,l} \theta_{Ai} \Delta DSVIA_{it-q} + \eta Z_{t-1} + \eta_t \quad (13)$$

H_{03} : The ordered attention searches at E-attributes, P-attributes and H-attributes have no sustained homogeneity effect on the NSE Nifty and BSE Sensex market returns.

H_{13} : The ordered attention searches at E-attributes, P-attributes and H-attributes have sustained homogeneity effects on the NSE Nifty and BSE Sensex market returns.

3.3 Lag Selection Criteria

To operationalize these models, we set appropriate lag-lengths (r, q) for the endogenous and exogenous variables. The variance estimation of SVI, DSVI and RSVI data along with the market's returns in groups shows that LR, FPE and AIC methods identify five lags as optimal length and SC (HQ) method suggests for 1(2) lag/s. The SC method under-specifies and LR, FPE and AIC methods over-specify. We follow the AIC to avoid under-specification. In models' runs, we face system crash with lag-length (p, q) at $r > 4$ & $q > 1$ for the full-length models and at $r > 4$ & $q > 3$ with H-attributes at group-effect. With both E-attributes and P-attributes at group-effects, we find their models sound at lag-length of ($r, q \leq 5$). For consistency, we use the lag-length of ($r, q \leq 4$) and the regression system allows for dynamic specification and selection of the best AIC based model at the lags of the dependent variable and regressors. We avoid over-parametrization at automatic selection, identify unrestricted constant and unrestricted trend effects and regress them.

3.4 Spotting Noise of IAM

We explore the noise of IAM. At presence of two competitive stock markets in India, a manic disposition of attention to economic (political) attributes in a stock market may show familiarity bias (political nexus) and local vis-à-vis global attention effects (Sinha, 2021a), (Sinha, 2021b). H-attributes are attuned to government formation and national policy makings. Investors' attention noise at H-attributes can lead to decision dilemmas and cause intra-layer or inter-layer attention confusion or attention confidence. At intra-layer attention noise, different attention impacts are expected for the keywords at different lags and/or at long-run and short-run impacts. We call this attention confusion as attention duality and similarity in attention influence leads to decisive attention mania at attention confidence. Attention confusion (confidence) may arise at keywords in the form of attention string and so an attention diffusion (cartel) suggests for a presence of substitutive (complimentary) attention situation and this may aggravate (dilute) noise of attention duality. Nonetheless, these may have either positive or negative attention impacts on the stock market returns. In contrast, at inter-layer attention confusion or confidence, attention impacts are likely to be either different or similar in direction/s for the different attention layers. We discuss the results in the following.

4 Results and Findings

The stock markets' monthly returns R_t data are stationary, and $I(0)$ even at breakpoint situations. The DSVI data series are stationary and $I(0)$ while SVI and RSVI data series are mixed, $I(0)$ and $I(1)$ but not $I(2)$ in nature. We discuss the results in the unrestricted ARDL (r, q) models, their conditional long-run ARDL forms and their conditional ECF versions across the three levels of attention. We report and analyse the impacts of Investors' Attention Mania (IAM) on the NSE Nifty and BSE Sensex monthly returns in sequence.

4.1 Attention Mania and Market Returns

With the SVI, DSVI and RSVI data sets for the E-attributes, P-attributes and H-attributes, we firstly reveal their group-wise attention effects and then, their full-length ones. To make it reader-friendly, we abstract these all in Table 2. At the recursive effects, we briefly report the results on the CUSUM recursive residuals' diagnosis tests.

4.2 Group-Wise Attention Impacts

Our results with these attention attributes in the unrestricted ARDL models are likely to show investors' general attention search impacts and these illustrate long-run and short-run impacts at their lag-level effects. Their conditional long-run models very minutely show the distinction of attention impacts across the attention spectrum. Their respective ECFs of the ARDL models show the short-run effects distinctively but the long-run impacts in aggregate.

4.2.1 Impacts of E-attributes

With the unrestricted ARDL models, the NSE market return shows endogenous effects at its 4th lag while the same is influenced by investor's focused, selective and homogenised attention to "risk free interest rate". "BSE Sensex", "stock market index" and "stock market return" have focused and selective attention impacts on the NSE market returns but "internal rate of return" has selective and homogenised attention impacts. Besides, attention to "risk free rate" ("NSE Nifty 50") has only focused (homogenised) attention impacts on the NSE market returns. These unrestricted ARDL models have explanatory powers of about 38.30% at focused attention but 35% at both selective and homogenised attention. These show a good fit at F-statistics, DW statistics, least residual serial correlations and stability at the CUSUM tests for recursive estimates.

We find short-run and long-run attention impacts in the conditional long-run ARDL models. Investors' long-run attention to "risk free interest rate" is insignificant across the attention levels but at the different lags, it

has short-run focused, selective and homogenised attention impacts. We find short-run endogenous impact at the 3rd lag across the levels and the keywords “BSE Sensex”, “stock market index” and “stock market return” are robust at focused and selective attention. Attention to “internal rate of return” is significant at both selective and homogenised attention levels. Attention to “risk free rate” (“NSE Nifty 50”) is significant only at selective (homogenised) layer. The F-bound test statistics also confirm the cointegration relationship in the models.

With the conditional ECFs of ARDL models, we find that that the E-attributes mostly have short-run attention impacts on the NSE market returns. It shows that investors’ attention searches have greater impacts at focused and selective attention than that at homogenised attention. This less impulse at short-run attention dynamics can be compensated by long-term adjustment speed. The attention impact on the long-run dynamics is more (less) than unity at homogenised (focused and selective) attention. Homogenised attention is more tuned on to long-run dynamics and less impulsive to short-run attention impacts while their focus and selective attention are less tuned. The inclusion of lagged cointegrating factor in the conditional ECFs i.e., $\text{CointEq}(-1)$, makes the ARDL regression system able to provide greater explanatory powers more than 70% at Adj. R^2 values. The ECFs of ARDL models have information edges over the other two ARDL models.

At unrestricted models for the BSE market returns, we find both parallel and contrary observations to the NSE market returns. We highlight the cruxes only. In addition to similar unique focused attention effects of “NSE Nifty 50”, the BSE market returns show effects of focused attention to “BSE Sensex”, “stock market index” and “stock market return”. At selective attention, we find a difference in their attention effects. For examples, selective attention to “BSE Sensex” has robust positive impacts, “risk free rate” has sustained positive effects at different lags and “risk free interest rate” at its 2nd lag has significant negative impacts while “internal rate of return” at its 1st lag has significant positive effects on the BSE market returns. The said market return is significantly influenced by investors’ homogeneous attention to “risk free rate” at its 1st lag and “risk free interest rate” at level data. These unrestricted models are stable and good-fit at DW statistics, F-statistics and insignificant residual serial correlations at explanatory powers of 10%, 21% and 8% at Adj. R^2 respectively for focused, selective and homogenised attention. Hence, investors’ attention levels have local vis-à-vis global effects and we examine and cross-check the same in the following.

At the conditional long-run ARDL models, we show significant endogenous long (short)-run effects at 1st (3rd) lag and short-run focused attention impacts of “BSE Sensex”, “NSE Nifty 50” and “stock market index” on the BSE market returns. The short-run impacts of “BSE Sensex” and “stock market index” are positive (negative) for the BSE (NSE) market returns. These confirm market-specific local impacts. With selective attention, the results depict that the intercept and coefficients for short-run and long-run effects of endogenous BSE market returns are significant, and these are in tune with the global effects. Moreover, we find robust positive long-run (short-run) selective attention effects to “BSE Sensex” (“risk free rate”) for the BSE market returns while these are at the reverse on the NSE market returns. Again, the short-run selective attention impact of “risk free interest rate” on the BSE market is somewhat opposite to that on the NSE market. At homogenised attention, the intercept and lagged endogenous market return at both short-run and long-run impacts are alike on the BSE and NSE market returns while we find varying local impacts at long-run attention to “risk free rate” and “risk free interest rate”. Hence, short-run attention to “risk free interest rate” in the BSE market shows attention duality. We validate local and global effects at the E-attributes while the F-bound test confirms their cointegrating relationships.

We also confirm the above cointegrating results for the E-attributes with the conditional ECFs of the ARDL models. Here, with the respective coefficients of intercept and lagged endogenous BSE market return variables, we show parallel findings for the BSE and NSE market returns. Besides the above, an interesting corollary of the said global vis-à-vis local attention impacts suggests that investors’ focused attention demonstrates familiarity bias as well.

For example, we find a robust positive (negative) impact of short-run focused attention to “BSE Sensex” on the BSE (NSE) market return. In the BSE market, this familiarity bias is not faded away as it does in the NSE market. The role of familiarity bias is more visible in the BSE market than that in the NSE market. The focused attention to “stock market index” has positive (negative) impact on the BSE (NSE) market returns while amongst the other attention variables, we only find that “internal rate of return” has significant negative impact on the BSE market returns. These show investors’ myopic focused attention spectrum in the BSE market while that is much open and general at the NSE market. Apart from the said global vis-à-vis local effects, we find that the BSE market returns are highly sensitive to selective attention to “risk free rate”. Our results with investors’ homogeneous attention variables also confirm the stated myopic short-run attention impacts of “risk free interest rate” on the BSE market returns while their presence on the NSE market returns is diverse. The Adj. R^2 values with the conditional ECFs in regressing the BSE market returns show mostly satisfactory explanatory powers at 56%–60%. The coefficients of the cointegrating factor in the models illustrate the degree of adjustments to their long-run relationships and this is at the pick at homogeneous attention but moderately higher at focused attention than that at selective attention. Investors show greater short-run attention dynamics at selective attention than that at focused and homogenised attention.

In brief, our results with the E-attributes, firstly, corroborate the presence of local vis-à-vis global attention effects across the two market returns, secondly, show familiarity bias at some attention keywords, and thirdly, depict a difference in the adjustment speeds at the long-term cointegrations: a high adjustment speed at selective

attention, moderately higher at focused attention and the highest at homogenised attention. Finally, we document a greater (lesser) short-run dynamism at selective (homogenised) attention than that at focused attention.

4.2.2 Impacts of P-attributes

In explaining the NSE market's returns with the P-attributes, we find that the respective intercept coefficients of the unrestricted ARDL models are significant at focused, selective and homogenised attention. We show that attention keyword "electronic voting machine", popularly called "EVM", has positive attention impact on the NSE market returns only at selective attention while their effects at focused and homogenised attention are chaotic in signs at their different lags. We identify that attention to "Next PM" has significantly negative impact at selective attention but the impact is chaotic at focused and homogenised attention. At these different attention levels, we further show such chaotic impacts regarding signs of the coefficients at different lags of the keywords viz., "Lok Sabha", "LS Election" and "Lok Sabha Election" (used alternatively by the general public in India). We find little trend effects across the attention levels. The endogenous NSE market return is significant at 4th lag at homogenised attention only. These unrestricted ARDL models have explanatory powers within 21%–28% at Adj. R^2 values and these are good-fit at their model stability and are free of residual serial correlations.

With the conditional long-run models, we show attention impacts on the NSE market returns. It shows a positively significant intercept while the endogenous market return at 1st lag is negatively significant. Investors' attention to "electronic voting machine" and/or its alternative proxy, "EVM" has stronger short-run positive impacts at focused attention than at selective attention while that dims off at homogenised attention even of its significant impacts. Attention to "Next PM" has robust negative impacts at both focused and selective attention while at homogenised attention, it has a positive impact at dimmed-off magnitude. With the different attention data, attention to "Lok Sabha", "LS Election" and "Lok Sabha Election" have chaotic impacts with positive and negative signs for coefficients at different lags. Such chaos at the long-run and short-run dynamics is robust at focused attention and also visible at short-run effects for selective and homogenised attention. The presence of significant F-bound test statistics for the conditional long-run models suggests for long-run cointegration relationship between the NSE market returns and attention keywords at different attention levels. Does this attention chaos have an order?

With the conditional ECFs of the models, we show cointegration speeds higher than unity at focused and homogenised attention, and that is marginally lower at selective attention. These results corroborate that there is less room left for investors' short-run attention intervention at focused and homogenised attention, and at selective attention, that is slightly high. These observations can also be confirmed at presence of chaotic attention impacts (opposite signs of the coefficients) for the attention keywords at across attention levels. The conditional ECFs show the noise of investors' political attention with greater explanatory powers, mostly at 63%–67% in terms of Adj. R^2 values, than that we have observed with the unrestricted ARDL models.

Now in a cross-check, we look into the results for the BSE market returns and make a concise understanding. Besides the presence of significant intercept coefficients with the unrestricted ARDL models for our focused, selective and homogenised attention data, we confirm chaotic impacts of the alternative P-attributes "Lok Sabha", "LS Election" and "Lok Sabha Election" on the BSE Sensex stock-market returns. We find positive attention impact of "Next PM" only at the focused attention. We also find significantly negative attention impact of "electronic voting machine" at the selective attention on the BSE market returns and that of "EVM" is chaotic at homogenised attention. These results with the unrestricted ARDL models are stable and these have a good fit with explanatory powers within 8.58%–14% at Adj. R^2 values for the three attention levels.

We show political attention impacts on the BSE market returns with the conditional long-run models. Attuned to the said observations, both short-run and long-run attention effects of P-attributes are chaotic in signs of coefficients significantly positive or negative at their different lags and such chaos is loud at focused attention while it moderates at selective attention and dims off at homogenised attention. We find negatively significant short-run attention impact of "Next PM" ("EVM") on the BSE market returns at focused (homogenised) attention while the joint impact of short-run and long-run attention to "EVM" is negatively significant at selective attention. These chaotic attention impacts also illustrate an order of cointegration and F-bound test statistics confirms that for political attention with the BSE market returns across the attention levels.

This political chaos and cointegrated relationships across attention layers for the BSE market returns can be substantiated with the conditional ECFs of the models. The speed of adjustment towards the long-run relationship is higher than unity at focused attention but lower at selective and homogenised attention. At homogenised attention, it is different from the same one with the NSE market returns, where it is higher than unity. This difference confirms the extent of market-specific adjustments and short-run attention dynamism. Investors' homogenised attention to "Next PM" has a robust short-run positive impact on the NSE market returns but subdued in the BSE market. The models are stable and sound and explain 55%–60% at Adj. R^2 values.

On a concise note, investors' political attention has deterministic footprints of attention chaos on both the stock-markets' returns and this chaos varies across their attention levels while at focused attention, it remains robustly dynamic.

4.2.3 Impacts of H-attributes

With the H-attributes in the unrestricted ARDL models, we find significant intercept coefficients for attention layers. Investors' focused attention to "National Democratic Alliance", "Bharatiya Janata Party" and "Lal Krishna Advani" has positively significant impact on the NSE Nifty market returns while "Sonia Gandhi" has negative impact. Focused attention to "UPA" is somewhat chaotic, long distant attention effect is negative, mostly double and in opposite direction of the short distant effect. Decisive focused attention to H-attributes shows pockets of attention chaos, and selective attention to "UPA" at 1st and 2nd lags is robust and decisive and that to "National Democratic Alliance" at 2nd lag is negative. Homogenised attention to "United Progressive Alliance" and "UPA" validates the chaotic duality. These ARDL models are stable, sound, and of good fit with explanatory powers of 19%–27% at Adj. R^2 values. But why does attention duality appear at focus and homogenised attention rather than at selective attention?

With the conditional long-run ARDL models, we find significant intercept and robust effects of the endogenous market return across attention levels. At focused attention, impacts of "Bharatiya Janata Party" in aggregate and "Lal Krishna Advani" at 1st lag on the NSE market returns are positive while the short-run attention effect of "National Democratic Alliance" is negative. That is, decisive focused attention coexists with attention duality. We reveal a coexistence of attention chaos at robust negative effect of "Sonia Gandhi" at an aggregate but positive short-run impact of "UPA" both at 1st and 2nd lags. At selective attention, we depict attention duality – positive long-run effect of "UPA" at 1st lag and opposite short-run (long-run) effect of "UPA" ("Manmohan Singh") at 1st lag. At another chaotic duality at selective attention, "National Democratic Alliance" shows opposite long-run impact to short-run impact. At short-run and long-run endogenous effects of the NSE market returns, chaotic dualities dim off except at homogenised attention. Attention duality is recognised with F-bound test statistics as well. We now respond to the query raised earlier.

With the conditional ECFs of the ARDL models for the NSE returns, we find a cointegration multiplier greater than unity along with positive (negative) short-run effects of focused attention to "UPA" ("National Democratic Alliance") at 1st and 2nd lags. A similar impact on the NSE market returns is visible at homogenised attention, where the long-run adjustment multiplier exceeds unity at robust and decisive short-run impact. These alternatively suggest that attention duality becomes visible only if weak long-run attention dynamics exist at noisy short-run attention impacts. Once the duality is trapped into its far-distant multiplier effects, investors' short-run attention effects to H-factors become more informative. These are parallel corollary to attention duality and such duality is recognized at selective attention impacts with "UPA" and "NDA". We confirm these twin corollaries of attention noise at H-attributes for the NSE returns.

On the BSE Sensex stock-market's returns with the unrestricted ARDL model, we find decisive focus attention impacts: "National Democratic Alliance" at 2nd lag and "Lal Krishna Advani" have positive attention impacts while "UPA" has a negative impact. At selective attention, "United Progressive Alliance" and "UPA" show attention chaos while "Lal Krishna Advani" and "National Democratic Alliance" show decisive effects. Homogenised attention to "Sonia Gandhi" at 2nd and 3rd lags, "UPA" at 3rd lag and both "Lal Krishna Advani" and "Narendra Modi" at 1st lag depict low attention impacts at chaotic attention duality. In brief, there is attention duality at selective and homogenised levels but not at focused attention. These models have less powers at Adj. R^2 values in 12%–19% but they are stable, good-fit and free from residual serial correlations.

With the conditional long-run models for the BSE market returns, we depict decisive positive impacts of short-run and long-run focused attention to "Lal Krishna Advani". Such stance is eroded by attention diffusion caused by short-run focused attention to "National Democratic Alliance" and "UPA" at their 1st lags. Attention diffusion can also be spotted at substitutive selective attention to "Lal Krishna Advani" and "National Democratic Alliance" and these coexist with chaotic duality caused by short-run selective attention to "United Progressive Alliance" and "UPA" at their 2nd lags. At homogenised level, attention diffusion is caused by attention to "Sonia Gandhi" and the noise dims off at decisive short-run attention to "UPA" at 1st and 2nd lags. Such duality and attention diffusion on the BSE market returns are recognised by the F-bound statistics as well.

With the H-attributes on the BSE market returns, we confirm decisive focused short-run attention impact of "National Democratic Alliance" and "UPA" but attention duality at short-run focused attention to "Lal Krishna Advani". These reveal investors' attention mania on the BSE market returns. Selective short-run attention to "United Progressive Alliance", "UPA" and "National Democratic Alliance" are highly robust and decisive in directions and show an absence of attention mania on the BSE Sensex returns at selective attention. Homogenised short-run negative attention impact of "UPA" at opposite impacts of "Narendra Modi" and "Sonia Gandhi" shows the presence of decisive attention but dimmed off at attention diffusion for "Sonia Gandhi".

In brief, we find diverse dynamics of investors' attention mania across their focused, selective and homogenised attention even with long-run speeds of adjustment while its magnitudes are higher (lesser) than unity at focused (selective) attention but marginally equal at homogenised attention. There are attention duality vis-à-vis decisive impacts on the BSE market returns.

4.2.4 Full-Length Attention Effects

In examining the noise of IAM with the full-length attention models, we firstly explore the NSE Nifty returns followed by those on the BSE Sensex returns.

With the NSE market returns in unrestricted ARDL models, focused attention shows diffusion effect at current and lagged “BSE Sensex”, at lagged “risk free return” and “internal rate of return”, “Lok Sabha” and “Lok Sabha Election”, and “Sonia Gandhi” and “Manmohan Singh”. There is focused attention diffusion at “Bharatiya Janata Party” and “National Democratic Alliance”. At selective attention, attention cartels exist at “BSE Sensex”, “internal rate of return”, and “stock market index”, at “Next PM” and “Sonia Gandhi” but attention diffusion at “LS Election”. These depict less attention diffusion at high attention cartels. Homogenised attention shows attention duality with “NSE Nifty 50” at its level data and 1st lag and attention diffusion with “risk free rate”, “internal rate of return” and “stock market return” at their 1st lags. Homogenised attention to “EVM” and “United Progressive Alliance” spots an attention cartel. This diverse attention suggests for sustained noise of IAM at homogenised attention. The impacts across attention layers are robust, stable and good-fit at Adj. R^2 values within 39%–45% and at the absence of residual serial correlations.

At conditional long-run models with the NSE returns, focused attention shows one (four) case/s of short-run (long-run) attention cartel (attention diffusion). Attention cartel exists for “BSE Sensex” and “Stock market index”. The diffusions are spotted at focused attention to “risk free rate” and “internal rate of return” at 1st lags, at aggregate attention to “Lok Sabha” and “Lok Sabha Election”, “National Democratic Alliance” and “Bharatiya Janata Party”, and “Sonia Gandhi” and “Manmohan Singh”. At selective attention, “BSE Sensex”, “stock market index” and “internal rate of return” at 1st lags show long-run attention cartel while we find decisive long-run impact for “Next PM” at its 1st lag and short-run impacts but attention diffusion at long-run attention to “Sonia Gandhi” and “LS Election” at 1st lag. We reiterate the noise of IAM at long-run homogenised economic attention to “risk free rate”, “internal rate of return” and “stock market return” at their 1st lags and attention diffusion for “EVM” at its 1st lag. Long-run noise of IAM is more (less) frequent at focused (selective) attention and dimmed off at homogeneous attention. The F-bound test statistics confirm such diverse cointegration of noise of IAM across attention levels. The said diverse noise of IAM is revalidated with the ECFs. We find attention diffusion due to divisive focused, selective and homogenised attention to the H-attributes, P-attributes and E-attributes respectively while their speed of long-run adjustment is higher (lower) than unity at homogenised (focused and selective) attention and these reveal higher (lower) multiplier effects. These ECFs are good-fit with explanatory powers of 75%–77% at no residual serial correlations. In brief, we detect short-run vis-à-vis long-run noise of IAM on the NSE Nifty market returns.

With the BSE market returns in unrestricted ARDL models, attention cartel (attention duality) is spotted at focused attention to “internal rate of return” and “stock market return” (“NSE Nifty” at current level and 1s lag). “BSE Sensex” at its 1st lag shows negative focused attention while “Next PM” at 1st lag and “Lal Krishna Advani” at current level show positive attention cartel. At selective attention, “BSE Sensex” (“risk free interest rate” at 1st lag) and “NSE Nifty” (“stock market return”), and “EVM” and 1st lag of “LS Election” show attention diffusion while “UPA” at current level and 1st lag show decisive attention at complimentary attention to “Lal Krishna Advani”. At homogenised attention, attention duality (attention cartel) exists for “BSE Sensex” and “NSE Nifty”, and “EVM” and “LS Election” (“internal rate of return” and “stock market return”). These models are of good-fit at Adj. R^2 values within 16%–34% and all are stable except at focused attention.

In the conditional long-run models for the BSE market, attention cartel is found at focused attention to “stock market return”, short-run attention to “NSE Nifty 50” and “internal rate of return” but attention diffusion at “Lal Krishna Advani”. Selective attention cartel (attention diffusion) is observed at decisive short-run (long-run) attention impacts of “EVM” and “Lal Krishna Advani” (“BSE Sensex” and “NSE Nifty 50”) and “UPA” (“UPA” at its 1st lag). At homogenised attention, “BSE Sensex” and “NSE Nifty 50” show short-run attention diffusion while aggregate attention to “stock market return” and short-run attention to “internal rate of return” shows attention cartel that can be diffused by attention to “risk free return”. We find decisive short-run (long-run) homogenised attention impact for “LS Election” (“LS election” at 1st lag) at the exposure of negative short-run impacts of “EVM”. The F-bound test also confirms such cointegrated attention chaos.

With the conditional ECFs of the models for the BSE returns, we further reveal short-run focused attention cartel for “NSE Nifty 50”, “internal rate of return” and “LS Election” but attention diffusion for “UPA”. At selective attention, there are attention cartels for short-run selective attention to “internal rate of return”, “electronic voting machine”, “LS Election”, “Next PM”, and “Atal Bihari Vajpayee” but at attention diffusion for “UPA”. At homogenised attention, we identify attention cartel for “internal rate of return” and “NSE Nifty 50” and for “EVM” and “LS Election” as well but attention diffusion for “BSE Sensex”. At Adj. R^2 values within 63%–71%, their long-run adjustment speed is higher (lower) than unity at homogenised (focused and selective) attention and that is higher at focused attention than that at selective attention.

4.2.5 Recursive Effects

The CUSUM residual footprint in the NSE (BSE) market involves least focused economic attention during 2009–2010 (2009–2011) while at selective economic attention, it is stressed till the mid of 2012 (beyond 2012) and at homogenised economic attention, it is bell-shaped until the mid of 2011 (beyond 2012). The same in the said market/s at focused political attention is symmetrical and bell-shaped (neutralised) at 2014 (since 2014), at selective political attention – it has sustained footprints, and at homogeneous political attention – it has long-length twin bell-shapes up to and beyond 2014. At attention to H-attributes, the residual footprints in the NSE market appear

in a scaled-down shape at the BSE market. At full-length attention, the said group-wise footprints wash up and the NSE market show sustained footprints across layers, while the BSE market show such presence at selective and homogenised attention only and at focused attention, the same becomes unstable but reverts to robustly stable if the NSE market returns is kept as a fixed factor control variable.

5 Conclusion

At scarce cognitive resources, neoclassical investors listen to their information needs. At its distribution across focused, selective and homogenized attention, cognitive capacity limits their attention searches. On this insight, we explore online attention search impacts on the NSE Nifty and BSE Sensex market returns for E-attributes, P-attributes and H-attributes and show attention impacts across issues. At the groups, attention impacts show scatteredness across attributes where economic attention exhibits local vis-à-vis global attention effects and familiarity bias while both P-attributes and H-attributes show deterministic footprints of attention chaos on the stock-markets' returns. At the full-length, we find attention cartels and attention diffusions. The impacts of attention chaos vary across attention levels and we originally contribute with an in-depth examination.

This study can be used to recognise firms' manager's attention impetus in the stock-markets. Mutual fund managers can use it to detect clients' attention needs and to identify impacts of the noise of IAM on their portfolio returns, and to course corrections. At welfare implication, attention-specific long-run adjustment speeds can be used to get stock-specific target adjustment speeds and to control at attention portfolio construction. It can be used to educate the general investors and insulate them from falling into the traps of familiarity attention bias in the stock-markets. The governments can use it at sustainable policy formulation and at precautions as well while finance marketers can hedge the attention chaos at governments' policy choices and to identify proxy variables at predicting market movements at different time frames. Our results can be used as hands-on references.

Our findings are subject to selection criteria of the appropriate lag-length. A higher lag-length can be incorporated at a lesser number of independent regressors to develop a parsimonious model. A relook with the Open Index, Close Index or High Index instead of Low Index can check persistency. Future researchers may extend at volume-predictability of the stock markets in India.

Table 2: Significant Results on Noise of Investors' Attention Mania in the NSE/BSE Stock Market Returns

Attributes, Attention Level, & Stock-Market		Unrestricted ARDL Model	Conditional LRF of ARDL Model	ECFs of ARDL Model	
E- attributes	NSE Nifty Returns	SVI	BSE<0, BSE(-1)>0, RFR(-1)>0, RFR(-3)<0, RFR(-4)>0, SMI<0, SMI(-2)>0, SMR(-1)<0, SMR(-4)>0	$\Delta RFR(-3)<0, \Delta BSE<0, RFR(-1)>0, \Delta SMI<0, \Delta SMI(-1)<0, \Delta SMR(-1)<0, \Delta SMR(-3)<0$	$\Delta BSE<0, \Delta BSE(-1)>0, \Delta RFR(-1)<0, \Delta RFR(-1)<0, \Delta RFR(-3)<0, \Delta SMI<0, \Delta SMI(-1)<0, \Delta SMR(-1)<0, \Delta SMR(-2)<0, \Delta SMR(-3)<0,$ and $\eta = -0.721211.$
		DSVI	D_RFR(-2)>0, D_BSE<0, D_BSE(-1)>0, D_IRR(-1)<0, D_SMI<0, D_SMI(-1)<0, D_SMR<0, D_SMR(-1)<0	$\Delta D_RFR(-1)<0, \Delta D_BSE<0, \Delta D_SMI<0, D_SMI(-1)<0, D_IRR(-1)<0, \Delta D_SMR<0$	$\Delta D_BSE<0, \Delta D_RFR(-1)<0, \Delta D_RFR(-1)<0, \Delta D_SMI<0, \Delta D_SMR<0, \Delta D_SMR(-2)<0, \Delta D_SMR(-3)<0,$ and $\eta = -0.590443.$
		RSVI	R_RFR(-3)>0, R_NSE>0, R_NSE(-1)<0, R_IRR(-2)<0, R_NSE(-3)>0, R_NSE(-4)<0,	$\Delta R_RFR(-2)<0, \Delta R_NSE>0, \Delta R_NSE(-3)>0, R_IRR(-1)>0, \Delta R_IRR(-2)<0$	$\Delta R_NSE>0, \Delta R_NSE(-3)>0, \Delta R_RFR(-1)<0, \Delta R_RFR(-2)<0, \Delta R_IRR(-2)<0, \Delta R_IRR(-3)<0, \Delta R_SMR(-1)>0,$ and $\eta = -1.058927.$
	BSE Sensex Returns	SVI	BSE>0, BSE(-1)<0, NSE(-3)>0, SMI(-4)<0, SMR(-1)>0	$\Delta BSE>0, \Delta NSE(-2)<0, \Delta SMI(-3)>0$	$\Delta BSE>0, \Delta NSE(-2)<0, \Delta IRR<0, \Delta SMI(-3)>0,$ and $\eta = -0.767087.$
		DSVI	D_BSE>0, D_RFR(-2)<0, D_RFR(-1)>0, D_RFR(-2)>0, D_RFR(-3)>0, D_RFR(-4)>0, D_IRR(-1)>0	$D_BSE>0, D_RFR(-1)>0, \Delta D_RFR(-1)<0, \Delta D_RFR(-2)<0, \Delta D_RFR(-3)<0, \Delta D_RFR(-1)>0$	$\Delta D_RFR>0, \Delta D_RFR(-1)<0, \Delta D_RFR(-2)<0, \Delta D_RFR(-3)<0, \Delta D_RFR(-1)>0, \Delta D_SMI<0,$ and $\eta = -0.689907.$
		RSVI	R_RFR>0, R_RFR(-2)>0, D_RFR(-1)<0,	$R_RFR(-1)<0, R_RFR(-1)>0, \Delta R_RFR>0, \Delta R_RFR(-1)<0$	$\Delta R_IRR(-1)<0, \Delta R_RFR>0, \Delta R_RFR(-1)<0,$ and $\eta = -0.972817.$

P-Attributes	NSE Nifty Returns	SVI	EVM>0, EVM(-1)<0, LS<0, LS(-3)<0, LS(-4)>0, LS_E(-2)<0, LS_E(-3)<0, LSE(-3)>0, NXPM<0, NXPM(-1)>0	$\Delta EVM > 0, \Delta LS(-2) > 0, \Delta LS_E(-1) > 0, \Delta LSE(-1) < 0, \Delta LS < 0, LS(-1) < 0, \Delta LS(-1) > 0, \Delta LS(-3) < 0, LSE(-1) > 0, \Delta LSE(-2) < 0, \Delta LS_E(-2) > 0, \Delta NXPM < 0$	$\Delta EVM > 0, \Delta LS < 0, \Delta LS(-1) > 0, \Delta LS(-2) > 0, \Delta LS(-3) < 0, \Delta LS_E(-1) > 0, \Delta LS_E(-2) > 0, \Delta LSE > 0, \Delta LSE(-1) < 0, \Delta LSE(-1) < 0, \Delta NXPM > 0, \text{ and } \eta = -1.185085.$	
		DSVI	D_EVM>0, D_LS(-3)<0, D_LS_E(-1)>0, D_LSE(-3)>0, D_NXPM<0, D_NXPM(-1)<0, R_EVM_A(-1)<0, R_EVM_A(-2)>0, R_LS>0, R_LS(-3)>0, R_LS(-4)<0, R_LS_E(-2)<0, R_LSE(-2)>0, R_NXPM>0, R_NXPM(-3)<0,	$D_EVM * > 0, \Delta D_LS(-2) > 0, D_LS_E(-1) > 0, \Delta D_LSE(-2) < 0, \Delta D_NXPM < 0, D_NXPM(-1) < 0, \Delta R_EVM_A(-1) < 0, \Delta R_LS_E(-1) > 0, \Delta R_LSE(-1) < 0, \Delta R_LS > 0, \Delta R_LS(-3) > 0, \Delta R_NXPM > 0, \Delta R_NXPM(-1) > 0, \Delta R_NXPM(-2) > 0$	$\Delta D_LS < 0, \Delta D_LS(-1) > 0, \Delta D_LS(-2) > 0, \Delta D_LS_E > 0, \Delta D_LSE > 0, \Delta D_LSE(-1) < 0, \Delta D_LSE(-2) < 0, \Delta D_NXPM < 0, \Delta D_NXPM(-1) > 0, \text{ and } \eta = -0.950922. \Delta R_EVM_A(-1) < 0, \Delta R_LS > 0, \Delta R_LS(-3) > 0, \Delta R_LS_E(-1) > 0, \Delta R_LSE(-1) < 0, \Delta R_NXPM > 0, \Delta R_NXPM(-1) > 0, \Delta R_NXPM(-2) > 0, \text{ and } \eta = -1.126260.$	
		RSVI	R_EVM_A(-1)<0, R_EVM_A(-2)>0, R_LS>0, R_LS(-3)>0, R_LS(-4)<0, R_LS_E(-2)<0, R_LSE(-2)>0, R_NXPM>0, R_NXPM(-3)<0,	$LS(-1) < 0, LS_E(-1) < 0, LSE(-1) > 0, \Delta LS(-1) > 0, \Delta LSE(-1) < 0, \Delta LSE(-2) < 0, \Delta NXPM(-1) < 0,$	$\Delta LS(-1) > 0, \Delta LSE(-1) < 0, \Delta LSE(-2) < 0, \Delta LSE(-3) < 0, \Delta NXPM(-1) < 0, \text{ and } \eta = -1.170961.$	
	BSE Sensex Returns	SVI	LS(-2)<0, LS_E(-1)<0, LSE(-2)>0, NXPM(-2)>0,	$D_EVM * < 0, D_LS_E * > 0, \Delta D_LS(-1) > 0, \Delta D_LSE(-1) < 0$	$\Delta LS(-1) > 0, \Delta LSE(-1) < 0, \Delta LSE(-2) < 0, \Delta LSE(-3) < 0, \Delta NXPM(-1) < 0, \text{ and } \eta = -1.170961.$	
		DSVI	D_LS(-2)<0, D_LS_E>0, D_LSE(-2)>0, D_EVM<0,	$R_LS(-2) > 0, R_LS(-3) < 0, R_LSE(-1) > 0, R_EVM_A < 0, R_EVM_A(-1) > 0$	$\Delta D_LS(-1) > 0, \Delta D_LSE(-1) < 0, \text{ and } \eta = -0.893772.$	
		RSVI	R_LS(-2)>0, R_LS(-3)<0, R_LSE(-1)>0, R_EVM_A<0, R_EVM_A(-1)>0	$\Delta R_EVM_A < 0, \Delta R_LS(-2) > 0$	$\Delta R_EVM_A < 0, \Delta R_LS(-2) > 0, \text{ and } \eta = -0.972441.$	
	H-attributes	NSE Nifty Returns	SVI	UPA_A(-1)>0, UPA_A(-3)<0, NDA(-3)>0, BJP>0, SG<0, LKA(-1)>0	$BJP * > 0, SG * < 0, LKA(-1) > 0, \Delta UPA_A(-1) > 0, \Delta UPA_A(-2) > 0, \Delta NDA(-2) < 0$	$\Delta UPA_A(-1) > 0, \Delta UPA_A(-2) > 0, \Delta NDA < 0, \Delta NDA(-1) < 0, \Delta NDA(-2) < 0, \text{ and } \eta = -1.040645.$
			DSVI	D_UPA_A(-1)>0, D_UPA_A(-2)>0, D_NDA(-2)<0	$D_UPA_A(-1) > 0, D_NDA(-1) < 0, D_MS(-1) < 0, \Delta D_UPA_A(-1) < 0, \Delta D_NDA(-1) > 0$	$\Delta D_UPA_A(-1) < 0, \Delta D_UPA_A(-2) < 0, \Delta D_UPA_A(-1) > 0, \Delta D_NDA < 0, \Delta D_MS < 0, \Delta D_MS(-1) > 0, \text{ and } \eta = -0.994215.$
			RSVI	R_UPA>0, R_UPA_A(-1)<0, R_NM(-2)<0	$R_UPA * > 0, R_UPA_A(-1) < 0, R_NM(-1) > 0$	$\Delta R_UPA_A < 0, \Delta R_NM(-1) > 0, \text{ and } \eta = -1.107663.$
BSE Sensex Returns		SVI	UPA_A(-2)<0, NDA(-2)>0, LKA>0	$LKA(-1) > 0, \Delta UPA_A(-1) > 0, \Delta NDA(-1) < 0, \Delta LKA > 0$	$\Delta UPA_A(-1) > 0, \Delta NDA < 0, \Delta NDA(-1) < 0, \Delta LKA > 0, \Delta LKA(-1) < 0, \text{ and } \eta = -1.037390.$	
		DSVI	D_UPA(-3)>0, D_UPA_A(-3)<0, D_NDA(-2)>0, D_LKA>0	$D_LKA * > 0, \Delta D_UPA(-2) < 0, \Delta D_UPA_A(-2) > 0, \Delta D_NDA(-1) < 0$	$\Delta D_UPA(-1) < 0, \Delta D_UPA(-2) < 0, \Delta D_UPA_A(-1) > 0, \Delta D_UPA_A(-2) > 0, \Delta D_NDA < 0, \Delta D_NDA(-1) < 0, \text{ and } \eta = -0.880801.$	
		RSVI	R_UPA(-3)>0, R_SG(-2)>0, R_SG(-3)<0, R_LKA(-1)>0, R_NM(-1)<0	$\Delta R_UPA_A(-1) < 0, \Delta R_UPA_A(-2) < 0, \Delta R_SG(-2) > 0$	$\Delta R_UPA_A(-1) < 0, \Delta R_UPA_A(-2) < 0, \Delta R_UPA_A < 0, \Delta R_SG(-2) > 0, \Delta R_NM > 0, \text{ and } \eta = -0.982634.$	
Full-length	NSE Nifty Returns	SVI	BSE<0, BSE(-1)>0, RFR(-1)>0, IRR(-1)<0, SMI<0, LS<0, LSE>0, NXPM<0, NDA<0, BJP>0, SG<0, MS>0,	$RFR(-1) > 0, IRR(-1) < 0, LS * < 0, LSE * > 0, NXPM * < 0, NDA * < 0, BJP * > 0, SG * < 0, MS * > 0, \Delta BSE < 0, \Delta SMI < 0$	$\Delta BSE < 0, \Delta SMI < 0, \Delta UPA_A > 0, \Delta INC < 0, \text{ and } \eta = -0.848860.$	
		DSVI	D_BSE<0, D_IRR(-1)<0, D_SMI<0, D_LS_E(-1)>0, D_NXPM<0, D_NXPM(-1)<0, D_SG<0	$D_BSE * < 0, D_IRR(-1) < 0, D_SMI * < 0, D_LS_E(-1) > 0, D_NXPM(-1) < 0, D_SG * < 0, \Delta D_NXPM < 0$	$\Delta D_LS_E > 0, \Delta D_NXPM < 0, \Delta D_LKA < 0, \text{ and } \eta = -0.562149.$	

	RSVI	R_NSE>0, R_NSE(-1)<0, R_IRR(-1)>0, R_SMR(-1)>0, R_RFR(-1)<0, R_EVM_A(-1)<0, R_UPA_A(-1)<0	R_RFR(-1)<0, R_IRR(-1)>0, R_SMR(-1)>0, R_EVM_A(-1)<0, R_NSE>0	$\Delta R_NSE > 0$, $\Delta R_RFR < 0$, $\Delta R_IRR > 0$, and $\eta = -1.239687$.
BSE Sensex Returns	SVI	BSE(-1)<0, NSE<0, NSE(-1)>0, IRR<0, SMR<0, NXPM(-1)>0, LKA>0	SMR*<0, LKA*>0, $\Delta NSE < 0$, $\Delta IRR < 0$	$\Delta NSE < 0$, $\Delta IRR < 0$, $\Delta LS_E < 0$, $\Delta UPA_A > 0$, and $\eta = -0.986875$.
	DSVI	D_NSE<0, D_BSE>0, D_RFIR(-1)>0, D_SMR<0, D_EVM_A>0, D_LS_E(-1)<0, D_UPA_A>0, D_UPA_A(-1)>0, D_LKA>0	D_SMR*<0, D_BSE*>0, D_NSE*<0, D_EVM_A*>0, D_LS_E(-1)<0, D_UPA_A(-1)>0, D_LKA*>0, $\Delta D_UPA_A > 0$	$\Delta D_IRR < 0$, $\Delta D_EVM < 0$, $\Delta D_LS_E < 0$, $\Delta D_NXPM < 0$, $\Delta D_UPA_A > 0$, $\Delta D_ABV < 0$, and $\eta = -0.800113$.
	RSVI	R_BSE<0, R_BSE(-1)>0, R_NSE>0, R_NSE(-1)<0, R_RFR(-1)<0, R_IRR>0, R_SMR>0, R_EVM_A<0, R_LS_E<0, R_EVM_A(-1)>0, R_LS_E(-1)<0, R_LSE(-1)>0	R_SMR*>0, R_RFR(-1)<0, $\Delta R_BSE < 0$, $\Delta R_NSE > 0$, R_LS_E(-1)<0, $\Delta R_IRR > 0$, $\Delta R_EVM_A < 0$, $\Delta R_LS_E < 0$	$\Delta R_BSE < 0$, $\Delta R_NSE > 0$, $\Delta R_IRR > 0$, $\Delta R_EVM_A < 0$, $\Delta R_LS_E < 0$, and $\eta = -1.027042$.
Note: η refers to the cointegration multiplier in the ECF of the ARDL model. For variable acronyms see Table 1				

References

- Ahmad, S., 2019. Corruption free India and the Lokpal bill is it necessary for it? a critical analysis. *ELK Asia Pacific Journal of Social Science* 5(2), 63–70. URL: <https://doi.org/10.16962/EAPJSS/issn.2394-9392/2015>.
- Ahmed, W.M.A., 2017. The impact of political regime changes on stock prices: the case of Egypt. *International Journal of Emerging Markets* 12(3), 508–531. URL: <https://doi.org/10.1108/IJoEM-12-2015-0258>.
- Amore, M.D., Bennedsen, M., 2013. The value of local political connections in a low-corruption environment. *Journal of Financial Economics* 110(2), 387–402. URL: <https://doi.org/10.1016/j.jfineco.2013.06.002>.
- Ang, J.S., Ding, D.K., Thong, T.Y., 2013. Political connection and firm value. *Asian Development Review* 30(2), 131–166. URL: <http://hdl.handle.net/11540/1620>.
- Baloch, B., Vaishnav, M., 2020. Introduction to a special issue of India review: the consequences of the 2019 Indian general election for politics and policy in India. *India Review* 19(2), 109–116. URL: <https://doi.org/10.1080/14736489.2020.1744993>.
- Behl, A., Sethi, S., 2016. Impact of elections on stock price graph: a case of US elections. *International Journal of Management Practice*, 238–256 URL: <https://doi.org/10.1504/IJMP.2016.077817>.
- Bhargava, V.R., Velasquez, M., 2020. Ethics of the attention economy: The problem of social media addiction. *Business Ethics Quarterly* 31(3), 321–359. URL: <https://doi.org/10.1017/beq.2020.32>.
- Bhuyan, R., Robbani, M.G., Talukdar, B., Jain, A., 2016. Information transmission and dynamics of stock price movements: An empirical analysis of BRICS and US stock markets. *International Review of Economics and Finance* 46(C), 180–195. URL: <https://doi.org/10.1016/j.iref.2016.09.004>.
- Boubakri, N., Guedhami, O. and Mishra, D., W., S., 2012. Political connections and the cost of equity capital. *Journal of Corporate Finance* 18(3), 541–559. URL: <https://doi.org/10.1016/j.jcorpfin.2012.02.005>.
- Bradley, D., Pantzalis, C., Yuan, X., 2016. The influence of political bias in state pension funds. *Journal of Financial Economics* 119(1), 69–91. URL: <https://doi.org/10.1016/j.jfineco.2015.08.017>.
- Celis, E.E., Shen, L.J., 2015. Political cycle and stock market—the case of Malaysia. *Journal of Emerging Issues in Economics, Finance and Banking*, 1461–1512.
- Chakravartty, P., Roy, S., 2015. Mr. Modi goes to Delhi: Mediated populism and the 2014 Indian elections. *Television and New Media* 16(4), 311–322. URL: <https://doi.org/10.1177/1527476415573957>.
- Chien, W.W., Mayer, R., Wang, Z., 2014. Stock market, economic performance, and presidential elections. *Journal of Business and Economics Research* 12(2), 159–170. URL: <https://doi.org/10.19030/jber.v12i2.8530>.
- Dash, B.B., Raja, A.V., 2014. Do political determinants affect revenue collection? Evidence from the Indian states 61(3), 253–278. doi:10.1007/s12232-014-0210-z.
- Dash, P., 2016. The impact of public investment on private investment: Evidence from India. *Vikalpa* 41(4), 288–307. URL: <https://doi.org/10.1177/0256090916676439>.
- Datta, D., Ganguli, S.K., 2014. Political connection and firm value: an Indian perspective. *Asian Journal of Global Business Research* 3(2), 170–189. URL: <https://doi.org/10.1108/SAJGBR-03-2013-0020>.
- De Leon, C., Desai, M., Tuğal, C., 2009. Political articulation: Parties and the constitution of cleavages in the United States, India, and Turkey. *Sociological Theory* 27(3), 193–219. URL: <https://doi.org/10.1111/j.1467-9558.2009.01345.x>.
- Drazen, A., 2000. The political business cycle after 25 years. *NBER Macroeconomics Annual* 15(1), 75–117. URL:

<https://doi.org/10.1086/654407>.

- Duchin, R., Sosyura, D., 2012. The politics of government investment. *Journal of Financial Economics* 106(1), 24–48. URL: <https://doi.org/10.1016/j.jfineco.2012.04.009>.
- Durand, R.B., Koh, S., Tan, P.L., 2013. The price of sin in the pacific-basin. *Pacific-Basin Finance Journal* 21(1), 899–913. URL: <https://doi.org/10.1016/j.pacfin.2012.06.005>.
- Döpke, J., Pierdzioch, C., 2006. Politics and the stock market: Evidence from germany. *European Journal of Political Economy* 22(4), 925–943. URL: <https://doi.org/10.1016/j.ejpoleco.2005.11.004>.
- Ejara, D.D., Nag, R., Upadhyaya, K.P., 2012. Opinion polls and the stock market: evidence from the 2008 US presidential election. *Applied Financial Economics* 22(6), 437–443. URL: <https://doi.org/10.1080/09603107.2011.617692>.
- Falkinger, J., 2008. Limited attention as a scarce resource in information-rich economies. *The Economic Journal* 118(532), 1596–1620. URL: <https://doi.org/10.1111/j.1468-0297.2008.02182.x>.
- Frot, E., Santiso, J., 2013. Political uncertainty and portfolio managers in emerging economies. *Review of International Political Economy* 20(1), 26–51. URL: <https://doi.org/10.1080/09692290.2011.625916>.
- Grossberg, L., 2018. Under the cover of chaos: Trump and the battle for the American right. Pluto Press.
- Hong, H., Kacperczyk, M., 2009. The price of sin: the effects of social norms on markets. *Journal of Financial Economics* 93(1), 15–36. URL: <https://doi.org/10.1016/j.jfineco.2008.09.001>.
- Iyengar, M., Iyengar, N., Sampat, H., 2017. Impact of US election results on Indian stock market: An event study approach. *International Journal of Applied Research* 3(5), 9–13.
- Kabiru, J.N., Ochieng, D.E., Kinyua, H.W., 2015. The effect of general elections on stock returns at the nairobi securities exchange. *European Scientific Journal* 11(28), 435–460.
- Kapoor, K.K., Dwivedi, Y.K., 2015. Metamorphosis of Indian electoral campaigns: Modi's social media experiment. *International Journal of Indian Culture and Business Management* 11(4), 496–516. URL: <https://doi.org/10.1504/ijicbm.2015.072430>.
- Kaur, H., 2015. A study of impact of results of general election 2014 on national stock index. *International Journal of Advanced Research in Management and Social Sciences* 4(5), 31–37.
- Kramer, G., 1971. Short-term fluctuations in u.s. voting behavior, 1896–1964. *American Political Science Review* 65(1), 131–143. URL: <https://doi.org/10.2307/1955049>.
- Kronstadt, K.A., 2000. Nuclear weapons and ballistic missile proliferation in India and Pakistan: Issues for congress. Congressional Research Service, Library of Congress URL: <http://congressionalresearch.com/RL30623/document.php>?
- Kumar, S., 2004. Impact of economic reforms on Indian electorate. *Economic and Political Weekly* 39(16), 1621–1630. URL: <https://www.jstor.org/stable/4414902>.
- Kumari, J., Mahakud, J., 2015. Does investor sentiment predict the asset volatility? evidence from emerging stock market India. *Journal of Behavioral and Experimental Finance* 8(4), 25–39. URL: <https://doi.org/10.1016/j.jbef.2015.10.001>.
- Lehne, J., Shapiro, J.N., Eynde, O.V., 2018. Building connections: Political corruption and road construction in India. *Journal of Development Economics* 131(1), 62–78. URL: <https://doi.org/10.1016/j.jdeveco.2017.10.009>.
- Lei, X., 2018. Empirical analysis of the link between politics and stock market behaviour. Doctoral dissertation, School of Management URL: <https://lra.le.ac.uk/handle/2381/42163>.
- Lobo, B.J., Tufte, D., 1998. Exchange rate volatility: Does politics matter? *Journal of Macroeconomics* 20(2), 351–365. URL: [https://doi.org/10.1016/S0164-0704\(98\)00062-7](https://doi.org/10.1016/S0164-0704(98)00062-7).
- May, A.M., 1987. The political business cycle: an institutional critique and reconstruction. *Journal of Economic Issues* 21(2), 713–722. URL: <https://doi.org/10.1080/00213624.1987.11504663>.
- McCartney, S., Arnold, A.J., 2003. The railway mania of 1845–1847: Market irrationality or collusive swindle based on accounting distortions? *Accounting, Auditing and Accountability Journal* 16(5), 821–852. URL: <https://doi.org/10.1108/09513570310505970>.
- Mendes, J.B., 2015. Elections and stock market volatility: evidence in oecd countries and developing countries. Doctoral Dissertation URL: <https://bibliotecadigital.fgv.br/dspace/handle/10438/14123>.
- Newman, L.S., 2013. Do terrorist attacks increase closer to elections? *Terrorism and Political Violence* 25(1), 8–28. URL: <https://doi.org/10.1080/09546553.2013.733247>.
- Ofek, E., Richardson, M., 2003. Dotcom mania: The rise and fall of internet stock prices. *The Journal of Finance* 58(3), 1113–1137. URL: <https://doi.org/10.1111/1540-6261.00560>.
- Park, J.H., 2011. The economy and elections in korea: An analysis of the political business cycle. *International Review of Public Administration* 16(2), 117–142. URL: <https://doi.org/10.1080/12264431.2011.10805199>.
- Pesaran, M. H. and Shin, Y., Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics* 16(3), 289–326. URL: <https://doi.org/10.1002/jae.616>.
- Popescu, D., Radu, L.D., Păvăloaia, V.D., Georgescu, M.R., 2020. Psychological determinants of investor motivation in social media-based crowdfunding projects: A systematic review. *Frontiers in Psychology* 11, 3676. URL: <https://doi.org/10.3389/fpsyg.2020.588121>.
- Reddy, S., 2015. Impact of general elections 2014 on Indian stock market with special references to the stock of select companies in bse. *International Journal of Management Studies* 5(3), 123–132. URL: <https://doi.org/10.1080/09603107.2015.10805199>.

18843/ijms/v5i3(1)/15.

- Roman, M.D., Jaba, E.L.I.S.A.B.E.T.A., Roman, M.O.N.I.C.A., 2009. Economic development and political cycles in romania. In 7th WSEAS International Conference on Environment, Ecosystems and Development , 190–195.
- Sathyanarayana, D.S., Gargasha, P.S., 2016. Impact of brexit referendum on Indian stock market. *IRA- International Journal of Management and Social Sciences* 5(1), 104–121. URL: <http://dx.doi.org/10.21013%2fjmss.v5.n1.p12>.
- Schaefer, D.O., 2020. American mania. *Cultural Studies* 34(1), 169–171. URL: <https://doi.org/10.1080/09502386.2019.1584904>.
- Scholl, A., 2017. The dynamics of sovereign default risk and political turnover. *Journal of International Economics* 108(1), 37–53. URL: <https://doi.org/10.1016/j.jinteco.2017.05.002>.
- Sengupta, M., 2018. What can human rights add to the fight against corruption? Some lessons from India. Routledge India. URL: <https://doi.org/10.4324/9780429448256-7>.
- Sieg, G., Batool, I., 2012. Pakistan, politics and political business cycles. *The Pakistan Development Review* 51(2), 153–166. URL: <https://www.jstor.org/stable/23733836>.
- Sinha, P.C., 2019a. Market microstructure noise, intraday stock market returns and adaptive learning: Indian evidence. *Colombo Business Journal* 10(2), 25–47. URL: <https://doi.org/10.4038/cbj.v10i2.50>.
- Sinha, P.C., 2019b. Does popularity of political leaders matter in the Indian stock markets? a comparative study of four lok sabha elections from 2004 to 2019. *Ramanujan International journal of Business and Research* 4(1), 37–78. URL: <https://doi.org/10.51245/rijbr.v4i1.2019.162>.
- Sinha, P.C., 2021a. Noise of investors' attention mania in the twenty-first-century Indian stock markets: Ardl and augmented garch-x models. *Global Business Review*, Published on: January 28, 2021. URL: <https://doi.org/10.1177/0972150920982507>.
- Sinha, P.C., 2021b. Attention to the election–economics–politics (eep) nexus in the Indian stock markets. *The Review of Finance and Banking* 13(1). URL: <http://www.rfb.ase.ro/vol13-june2021.asp>.
- Sohlberg, M.M., Mateer, C.A., 1987. Effectiveness of an attention–training program. *Journal of Clinical and Experimental Neuropsychology* 9(2), 117–130. URL: <https://doi.org/10.1080/01688638708405352>.
- Suri, K.C., 2004. Democracy, economic reforms and election results in India. *Economic and Political Weekly* 39(51), 5404–5411. URL: <https://www.jstor.org/stable/4415923>.
- Vadlamannati, K.C., 2008. Do Elections Slow Down Economic Globalization Process in India? It's Politics Stupid! University Library of Munich, Germany. URL: <https://mpa.ub.uni-muenchen.de/10139/>.
- Varshney, A., 1998. Mass politics or elite politics? India's economic reforms in comparative perspective. *The Journal of Policy Reform* 2(4), 301–335. URL: <https://doi.org/10.1080/13841289808523388>.
- Whybrow, P.C., 2006. American mania: when more is not enough .
- Wisniewski, T.P., 2016. Is there a link between politics and stock returns? a literature survey. *International Review of Financial Analysis* 47(1), 15–23. URL: <https://doi.org/10.1016/j.irfa.2016.06.015>.

APPENDIX

Noise of Investors' Attention Mania in the 21st Century Indian Stock Markets

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Appendix 1: A Conceptual Foundation of the Noise of Investors' Attention Mania

An early study at noise-based theory is (Grossman and Stiglitz, 1980), where the unknown true return of a risky asset is viewed as the joint effect of observable information and unobservable noise. The true value of observable information is subject to average information cost to informed traders while that of unobservable noise is always conditional to ex-post prices of the stock. Hence, the presence of a large (small) number of noise-traders lead to persistency of more (less) noise in pricing systems. In synchronization, the stock-markets' indices reveal effects of both information and noise and the stocks' market returns show noise traders' heterogeneity bias and informed traders' information effects as well.

In essence, noise is the presence of misinformation and it reflects uncertainty. It represents a large set of insignificant things with more powerful causal effects than a small set of significant things (Black, 1986). Noise is also observed within the microstructures of the financial markets (Sinha, 2019a). In econometric modelling of the expectations, noise represents two random elements - *white noise* and *correlated noise*. In political science, noise is deception in political agenda to the singular voice that is succeeded vis-à-vis the ordered array of unsuccessful political policies (Kallio, 2012). Noise represents informal groups within a formal structure. In exploring how informal groups or norms are formed or how they persist, (Goodfellow, 2013) has showed that regular impetus (to the urban groups towards making the protests and riots at a continued existence) institutionalizes "noise" in national political participation. Political noise may also appear due to the administrative reforms (Bäcklund et al., 2014), migration stories of the people, cultural varieties and racism (Ruez, 2017), and presence of children and young people in politics (Bartos, 2016; Kallio, 2016). The political noise may also appear as the *noise of election mania* (NOEM). It may even be referred to reflect voters' psychological disorders, biases, or obsessions, and these are observed during the run-up of the national elections in Japan (Rawnsley, 2003).

The noise of *attention mania* may arise due to investors' attention asymmetry to the political awareness of election issues, their supports to or trusts on the political leaders, and their political marketing strategies, agenda, slogans, tag-lines, targets and rivalry, their election activities and manifestos, branding of old or new leaders, political positioning, political fears, mistrust, disbelief, agonies or misconceptions about the concerned elections. For example, attention to "electronic voting machine" ("EVM") can be an IAM element in India. The EVM system is first used in 1982 in a few polling stations in Kerala and its full implementation in the Lok Sabha election has come in force only in 2004. On the use of the EVMs vis-à-vis fair elections in India, there are political debates of trust deficits and misuses of the technology amongst the political leaders, technical experts, and academics as yet (Avgerou et al., 2019). Trust deficit or mistrust results in the noise of IAM. The other IAM elements may be the voters' information confusion or search interests about the election candidates or the prime ministerial candidates or the leader of the opposition in legislative houses or the proposed economic and administrative reforms in the country.

On the contexts of the four Lok Sabha elections in India from 2004 to 2019, this study assumes that the effects of NOEM attract investors' attention to the market-related issues, and thereby, these influence stocks' monthly returns in the NSE Nifty and BSE Sensex in India. We call this particular political attention noise as the "noise of *investors' attention mania*".

We further assume that individuals use the Google search engine for their primary information needs.

Now, the elements in the set of general voters' attention interest P and those in the set of investor-voters' attention interest I are objective-driven and heterogeneous at their keywords' search. A behavioral mania IAM within the both can serve impetus to repetition or homogeneity at election expectations and political attention interests. The IAM at the presence of economic and political phenomena now involves homogenized co-joined attention element $X_i - s$ in set A such that $X \in A$ and $A = I \cap P$. This study considers the $X_i - s$ are being the Google Search keywords representing the IAM. The search volume index ($SVI_{x,it}$) in the Google Trends for an i^{th} keyword's search at the t^{th} point in time can proxy for relative popularity within a given time-period T in the terms of days, months, or years in a geographical area viz., in our case, India. It has used $SVI_{x,it}$ data to proxy for investors' attention mania. With the attention search variables, it explores the causal effects of attention mania on the performances of the NSE Nifty and BSE Sensex stock markets' returns in India.

In developing the core concepts, we hereinafter firstly explore findings in (Joseph et al., 2011; Takeda and Wakao, 2014; Dimpfl and Jank, 2015), and (Tantaopas et al., 2016). Then, we develop the theoretical proposition and it is followed by theorizing a dynamic framework for the Autoregressive Distributed Lag (ARDL) Model along with both short-run and long-run attention effects.

(Joseph et al., 2011) have used (Fama and French, 1993) three-factors model augmented with two risk factors - UMD (Up Minus Down portfolio returns) and $SENT$ (the Sentiments' return effect). The UMD , a proxy for the momentum risk factor, is the difference of returns of the last year's prime mover portfolio and the prime loser portfolio. The risk $SENT$ is measured as the time-series data of the daily stocks' return of the most searched stocks (Q_5) less that of the daily returns of the least searched stocks (Q_1). They have found that the $SENT$ measure involves significant negative (positive) effects on the portfolio returns at the lower (higher) quantiles of the portfolio returns if sorted for returns' volatility while at the sixth quantile, the effect is insignificant. These reveal that the higher (lower) is the difference between the returns of the higher and lower searched stocks, the lower (higher) is the portfolio return of the stocks those are exposed to lower volatility in returns. Such effects are in the opposite for the stocks those are exposed towards upper volatility in returns. These results can be explained by information asymmetry, attention effects, and arbitrage opportunity. Since $SENT$ is the difference between the stock's return at Q_5 for the internet search index from that one at Q_1 , $SENT$ is a composite measure. $SENT$ may proxy for an attention impact on the stock's return, the return's impact on the stock's attention, or a joint impact on stock prices. (Joseph et al., 2011) have used $SENT$ to proxy for the arbitrage and its use becomes noisy in this study.

In exploring the attention effect of Google Search on stocks' returns, (Takeda and Wakao, 2014) have augmented individual stocks' SVI data within the (Fama and French, 1993) three-factor model. They have found a strong (weak) positive correlation between stocks' search intensity and trading volume. In explaining stock market volatility with the search queries, (Dimpfl and Jank, 2015) have used the Vector Autoregressive models for the time series of realized volatility of market returns, search queries, and trading volume. In eliminating the noise traders' effects in the heterogeneous autoregressive (HAR) models towards forecasting performances of volatility, they have used two loss functions for the mean squared errors and quasi-likelihood of the realized market volatility variable. They have showed that the HAR model along with lagged variables of weekly and monthly volatilities captures the long memory presence of noise effects within the realized volatility of the stock markets. Since the present study explores the attention search effects on the stock market returns rather than on individual stocks' returns and/or their volatility, we avoid using the HAR model. The same may be explored in future works along with the appropriate setup.

On examining investors' attention effects and the stock markets' returns in Hong Kong, Japan, Korea, Singapore, India and Malaysia, (Tantaopas et al., 2016) have used the Google SVI data as the attention variable and they have explored the attention effects in a pairwise Granger causality model. They have found a one-way Granger causality effect such that the changes in the stock market variables (viz., returns, volatility, and trading volume) drive the changes in investors' attention interests. They have found that the presence of investors' attention effects reduces the predictabilities of stocks' returns and volatility but with little effect on their volume predictability. They have provided inconclusive evidence on the asymmetry effect of market variables on investors' attention. Since noise includes misinformation, we avoid using the Granger causality test as the central methodology in exploring the effects of IAM on the stock markets rather we use the same as the supplementary robustness checks for attention popularity.

We frame the following general theoretical proposition P_1 for investors' long-run attention effects on the stock markets' returns in the model equation 1. The model specificity in developing short-run manic effects of investors' attention mania (IAM) and the relevant testable hypotheses are dealt with in the next section.

P_1 : The Google search volume index (SVI) data for attention to economic attributes ($SVIE$), political attributes ($SVIP$) and political parties and personalities ($SVIH$) demonstrate effects of investors' attention mania (IAM) on the stock markets' (NSE Nifty and BSE Sensex) returns in India.

$$R_t = \alpha_0 + \sum_{i,t=1}^{e,l} \beta_i SVIE_{it} + \sum_{j,t=1}^{p,l} \gamma_j SVIP_{jt} + \sum_{k,t=1}^{h,l} \delta_k SVIH_{kt} + \theta_t \quad (1)$$

To accommodate both short-run and long-run attention effects on the market return dynamics, this long-run model needs to be revised in the cointegrated dynamic frames. There are three complementary versions of dynamic ARDL model viz., the unrestricted Autoregressive Distributed Lag (ARDL) model, its conditional long-run ARDL form, and its conditional

Error Correction Form (ECF). In an unrestricted ARDL (r,q) set up in the following equation 2 at their levels' data, the dependent variable R_t is regressed with the endogenous dependent and exogenous independent variables at their respective lag orders of r and q to capture their dynamic past effects and that with the exogenous independent variables at current time t, i.e., at lag order of q = 0 to capture their short-run or current effects. In the conditional long-run ARDL (r,q) set up in equation 3 at a mix of data levels, the first difference of market return, i.e., the variable ΔR_t is regressed with the endogenous dependent and exogenous independent variables at their respective lag orders of $r > 0$ and $q \geq 0$ [the first two parts in equation 3] along with the first differences of the dependent and independent variables at their respective lag orders of $r > 0$ and $q = 0$ [the next two parts in equation 3]. The variables in first differences capture the short-run effects while their current and/or lagged levels address the long-run dynamics. The last part η_t is the residual error component in the model. Further, in the conditional error correction form (ECF) of the long-run ARDL model, given in equation 4, the first differences of both dependent and independent variables at their respective lag lengths of $r > 0$ and $q = 0$ reflect the short-run effects as those mentioned in the conditional long-run ARDL (r,q) model. The long-run effect is specified at its one-period lagged error correction term ηZ_{t-1} , and it surrogates for the speed of adjustment as observed in the dependent variable towards the long-run relationship.

$$R_t = \theta_0 + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=1}^q \sum_A^{E,P,H} \sum_{i,t}^{e,l} \theta_{Aiq} SVIA_{it-q} + \sum_A^{E,P,H} \sum_{i,t}^{e,l} \eta_{Ai} SVIA_{it} + n_t \quad (2)$$

$$\Delta R_t = \theta_0 + \sum_{r=1}^r \sum_i^n \theta_{1r} R_{t-r} + \sum_{q=0}^q \sum_A^{E,P,H} \sum_{i,t}^{e,l} \theta_{Aiq} SVIA_{it-q} + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t}^{e,l} \eta_{Ai} \Delta SVIA_{it} + n_t \quad (3)$$

$$\Delta R_t = \theta_0 + \sum_{r=1}^r \sum_i^n \theta_{1r} \Delta R_{t-r} + \sum_A^{E,P,H} \sum_{i,t}^{e,l} \theta_{Ai} \Delta SVIA_{it-q} + \eta Z_{t-1} + \eta_t \quad (4)$$

The first two ARDL models augment the behavioral autocorrelation features of the data within the system and use the different lagged dependent variables as explanatory variables. These models are also free from the restriction of levels of autocorrelations of the variables - if both are of I(0)s, or of mixed nature i.e., some are of I(0) and the rest of I(1), but not I(2) or higher. The conditional ECF of the ARDL model derives its long-run adjustments systematically within the conditional Long Run ARDL model as mentioned in equation 3. Further, the missing of long-term influences of variables at level data in equation 4 results in under-specification in dynamic equilibrium, and hence the conditional ECF leads to loss of valuable information. In exploring IAM, we avoid any confirmation bias in the specific model selection and so, we use both the unrestricted and conditional ARDLs in equation 2 and equation 3 along with the ECF(r,q) of the conditional long-run ARDL model.

It is thought-provoking to find that the long-run static model specified in equation 1 results in model instability and/or spurious regression at the presence of dependent variable R_t being of I(0) in nature (stationary) but independent attention variables are mixed I(0) and I(1). A linear transformation of I(1) data for these independent attention variables leads to loss of information. Furthermore, since investors do not view their attention choice in linear transformations at times of decision choice, the said transformation will also warrant the need for further theoretical justifications. Investors' different attention layers also restrict us from using the first difference in converting the I(1) data sets into the I(0) ones. Hence, we avoid regressing the theoretical long-run regression model equation 1 even with augmented lagged dependent variables but incorporate intercept and time trend in formulating the hypothesis. Interested readers may find theoretical backings of these ARDL models in (Banerjee et al., 1993), and (Banerjee et al., 1998).

Appendix 2: A brief communique on Indian political parties and personalities (Source : wikipedia.org)

Indian National Congress (INC): Indian National Congress, INC, is a century-old political party established in 1885. Under the leadership of Mahatma Gandhi, the INC had become the center of the Indian independence movement. During the post-independence period, the INC has become the core political party in the central government in India till 1998. This political party has contributed India with four Prime Ministers from 1947 to 1998.

United Progressive Alliance (UPA): At the 2004 general election debacle for the large political parties when no single political party could lead to stake the claim to form the government, the concept of UPA came. The United Progressive Alliance (UPA) is a concept of coalition alliance since 2004. At the center of it, there is INC and the other parties are the regional parties. The alliance has successfully run two governments during 2004-2014 under the former Prime Minister, Dr. Manmohan Singh.

Bharatiya Janata Party (BJP): Bharatiya Janata Party (BJP), a right-wing political party, presently is the largest political party in the world in terms of primary membership of its cadres. The party was formed in 1951 and it was previously named Bharatiya Jana Sangh. The party has received tremendous growth in political acceptance from its two members

in the parliament in 1984 to the largest political party in 1996. In the 1998 general election, the party in coalition with other regional political parties formed the central government with its Prime Minister, Atal Bihari Vajpayee. Despite its political downfall in the 2004 general election, it has received huge political supports from the public in the 2014 and 2019 general elections.

National Democratic Alliance (NDA): National Democratic alliance is the BJP dominated right-wing political alliance in India. Following the 1998 general election and lack of any single party to form the government at the Center, NDA was formed along with the BJP and like-minded right-wing political parties. The alliance had led a successful full-term government during 1999–2004. In the 2014 and 2019 general elections, the coalition has received tremendous growth in the center and the state assembly elections in India.

Sonia Gandhi: Ms. Sonia Gandhi is an Indian politician from the right-wing political party of the Indian National Congress (INC). She has been serving the INC since 1998. Under her leadership, her political party had formed two successive governments in the Centre in India since 2004. She had stepped down as the President of the INC in December 2007 due to bad health but resumed to lead in August 2019.

Manmohan Singh: Dr. Manmohan Singh is an Indian economist, academic and politician as well. He had served the central United Progressive Alliance (UPA) government as the Prime Minister of India for two consecutive terms from 2004–2009 and 2009–2014. On the occasion of Ms. Sonia Gandhi declined to take charge of the Prime Minister of India in 2004, he had been nominated for that post.

Rahul Gandhi: Rahul Gandhi is a young Indian politician from the INC. He has entered into politics in 2004 and had been serving in the capacity of a Member of the Parliament since 2004. During 2007–2013, he has served the Indian Youth Congress. He has served the INC as its Vice-President since 2013, and he has been elected as President of the INC in December 2017 and served the post till 2019 general election in India. During his political career, he has spent much time in 2015 for Farmers and Land Agitation at different parts of India.

Atal Bihari Vajpayee: Atal Bihari Vajpayee was an Indian politician, statesman, and poet as well. He had served as the Prime Minister of the Indian Central Government for two short terms for 13 days in 1996 and 13 months during 1998–1999 and a full term from 1999 to 2004. He had served the Indian Parliament for more than five decades of periods. Under his second short tenure, the Indian Government had successfully carried out Pokhran-II nuclear tests in 1998. He has been awarded Bharat Ratna, the highest civilian award in 2015. His birthday 25th December is marked as Good Governance Day since 2014.

Lal Krishna Advani: Lal Krishna Advani is an Indian Politician. He is a founder member of the political party – the Bharatiya Janata Party (BJP). He has served the central government of India as Deputy Prime Minister of India under the Prime Minister Atal Bihari Vajpayee during 2002–2004. He has served the Government as the Home Minister of the National Democratic Alliance (NDA) during 1998–2004. He had been the leader of the opposition in the parliament during 2004–2009. He has been the Prime Ministerial candidate from the BJP in the 2009 general election in India.

Narendra Modi: Narendra Modi is an Indian politician and the 14th and 15th Prime Minister of India respectively for 2014–2019 and 2019 to date. He has been the Chief Minister during 2001 – 2014 consecutively for three terms in Gujrat, a prosperous state in India. He has been famous for his good governance and minimum government across the nation. His “Make in India” project, health and sanitation drive, foreign policy and defence policy are mostly iconic and path-breaking in Indian history. He has been conferred with many national and international awards from 2007 to till date. He has received many international awards from Saudi Arabia, Afghanistan, Palestine, the United States of Emirates, Russia, Maldives, and Bahrain during 2016–2019.

Appendix 3: Data Characteristics

We find that the raw indices data i.e., “Low Index” of NSE Nifty and BSE Sensex are non-stationary at their levels data. At first differences, the ADF Unit Root tests show that both indices are stationary with intercept and with trend and intercept as well. The unit root tests of both NSE Nifty and BSE Sensex market returns reject the null hypothesis of the presence of unit roots at data levels, at the first difference, and the second difference with or without intercepts, and with or without intercepts and trends. We use relatives of the log-transformed index as the returns data. The ADF Unit Root tests show that both these market returns are stationary at their level data: with the intercept, and with the trend and intercept as well. Hence, our two stock markets’ monthly returns are stationary, and $I(0)$. A correlogram test of both markets’ returns shows insignificant autocorrelations with a weak change in its sign at 9th lag. The Unit Root with Break test rejects a presence of unit root even at breakpoints of both returns’ data. The market returns are stationary even at breakpoint situations. These results are not depicted in tables and figures to save space.

The unit root test results with the explanatory variables are now described. The detail can be produced with annexures on demand from the readers. The unit root test results of SVI, DSVI, and RSVI data for different attributes show that at first difference along with intercept, these data sets have significantly rejected the presence of unit root. The first-differences of Google keywords search data are stationary and $I(0)$ type. Since the DSVI data sets for the attributes are at first differences of the respective SVI data, unit root tests for these data sets also have rejected the presence of any unit root at levels with or without intercepts, and also with or without intercepts and trends, and the DSVI data series are stationary and $I(0)$ in nature at all levels’ data.

At level data with an intercept but without trend effects, our SVI data have an absence of unit roots with E-attributes “BSE Sensex” and “Stock Market Return”, with all P-attributes, and with the most H-attributes except for “National

Democratic Alliance”, “NDA”, “Bharatiya Janata Party”, and “Rahul Gandhi”. Level data of these specific variables are stationarity and I(0) type while the others are of I(1) type. Further, at level data with intercept and trend effect, our SVI data show significant trend impacts with E-attributes “Risk Free Rate”, “Risk Free Interest Rate”, and “Stock Market Returns”, P-attributes – “electronic voting machine”, and “EVM”, and H-attributes “Bharatiya Janata Party”, “Manmohan Singh”, “Rahul Gandhi”, and “Narendra Modi”. These data are trend stochastic and I(0) type but the rests are I(1). At level data with an intercept but without trend effect, our RSVI data for “Risk Free Rate”, “Stock Market Return”, “electronic voting machine”, “EVM”, “Next PM”, “United Progressive Alliance”, “UPA”, “National Democratic Alliance”, “Indian National Congress”, “Atal Bihari Vajpayee”, and “Lal Krishna Advani” show absence of unit roots and their data are stationary at I(0) while the rests are I(1) type. With trend and intercept effects at level data, RSVI data for E-attributes neither show trend effects nor reject the presence of unit roots and these variables are of I(1) type, but for P-attributes and H-attributes, we find a mixed presence of significant trend effects and/or absence of unit roots and these are of mixed, I(0) and I(1).

Appendix 4: NSE Nifty Returns at Attention to E-attributes with Unrestricted ARDL (4, 4) Model

SVI Data (Focus Attention)					DSVI Data (Selective Attention)					RSVI Data (Homogeneous Attention)				
Variables	Coef.	Std. Error	t-Stat	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.
C	0.722125	0.140130	5.153	0.000	C	0.59216	0.13796	4.292	0.000	C	1.065389	0.122868	8.671	0.000
RNSE(-4)	0.193736	0.063630	3.045	0.003	RNSE(-4)	0.21440	0.06307	3.399	0.001	RNSE(-4)	0.043652	0.008879	4.916	0.000
RFIR(-3)	-0.000107	0.000053	-2.048	0.042	D_RFIR(-2)	0.00011	0.00005	2.296	0.023	R_RFIR(-3)	0.000042	0.000018	2.378	0.019
RFIR(-4)	0.000127	0.000050	2.565	0.011	@TREND	-0.00001	0.00001	-0.841	0.402	@TREND	-0.000139	0.000054	-2.562	0.011
BSE	-0.000223	0.000094	-2.378	0.019	D_BSE	-0.00020	0.00009	-2.384	0.018	R_NSE	0.000222	0.000045	4.893	0.000
BSE(-1)	0.000430	0.000099	4.359	0.000	D_BSE(-1)	0.00021	0.00008	2.622	0.010	R_NSE(-1)	-0.000197	0.000055	-3.579	0.001
RFR(-1)	0.000137	0.000045	3.027	0.003	D_IRR(-1)	-0.00019	0.00006	-3.349	0.001	R_IRR(-2)	-0.000084	0.000030	-2.796	0.006
SMI	-0.000442	0.000094	-4.722	0.000	D_SMI	-0.00034	0.00009	-3.968	0.000	R_NSE(-3)	0.000143	0.000055	2.591	0.011
SMI(-2)	0.000174	0.000086	2.025	0.045	D_SMI(-1)	-0.00020	0.00008	-2.386	0.018	R_NSE(-4)	-0.000096	0.000045	-2.115	0.036
SMR(-1)	-0.000099	0.000049	-2.016	0.046	D_SMR	-0.00010	0.00005	-2.022	0.045	RNSE(-1)	0.026145	0.070825	0.369	0.713
SMR(-4)	0.000105	0.000049	2.159	0.032	D_SMR(-1)	-0.00010	0.00005	-1.974	0.050	RNSE(-2)	-0.052628	0.070415	-0.747	0.456
RNSE(-1)	0.057928	0.076145	0.761	0.448	RNSE(-1)	0.09276	0.07192	1.290	0.199	RNSE(-3)	-0.076095	0.070210	-1.084	0.280
RNSE(-2)	0.001466	0.067437	0.022	0.983	RNSE(-2)	0.04642	0.06581	0.705	0.482	R_BSE	0.000013	0.000026	0.494	0.622
RNSE(-3)	0.025660	0.066518	0.386	0.700	RNSE(-3)	0.05598	0.06561	0.853	0.395	R_NSE(-2)	-0.000105	0.000056	-1.886	0.061
BSE(-2)	-0.000171	0.000088	-1.953	0.053	D_NSE	-0.00002	0.00011	-0.179	0.858	R_RFR	-0.000015	0.000015	-1.012	0.313
NSE	0.000078	0.000076	1.030	0.305	D_RFR	0.00000	0.00004	0.125	0.901	R_RFIR	-0.000031	0.000020	-1.552	0.123
RFR	0.000058	0.000044	1.344	0.181	D_RFR(-1)	0.00008	0.00004	1.880	0.062	R_RFIR(-1)	0.000002	0.000020	0.103	0.918
RFR(-2)	0.000077	0.000047	1.631	0.105	D_RFR(-2)	0.00006	0.00004	1.773	0.078	R_RFIR(-2)	-0.000009	0.000019	-0.456	0.649
RFIR	-0.000089	0.000055	-1.599	0.112	D_RFIR	-0.00001	0.00005	-0.179	0.858	R_IRR	0.000051	0.000031	1.651	0.101
RFIR(-1)	0.000075	0.000055	1.363	0.175	D_RFIR(-1)	0.00009	0.00005	1.743	0.083	R_IRR(-1)	0.000050	0.000029	1.701	0.091
RFIR(-2)	0.000086	0.000052	1.644	0.102	D_IRR	-0.00006	0.00006	-1.035	0.302	R_IRR(-3)	0.000049	0.000030	1.611	0.109
IRR	-0.000067	0.000072	-0.929	0.355						R_IRR(-4)	0.000055	0.000030	1.842	0.067
SMI(-1)	0.000106	0.000097	1.095	0.275						R_SMI	-0.000010	0.000024	-0.406	0.685
SMR	0.000007	0.000056	0.122	0.903	D_SMR(-2)	-0.00004	0.00005	-0.871	0.385	R_SMR	0.000021	0.000014	1.506	0.134
SMR(-2)	0.000083	0.000048	1.730	0.086	D_SMR(-3)	0.00001	0.00005	0.290	0.772	R_SMR(-1)	0.000018	0.000015	1.237	0.218
SMR(-3)	0.000005	0.000050	0.098	0.922	D_SMR(-4)	0.00008	0.00004	1.914	0.057	R_SMR(-2)	-0.000026	0.000014	-1.828	0.070
TREND	-0.000007	0.000040	-0.169	0.866										
R ²	0.472	MDV	1.0013		R ²	0.43	MDV	1.0015		R ²	0.44	MDV	1.0013	
Adj. R ²	0.383	SDDV	0.0091		Adj. R ²	0.35	SDDV	0.0086		Adj. R ²	0.35	SDDV	0.0091	
S.E.R.	0.0072	AIC	-6.900		S.E.R.	0.0069	AIC	-6.9816		S.E.R.	0.0074	AIC	-6.8526	
S.S.R.	0.0080	SC	-6.424		S.S.R.	0.0076	SC	-6.5575		S.S.R.	0.0085	SC	-6.3949	
Log p ^λ	654.85	HQ	-6.707		Log p ^λ	655.84	HQ	-6.8097		Log p ^λ	649.59	HQ	-6.6671	
F-stat.	5.329	DW stat.	2.025		F-stat.	5.13	DW stat.	1.92		F-stat.	4.91	DW stat.	1.93	
P(F-stat.)	0.001	BGSCLM(1)	0.588(0.444)		P(F-stat.)	0.001	BGSCLM(1)	1.114(0.292)		P(F-stat.)	0.001	BGSCLM(1)	0.592(0.443)	
B-P-G HT	1.51(0.12)	BGSCLM(2)	0.933(0.395)		B-P-G HT	1.58(0.10)	BGSCLM(2)	0.761(0.469)		B-P-G HT	1.53(0.12)	BGSCLM(2)	0.728(0.485)	
CUSUM Recursive Estimates Stable at 5% Level					CUSUM Recursive Estimates Stable at 5% Level					CUSUM Recursive Estimates Stable at 5% Level				

Search Keywords (Acronyms): “BSE Sensex” (BSE), “NSE Nifty 50” (NSE), “Risk Free Rate” (RFR), “Risk Free Interest Rate” (RFIR), “Internal Rate of Return” (IRR), “Stock Market Index” (SMI), “Stock Market Return” (SMR), “Electronic Voting Machine” (EVM), “EVM” (EVM_A), “Lok Sabha” (LS), “LS Election” (LS_E), “Lok Sabha Election” (LSE), “Next PM” (NXP), “United Progressive Alliance” (UPA), “UPA” (UPA_A), “National Democratic Alliance” (NDA), “NDA” (NDA_A), “Bharatiya Janata Party” (BJP), “Indian National Congress” (INC), “Sonia Gandhi” (SG), “Manmohan Singh” (MS), “Rahul Gandhi” (RG), “Atal Bihari Vajpayee” (ABV), “Lal Krishna Advani” (LKA), & “Narendra Modi” (NM).

Parameters Test Acronyms: “S.E.R.” is S.E. of regression; “S.S.R.” is Sum squared residuals; “Log p^λ” is the Log likelihood value; “DW” is Durbin-Watson statistics; “B-P-G HT” denotes F statistics value for Breusch-Pagan-Godfrey Heteroskedasticity Test, and the relevant value in parenthesis represents its probability value. “BGSCLM(1/2)” denotes F-statistics value at 1st / 2nd order Breusch-Godfrey Serial Correlation LM Test and the value in parenthesis represents its probability value. “MDV” is Mean Dependent Variance; “SDDV” is S.D. Dependent Variance; “AIC” is Akaike info criterion; “SC” Schwarz criterion; “HQ” is Hannan-Quinn criterion.

Appendix 5: NSE Nifty Returns at Attention to E-attributes with Conditional Long Run ARDL (4, 4) Model and Bound Tests

Table with columns: SVI Data (Focus Attention), DSVI Data (Selective Attention), and RSVI Data (Homogeneous Attention). Each column contains coefficients, standard errors, t-statistics, and probabilities for various variables like C, RNSE, RFR, BSE, SMR, etc.

Levels Equation at Unrestricted Constant and Unrestricted Trend
EC = RNSE - (0.00005*BSE + 0.000108*NSE + 0.000378*RFR + 0.000127*RFIR - 0.000093*IRR - 0.000224*SMI + 0.000140*SMR)

AF-Bound Test: Ho: No levels relationship; Actual Sample Size: n = 182, Asymptotic n = 1000; Sample; K = 7;
At alpha = 0.10, For I(0) - Asymptotic F-stat = 2.38, and For I(1) - Asymptotic F-stat = 3.45;
At alpha = 0.05, For I(0) - Asymptotic F-stat = 2.69, and For I(1) - Asymptotic F-stat = 3.83;
At alpha = 0.025, For I(0) - Asymptotic F-stat = 2.98, and For I(1) - Asymptotic F-stat = 4.16; and
At alpha = 0.01, For I(0) - Asymptotic F-stat = 3.31, and For I(1) - Asymptotic F-stat = 4.63

Appendix 6: NSE Nifty Returns at Attention to E-attributes with Conditional ECF of ARDL Model

Table with columns: SVI Data (Focus Attention), DSVI Data (Selective Attention), and RSVI Data (Homogeneous Attention). Includes variables like @TREND, ARNSE, DRNSE, DRNSE, DR_BSE, DR_RFR, DR_RFIR, DR_IRR, DR_SMI, DR_SMR, CointEq, R^2, Adj. R^2, S.E.R., S.S.R., Log pA, F-stat, P(F-stat), B-P-G HT, F-Bound Test, and F-statistic Value.

Appendix 21: BSE Sensex Returns at Attention to H-attributes with Conditional ECF of ARDL Model

SVI Data(Focus Attention)					DSVI Data (Selective Attention)					RSVI Data (Homogeneous Attention)				
Variables	Coef.	Std. Error	t-Stat	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.
C	1.035960	0.069181	14.975	0.000	C	0.883010	0.061841	14.279	0.000	C	0.990870	0.072068	13.749	0.000
Δ UPA_A(-1)	0.000267	0.000048	5.594	0.000	Δ D_UPA_A(-1)	-0.000704	0.000215	-3.271	0.001	Δ R_UPA_A(-1)	-0.000038	0.000013	-2.811	0.006
Δ NDA	-0.000166	0.000074	-2.245	0.026	Δ D_UPA_A(-2)	-0.000589	0.000161	-3.649	0.000	Δ R_UPA_A(-2)	-0.000037	0.000013	-2.903	0.004
Δ NDA(-1)	-0.000380	0.000098	-3.883	0.000	Δ D_UPA_A(-1)	0.000749	0.000216	3.471	0.001	Δ R_UPA_A	-0.000049	0.000013	-3.810	0.000
Δ LKA	0.000170	0.000050	3.427	0.001	Δ D_UPA_A(-2)	0.000554	0.000161	3.440	0.001	Δ R_SG(-2)	0.000044	0.000017	2.588	0.011
Δ LKA(-1)	-0.000129	0.000051	-2.525	0.013	Δ D_NDA	-0.000122	0.000055	-2.224	0.028	Δ R_NM	0.000062	0.000028	2.246	0.026
Δ UPA_A	0.000074	0.000049	1.512	0.133	Δ D_NDA(-1)	-0.000302	0.000090	-3.352	0.001	Δ R_LKA	-0.000010	0.000012	-0.826	0.410
Δ LKA(-2)	-0.000101	0.000052	-1.958	0.052	Δ D_UPA	-0.000057	0.000162	-0.354	0.724	Δ R_LKA(-1)	0.000019	0.000012	1.540	0.126
					Δ D_UPA_A	0.000310	0.000162	1.910	0.058	Δ R_SG	0.000015	0.000017	0.879	0.381
										Δ R_SG(-1)	-0.000005	0.000019	-0.247	0.805
@TREND	0.000003	0.000009	0.271	0.787	@TREND	-0.000011	0.000009	-1.203	0.231	@TREND	-0.000015	0.000010	-1.548	0.124
CointEq(-1)	-1.037390	0.069255	-14.979	0.000	CointEq(-1)	-0.880801	0.061709	-14.274	0.000	CointEq(-1)	-0.982634	0.071437	-13.755	0.000
R ²	0.64	MDV	0.0000		R ²	0.64	MDV	0.0002		R ²	0.61	MDV	0.0000	
adj.R ²	0.62	S.D.DV.	0.0107		adj.R ²	0.62	S.D.DV.	0.0104		adj.R ²	0.58	S.D.DV.	0.0107	
S.E.R.	0.0066	AIC	-7.1465		S.E.R.	0.0064	AIC	-7.2144		S.E.R.	0.0069	AIC	-7.0488	
S.S.R.	0.0076	SC	-6.9711		S.S.R.	0.0069	SC	-7.0207		S.S.R.	0.0082	SC	-6.8383	
Log p ^A	663.91	HQ	-7.0754		Log p ^A	667.51	HQ	-7.1359		Log p ^A	656.96	HQ	-6.9635	
F-stat.	33.89	DW stat.	1.91		F-stat.	30.69	DW stat.	2.01		F-stat.	24.27	DW stat.	1.88	
P(F-stat.)	0.001	BGSCLM(1)	0.031(0.86)		P(F-stat.)	0.001	BGSCLM(1)	0.036(0.85)		P(F-stat.)	0.001	BGSCLM(1)	0.895(0.346)	
B-P-G HT	1.17(0.33)	BGSCLM(2)	0.196(0.82)		B-P-G HT	1.04(0.41)	BGSCLM(2)	0.391(0.68)		B-P-G HT	1.11(0.39)	BGSCLM(2)	0.445(0.642)	
F-Bound Test Δ		F-statistic Value	16.06		F-Bound Test Δ		F-statistic Value	14.57		F-Bound Test Δ		F-statistic Value	13.53	
CUSUM Recursive Estimates Stable at 5% Level; Note: For Acronyms of Test Parameters see Appendix 4														
AF-Bound Test: Ho: No levels relationship; Actual Sample Size: n = 183, Asymptotic n = 1000; Sample; K = 12; Note: For F-Bound Table Values See Appendix 17.														

Appendix 22: BSE Sensex Returns at Full-Length Attention Attributes with Conditional ECF of ARDL Model

SVI Data (Focus Attention)#					DSVI Data (Selective Attention)*					RSVI Data (Homogeneous Attention)*				
Variables	Coef.	Std. Error	t-Stat	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.
C	0.994278	0.0669	14.862	0.001	C	0.801593	0.044107	18.1738	0	C	1.03693	0.098476	10.53	0
@TREND	-4.8E-05	0.000009	-5.098	0.001	@TREND	-0.000006	0.000008	-0.7857	0.4333	@TREND	-7.2E-05	0.00001	-6.912	0
Δ NSE	-0.00027	0.000096	-2.784	0.006	Δ D_IRR	-8.3E-05	0.000022	-3.6841	0.0003	Δ R_BSE(-3)	-0.12579	0.055061	-2.285	0.024
Δ IRR	-0.00017	0.000039	-4.323	0.001	Δ D_EVM	-0.00011	0.000029	-3.9607	0.0001	Δ R_BSE	-0.00011	0.000026	-4.247	0
Δ LS_E	-0.0001	0.00005	-2.015	0.046	Δ D_LS_E	-7.3E-05	0.000027	-2.6974	0.0078	Δ R_NSE	0.000124	0.000041	3.019	0.003
					Δ D_NXPM	-9.3E-05	0.000018	-5.2276	0	Δ R_IRR	0.000057	0.000017	3.329	0.001
Δ UPA_A	0.000504	0.000046	10.88	0.001	Δ D_UPA_A	0.000515	0.000034	14.9585	0	Δ R_EVM_A	-6.1E-05	0.000009	-7.088	0
					Δ D_ABV	-7.4E-05	0.000024	-3.063	0.0026	Δ R_LS_E	-0.00005	0.000011	-4.48	0
Δ BSE	0.000121	0.000068	1.783	0.077	Δ D_RFIR	0.000002	0.000018	0.1297	0.897	Δ R_BSE(-1)	-0.000355	0.087847	-0.004	0.997
										Δ R_BSE(-2)	-0.1076	0.072515	-1.484	0.14
Δ NXPM	-0.000033	0.00003	-1.103	0.272						Δ R_RFR	-0.000002	0.000008	-0.247	0.805
										Δ R_LSE	-0.000013	0.000021	-0.625	0.533
										Δ R_LKA	0.000008	0.00001	0.822	0.413
CointEq(-1)	-0.98688	0.06639	-14.865	0.001	CointEq(-1)	-0.80011	0.044018	-18.1769	0	CointEq(-1)	-1.02704	0.097602	-10.523	0
R ²	0.63	MDV	0.00003		R ²	0.73	MDV	0.0001		R ²	0.7	MDV	0.0002	
Adj. R ²	0.63	S.D.DV.	0.0107		Adj. R ²	0.71	S.D.DV.	0.0107		Adj. R ²	0.68	S.D.DV.	0.0104	
S.E.R.	0.0065	AIC	-7.1959		S.E.R.	0.0057	AIC	-7.4315		S.E.R.	0.0059	AIC	-7.3562	
S.S.R.	0.0074	SC	-7.0392		S.S.R.	0.0057	SC	-7.2567		S.S.R.	0.0058	SC	-7.1098	
Log p ^A	674.62	HQ	-7.1324		Log p ^A	693.69	HQ	-7.3606		Log p ^A	683.42	HQ	-7.2563	
F-stat.	40.82	DW stat.	1.95		F-stat.	51.66	DW stat.	1.94		F-stat.	30.09	DW stat.	1.87	
P(F-stat.)	0.001	BGSCLM(1)	0.452(0.50)		P(F-stat.)	0.001	BGSCLM(1)	0.433(0.51)		P(F-stat.)	0.001	BGSCLM(1)	1.729(0.191)	
B-P-G HT	0.92(0.60)	BGSCLM(2)	0.254(0.78)		B-P-G HT	1.37(0.06)	BGSCLM(2)	0.573(0.565)		B-P-G HT	1.48(0.07)	BGSCLM(2)	0.869(0.421)	
F-Bound Test Δ		F-statistic Value	7.29		F-Bound Test Δ		F-statistic Value	10.88		F-Bound Test Δ		F-statistic Value	3.63	
*CUSUM Recursive Estimates Stable at 5% Level with DSVI and RSVI data.														
# CUSUM Recursive Estimates is not Stable at 5% Level with SVI. For stability, see Figure 22#A.														
Note: For Acronyms of Test Parameters see Appendix 4														
AF-Bound Test: Ho: No levels relationship; Actual Sample Size: n = 183, Asymptotic n = 1000; Sample; K = 12; Note: F-Bound Table Values Please are in Appendix 24.														

Appendix 27: : BSE Sensex Returns at Full-Length Attention Attributes with Conditional Long Run ARDL Model and Bound Tests

SVI Data (Focus Attention)					DSVI Data (Selective Attention)					RSVI Data (Homogeneous Attention)				
Variables	Coef.	Std. Error	t-Stat	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.
C	0.994278	0.097173	10.232	0.000	C	0.801593	0.081643	9.818	0.000	C	1.036930	0.152706	6.790	0.000
RBSE (-1)	-0.986875	0.095667	-10.316	0.000	RBSE (-1)	-0.800113	0.081508	-9.816	0.000	RBSE(-1)	-1.027042	0.152035	-6.755	0.000
SMR*	-0.000098	0.000043	-2.283	0.024	D_SMR*	-0.000125	0.000037	-3.427	0.001	R_SMR*	0.000031	0.000013	2.372	0.019
LKA*	0.000151	0.000058	2.592	0.011	D_BSE*	0.000222	0.000078	2.864	0.005	R_RFR(-1)	-0.000034	0.000017	-2.021	0.045
ΔNSE	-0.000268	0.000116	-2.303	0.023	D_NSE*	-0.000286	0.000112	-2.552	0.012	ΔR_BSE	-0.000109	0.000039	-2.836	0.005
ΔIRR	-0.000169	0.000066	-2.585	0.011	D_EVM_A*	0.000166	0.000070	2.372	0.019	ΔR_NSE	0.000124	0.000051	2.429	0.016
					D_LS_E (-1)	-0.000356	0.000114	-3.119	0.002	R_LS_E(-1)	-0.000083	0.000025	-3.310	0.001
					D_UPA_A(-1)	0.000806	0.000204	3.946	0.000	ΔR_IRR	0.000057	0.000027	2.102	0.037
					D_LKA*	0.000137	0.000055	2.469	0.015	ΔR_EVM_A	-0.000061	0.000013	-4.580	0.000
					ΔD_UPA_A	0.000515	0.000198	2.595	0.010	ΔR_LS_E	-0.000050	0.000019	-2.723	0.007
BSE(-1)	-0.000110	0.000088	-1.243	0.216						R_BSE(-1)	-0.000022	0.000030	-0.719	0.473
NSE(-1)	0.000079	0.000080	0.985	0.326						R_NSE(-1)	0.000003	0.000029	0.088	0.930
RFR*	0.000039	0.000039	0.995	0.321	D_RFR*	0.000035	0.000026	1.391	0.166	R_RFIR*	-0.000002	0.000017	-0.131	0.896
RFIR*	-0.000052	0.000054	-0.973	0.332	D_RFIR(-1)	0.000101	0.000061	1.672	0.097					
IRR(-1)	-0.000082	0.000086	-0.956	0.341	D_IRR(-1)	-0.000019	0.000080	-0.234	0.815	R_IRR(-1)	0.000017	0.000035	0.494	0.622
SMI*	0.000050	0.000077	0.650	0.516	D_SMI*	0.000118	0.000073	1.620	0.107	R_SMI*	0.000008	0.000029	0.284	0.777
EVM*	-0.000156	0.000084	-1.860	0.065	D_EVM(-1)	-0.000026	0.000115	-0.226	0.822	R_EVM*	0.000019	0.000016	1.208	0.229
EVM_A*	0.000093	0.000090	1.031	0.304						R_EVM_A(-1)	-0.000027	0.000018	-1.516	0.132
LS*	-0.000028	0.000581	-0.047	0.962	D_LS*	-0.000191	0.000421	-0.453	0.651	R_LS*	-0.000003	0.000020	-0.139	0.889
LS_E(-1)	-0.000221	0.000133	-1.664	0.098						R_LSE(-1)	0.000060	0.000043	1.393	0.166
LSE*	0.000319	0.000562	0.567	0.571	D_LSE*	0.000090	0.000387	0.233	0.816	R_NXPM*	0.000028	0.000020	1.389	0.167
NXPM(-1)	0.000087	0.000075	1.156	0.250	D_NXPM(-1)	-0.000142	0.000092	-1.539	0.126	R_UPA*	0.000008	0.000026	0.289	0.773
UPA*	-0.000355	0.000310	-1.147	0.253	D_UPA*	-0.000223	0.000198	-1.125	0.262	R_UPA_A*	-0.000039	0.000025	-1.558	0.121
UPA_A(-1)	0.000425	0.000309	1.374	0.172						R_NDA*	-0.000007	0.000012	-0.623	0.534
NDA*	-0.000249	0.000211	-1.182	0.239	D_NDA*	-0.000087	0.000176	-0.494	0.622	R_NDA_A*	-0.000023	0.000018	-1.284	0.201
NDA_A*	-0.000015	0.000045	-0.324	0.746	D_NDA_A*	-0.000006	0.000032	-0.201	0.841	R_BJP*	-0.000005	0.000024	-0.201	0.841
BJP*	-0.000040	0.000112	-0.351	0.726	D_BJP*	0.000025	0.000096	0.257	0.797	R_INC*	0.000016	0.000017	0.972	0.333
INC*	0.000038	0.000076	0.497	0.620	D_INC*	-0.000027	0.000073	-0.368	0.714	R_SG*	0.000001	0.000021	0.056	0.955
SG*	-0.000015	0.000142	-0.105	0.917	D_SG*	-0.000004	0.000104	-0.042	0.967	R_MS*	0.000005	0.000023	0.222	0.825
MS*	0.000124	0.000111	1.110	0.269	D_MS*	-0.000003	0.000087	-0.032	0.975	R_RG*	-0.000006	0.000020	-0.281	0.779
RG*	-0.000178	0.000113	-1.575	0.117	D_RG*	-0.000036	0.000098	-0.366	0.715	R_ABV*	-0.000016	0.000024	-0.678	0.499
ABV*	-0.000087	0.000075	-1.161	0.248	D_ABV(-1)	-0.000157	0.000101	-1.551	0.123	R_LKA(-1)	0.000034	0.000018	1.872	0.063
NM*	0.000088	0.000075	1.168	0.245	D_NM*	0.000037	0.000068	0.550	0.583	R_NM*	0.000012	0.000031	0.367	0.714
ΔBSE	0.000121	0.000094	1.282	0.202	ΔD_RFR	0.000002	0.000038	0.061	0.952	ΔRBSE(-1)	-0.000355	0.125387	-0.003	0.998
					ΔD_IRR	-0.000083	0.000049	-1.681	0.095	ΔRBSE(-2)	-0.107600	0.097341	-1.105	0.271
					ΔD_EVM	-0.000114	0.000065	-1.765	0.080	ΔRBSE(-3)	-0.125793	0.070068	-1.795	0.075
ΔLS_E	-0.000100	0.000107	-0.938	0.350	ΔD_LS_E	-0.000073	0.000075	-0.964	0.336	ΔR_LSE	-0.000013	0.000032	-0.410	0.683
ΔNXPM	-0.000033	0.000058	-0.575	0.566	ΔD_NXPM	-0.000093	0.000057	-1.629	0.105	ΔR_LKA	0.000008	0.000015	0.538	0.591
ΔUPA_A	0.000504	0.000305	1.654	0.100	ΔD_ABV	-0.000074	0.000058	-1.275	0.204	ΔR_RFR	-0.000002	0.000013	-0.165	0.869
@TREND	-0.000048	0.000047	-1.036	0.302	@TREND	-0.000006	0.000009	-0.717	0.474	@TREND	-0.000072	0.000059	-1.230	0.221
F-Bound Test Λ	F-statistic Value			7.29	F-Bound Test Λ	F-statistic Value			10.88	F-Bound Test Λ	F-statistic Value			3.63

Levels Equation at Unrestricted Constant and Unrestricted Trend

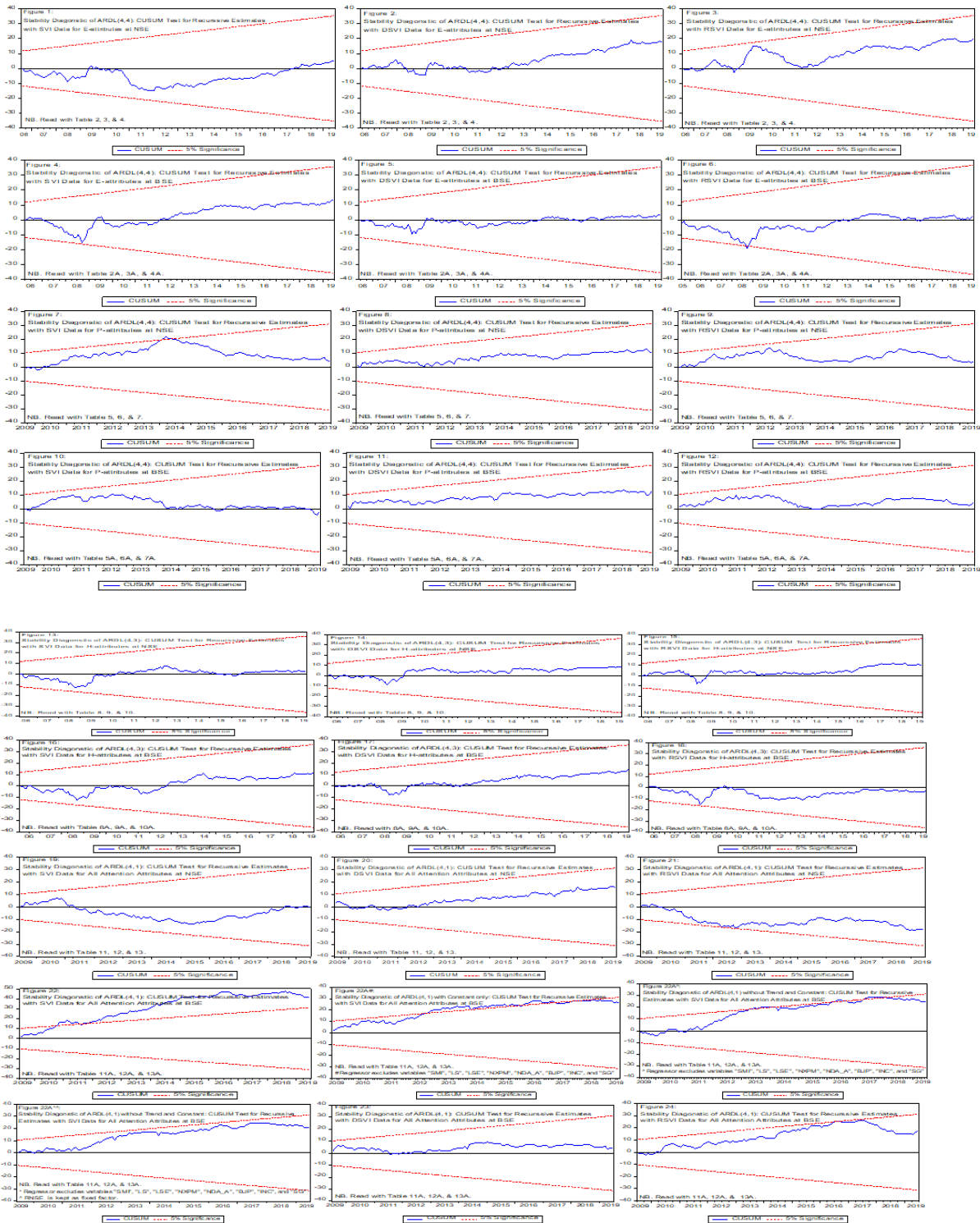
$$EC = RBSE - (-0.000111 * BSE + 0.00008 * NSE + 0.00004 * RFR - 0.000053 * RFIR - 0.000083 * IRR + 0.000051 * SMI - 0.000099 * SMR - 0.000158 * EVM + 0.000094 * EVM_A - 0.000028 * LS - 0.000224 * LS_E + 0.000323 * LSE + 0.000088 * NXPM - 0.00036 * UPA + 0.00043 * UPA_A - 0.000252 * NDA - 0.000015 * NDA_A - 0.00004 * BJP + 0.000038 * INC - 0.000015 * SG + 0.000125 * MS - 0.000181 * RG - 0.000088 * ABV + 0.000153 * LKA + 0.000089 * NM)$$

$$EC = RBSE - (0.000278 * D_BSE - 0.000357 * D_NSE + 0.000044 * D_RFR + 0.000126 * D_RFIR - 0.000024 * D_IRR + 0.000147 * D_SMI - 0.000156 * D_SMR - 0.000032 * D_EVM + 0.00021 * D_EVM_A - 0.000238 * D_LS - 0.000445 * D_LS_E + 0.000113 * D_LSE - 0.000178 * D_NXPM - 0.000278 * D_UPA + 0.0001 * D_UPA_A - 0.00011 * D_NDA - 0.00008 * D_NDA_A + 0.000031 * D_BJP - 0.000034 * D_INC - 0.000005 * D_SG - 0.000003 * D_MS - 0.000045 * D_RG - 0.000196 * D_ABV + 0.000171 * D_LKA + 0.000047 * D_NM)$$

$$EC = RBSE - (-0.000021 * RBSE + 0.000003 * R_NSE - 0.000033 * R_RFR - 0.000002 * R_RFIR + 0.000017 * R_IRR + 0.000008 * R_SMI + 0.000030 * R_SMR + 0.000019 * R_EVM - 0.000027 * R_EVM_A - 0.000003 * R_LS - 0.000081 * R_LS_E + 0.000058 * R_LSE + 0.000027 * R_NXPM + 0.000007 * R_UPA - 0.000038 * R_UPA_A - 0.000007 * R_NDA - 0.000023 * R_NDA_A - 0.000005 * R_BJP + 0.000016 * R_INC + 0.000001 * R_SG + 0.000005 * R_MS - 0.000005 * R_RG - 0.000016 * R_ABV + 0.000034 * R_LKA + 0.000011 * R_NM)$$
 Λ F-Bound Test: H0: No levels relationship; Actual Sample Size: n = 182, Asymptotic n = 1000; Sample; K = 25; Note: For F-Bound Table Values See Appendix 24.

* Variable interpreted as Z = Z(-1) + ΔZ; Note: For Acronyms of Test Parameters see Appendix 4.

Appendix 28: Figures 1 - 24 at the CUSUM recursive stability diagnosis test for the NSE and BSE market returns



References

- Avgerou, C., Masiero, S., Poulymenakou, A., 2019. Trusting e-voting amid experiences of electoral malpractice: The case of indian elections. *Journal of Information Technology* 34(3), 263–289. URL: <https://doi.org/10.1177/0268396218816199>.
- Banerjee, A., Dolado, J., Galraith, J.W., Hendry, F., 1993. Cointegration, error correction, and the econometric analysis of non-stationary data. URL: <https://doi.org/10.1093/0198288107.001.0001/acprof-9780198288107>.
- Banerjee, A., Dolado, J.J., Mestre, R., 1998. Error-correction mechanism tests for cointegration in a single equation framework. *Journal of Time Series Analysis* 19(3), 267–283. URL: <https://doi.org/10.1111/1467-9892.00091>.
- Bartos, A.E., 2016. Children and young people's political participation: A critical analysis, In Kallio, K., Mills, S. and Skelton, T. (Editors). *Politics, Citizenship and Rights. Geographies of Children and Young People 7*. Springer, Singapore.
- Black, F., 1986. Noise. *The Journal of Finance* 41(3), 528–543. URL: <https://doi.org/10.1111/j.1540-6261.1986.tb04513.x>.
- Bäcklund, P., Kallio, K.P., Häkli, J., 2014. Residents, customers or citizens? tracing the idea of youthful participation in the context of administrative reforms in finnish public administration. *Planning Theory and Practice* 15(3), 311–327. URL: <https://doi.org/10.1080/14649357.2014.929726>.
- Dimpfl, T., Jank, S., 2015. Can internet search queries help to predict stock market volatility? *European Financial Management* 22(2), 171–192. URL: <https://doi.org/10.1111/eufm.12058>.
- Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1), 3–56. URL: [https://doi.org/10.1016/0304-405X\(93\)90023-5](https://doi.org/10.1016/0304-405X(93)90023-5).
- Goodfellow, T., 2013. The institutionalisation of “noise” and “silence” in urban politics: Riots and compliance in uganda and rwanda. *Oxford Development Studies* 41(4), 436–454. URL: <https://doi.org/10.1080/13600818.2013.807334>.
- Grossman, S.J., Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. *The American Economic Review* 70(3), 393–408. URL: <https://doi.org/10.7916/D8765R99>.
- Joseph, K., Babajide Wintoki, M., Zhang, Z., 2011. Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting* 27(4), 1116–1127. URL: <https://doi.org/10.1016/j.ijforecast.2010.11.001>.
- Kallio, K.P., 2012. Political presence and the politics of noise. *Space and Polity* 16(3), 287–302. URL: <https://doi.org/10.1080/13562576.2012.733569>.
- Kallio, K.P., 2016. Youthful political presence: Right, reality and practice of the child. *Politics, citizenship and rights*, 89–110 URL: <https://doi.org/10.1007/978-981-4585-57-6>.
- Rawnsley, G.D., 2003. An institutional approach to election campaigning in taiwan. *Journal of Contemporary China* 12(37), 765–779. URL: <https://doi.org/10.1080/09636410903546673>.
- Ruez, D., 2017. I never felt targeted as an asian... until i went to a gay pub: Sexual racism and the aesthetic geographies of the bad encounter. *Environment and Planning A* 49(4), 893–910. URL: <https://doi.org/10.1177/0308518x16680817>.
- Takeda, F., Wakao, T., 2014. Google search intensity and its relationship with returns and trading volume of japanese stocks. *Pacific-Basin Finance Journal* 27(2), 1–18. URL: <https://doi.org/10.1016/j.pacfin.2014.01.003>.
- Tantaopas, P., Padungsaksawasdi, C., Treepongkaruna, S., 2016. Attention effect via internet search intensity in asia-pacific stock markets. *Pacific-Basin Finance Journal* 38(1), 107–124. URL: <https://doi.org/10.1016/j.pacfin.2016.03.008>.