Theoretical and Applied Economics
Volume XXIX (2022), No. 1(630), Spring, pp. 187-214

Attention economy and higher-order beliefs in voters' online attention searches

Paritosh Chandra SINHA
Rabindra Mahavidyalaya, Champadanga, W.B., India
paritoshchandrasinha@gmail.com

Abstract. *Presently we are living in an attention economy where individuals' attention-spectrum is becoming very basic to their social, political and economic decision choices. With the use of Google Trends search volume index (SVI) data, this study explores whether the voters' online attention searches around the context of the assembly election of West Bengal in 2021 show any higher-order beliefs or not. Methodologically, firstly, it has used the method of moments, then, followed both descriptive and inferential empirical analysis and finally, it has identified the cointegrating presence of voters' lower-order vis-à-vis higher-order beliefs in their online search-attention for a few selected socio-politico-economic keywords. The study offers a few policy implications of online attention searches at attention management by stakeholders.*

Keywords: higher-order beliefs, spatial dimension, behavioral economics, voters' attention.

JEL Classification: D72, D79.

Introduction

Attention is a vital and scarce cognitive resource. Its nature – economic or non-economic, depends on individuals' attention needs. Attention need is very basic to any decision choice – be it social, political or economic, etc. Given its greater utility, attracting the mass-attention spectrum has become an important decision issue during the rapid burst of ICT in our present days. The information spectrum includes information vis-a-vis misinformation (Black, 1986; Hofstetter et al., 1999). Interestingly, with the variety in the use of social media, misinformation spreads faster than information (Vosoughi et al., 2018; Figueira and Oliveira, 2017).

It is worth mentioning that the attention of the general public has gained the center stage in socio-politico-economic activities and this development is worthy of subsequent queries. In the presence of voters' online attention, we can structure the next set of queries as – Is the public equally attentive to their social issues? What do they identify once they pay attention to the masses? Do they pay attention to the present, past and future as well? What do the voters search for online? Do they search for the credibility of their favourite leaders or search for "credible leaders" only? Do they seek for new confirmatory news about their leaders' prospects to win the election? Does such online attention contribute to the fate of the leaders? Do they equally pay attention to economic issues as much as they pay to non-economic issues?

Even though the list of moderated queries is vast, the utility of voters' online attention search has remained a grey research area in the literature of behavioural and political economics. This study explores this specific area of research conceptually, and in the context, it empirically offers a brief study on the voters' online attention to socio-politico-economic issues about the 2021 assembly election in West Bengal, India. It puts forth that voters' online attention search demonstrates some higher-order beliefs and disbeliefs and thereby, contributes a confirmation of the election results to the literature of attention economy.

Towards the said development, the study now reviews the related literature in Section 1, then, it constructs the data and methodology in Section 2, and thereafter, presents the results and findings in Section 3 and finally, concludes the article in Section 4.

1. Literature review

In behavioural economics, the connotation of "higher-order beliefs" refers to individuals' judgments and decision choices about the others' judgments and decision choices (Sahlin, 1993). Individuals depend more on their beliefs about others' rationale for their own decision choices than that about their "own" rationale for their own decision choices. Individuals' higher-order beliefs are linked to the game theory models of decision choice at incomplete information (Angeletos and La'O, 2009; Morris and Shin, 2002). At presence of nominal shocks, peoples' obsession with the heterogeneous prior beliefs can also moderate the general public's reactions to the changes in the socio-economic environment through bringing "inertia" in the higher-order beliefs of the public (Angeletos and La'O, 2009, p. 35).

However, the condition of "nominal shocks" in Angeletos and La'O (2009) needs further qualification. A nominal shock may represent an absence of new information or a repackaging of existing information. In the other words, does public attention to new information influence the development of lower-order and/or higher-order beliefs? Do the individuals' higher-order beliefs also show inertia at presence of heterogeneity in attention search to new information? Does the mass population viz. voters refine their higher-order beliefs and disbeliefs about the political outcomes? These queries lead us to briefly explore the studies in behavioural economies in general and attention economics in particular.

Amongst the earlier studies, Keynes (1936) and Hayek (1945) have viewed attention economics in terms of individuals' coordination motive in decision choices identical to public voting. Amongst the modern studies, Da et al. (2011, 2015) and Dolgin (2012) have argued that availability of the high-speed internet connections, electronic contents for the relevant searches, vibrant social media, space for public attention and multiple search attempts by individuals – all contribute to the existence and persistency of attention economics. The extent and reach of misinformation can also be viewed in Marwick and Lewis (2017).

In a development of contemporary theory for attention economy, Franck (2019) has put forth that the "mental capitalism" where people presently live in has reframed the production function such that aspects of "mental world" rather than those of "material world" determine its economic forces. At presence of information and noise, interesting development of attention economy, news market, political bubbles and populism etc. can be observed in Hendricks and Vestergaard (2019). In a "canonical elaboration approach" from complete information set-up to incomplete information set-up, Kajii and Morris (2020) have showed that at limited common knowledge as well as at no restriction to new information, any refinement of the higher-order beliefs results in undominated correlated equilibrium. That is, the attempts of political attention attraction become a futile exercise in changing the higher-order beliefs of the voters.

Nonetheless, van Leeuwen and Vega (2021) have argued that the individuals' voting patterns are unevenly distributed over the decision space and at higher-order public discontents, the spatial dimensions offered by political parties appear in the form of populism-politics and thereby, consolidate their political supports.

Recent studies by Sinha (2021a, 2021b) explore that noise of investors' attention mania in the Indian stock markets is contributed by investors' attention searches for the mainstream Indian political parties and personalities. But why attention mania occurs in the public at the first place? In exploring it, this study proposes that higher-order beliefs in individuals' attention search are spatial in dimension and this makes attention economics to persist for long. There is little study in this direction of research and the paper fulfills this specific research gap.

2. Data and methodology

I have taken the case of assembly election in 2021 in an Indian state, West Bengal. I have used the Google Trends' search volume index (SVI) data for ten socio-politico-economic attention search keywords during January-June 2021 from the West Bengal region. These include the names of four major political parties in the state: All-India Trinamool Congress (AITMC) popularly known as "TMC", Bharatiya Janata Party popularly known as "BJP", Communist Party of India (Marxist) popularly known as "CPIM" and Indian National Congress popularly known as "Congress". The search keywords include two popular election songs – "Tumpa Sona" and "Khela Hobe". I use socio-politico-economic keywords – "Health Insurance", "Sonar Bangla", "NRC" and "CAA" as well. I assume that the SVI data represent voters' attention to socio-politico-economic affairs, analyse the data descriptively over their respective data periods and examine them with the inferential testing method towards finding cointegrations of search-attention at lower-order and higher-order beliefs.

Measures for beliefs

Beliefs are individuals' general tendencies in decision choices at given alternatives. Beliefs are influenced by the environmental and organisational stimuli (Hambrick and Mason, 1984; Markoczy, 1997). At any given situation, the organisational strategic choices and performance levels are partly determined by the underlying characteristics and partly by the managements' cognitive bases and value systems (Hambrick and Mason, 1984). Individual beliefs are influenced by the organisations' functional characteristics, the managerial age and their national identity but not by the throughput-decision process (Markoczy, 1997).

These studies have not differentiated the homogeneity and heterogeneity issues of the variable "individual belief" – beliefs of "own belief" and beliefs of "others' belief". The belief of someone's own conviction can be referred as lower-order belief or lower-order attributions (Smith, 1982, p. 441). Bosworth (2017) has showed that individuals' optimistic (pessimistic) beliefs about the partner's "beliefs optimistic" ("beliefs pessimistic") lead them towards greater (lesser) confidence on an issue of common knowledge. Therefore, higher-order beliefs include higher-order disbeliefs as well.

In developing the measures for higher-order beliefs, I use the method of moments. It suggests that the first two moments – the mean and variance of a sample communicate lower-order beliefs and the higher moments – skewness and kurtosis etc. communicate the higher-order beliefs (Rustichini, 1992; Chabi-Yo et al., 2008). Westfall (2014) showed that the kurtosis talks about the degree of tail-extremity of distribution. With the following four identities M1, M2, M3 and M4 respectively for the mean, variance, skewness and kurtosis, we define proxy measures for the attention variable/s (X_{ij}) – the search keywords viz., TMC, BJP, CPIM, Congress, Tumpa Sona, Khela Hobe, Health Insurance, Sonar Bangla, NRC and CAA. On the assumption that voters' learning takes a certain period of time, I have used a one month's window of lag-period to derive the respective time series values for the mean (x_{it}), variance (v_{it}), skewness (Sk_{it}) and kurtosis (Kt_{it}) in the MS Excel 2019 software. In reporting the results, I also align the search results with vital information dates related to the 2021 assembly election in West Bengal. A list of such events can be found at http://wikipedia.org[1].

$$\bar{x}_{it} = \frac{\sum_{t-30}^{t} x_{it}}{n} \ldots\ldots\ldots (M1)$$

$$v_{it} = \frac{\sum_{t-30}^{t}(x_{it} - \bar{x}_{it})^2}{n-1} \ldots\ldots\ldots\ldots (M2)$$

$$Sk_{it} = \frac{n}{(n-1)(n-2)} \sum_{t-30}^{t} \left(\frac{x_{it} - \bar{x}_{it}}{\sqrt{v_{it}}}\right)^3 \ldots\ldots\ldots (M3)$$

$$Kt_{it} = \left\{\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{t-30}^{t} \left(\frac{x_{it} - \bar{x}_{it}}{\sqrt{v_{it}}}\right)^4\right\} - \frac{3(n-1)^2}{(n-2)(n-3)} \ldots\ldots\ldots (M4)$$

Regression model

Besides a descriptive analysis for the SVI data and their moments, the study examines the presence of possible cointegration of the SVI data with both the lower-order and higher-order moments. In Annexure 1-4, the results for ADF unit root test and break point unit root test as well show that most of the SVI time-series data are stationary at their level data while most of their moments are non-stationary. The explanatory variables' set includes I(1) and I(0) variables but none of them are I(2). Hence, the methods of Granger causality and Johansen cointegration cannot be applied in exploring effects of lower-order vis-a-vis higher-order beliefs on voters' search attention during the period. Hence, with uses of appropriate lag lengths, this study follows the bound testing approach in the autoregressive distributive lagged (ARDL) model of Pesaran et al. (2001). The methodological issue is addressed here briefly. A detailed description of the same can be found in Sinha (2021a, 2021b).

Since voters' decision choice is mutually exclusive amongst the given political parties, instantaneous attention, A_{it} to i-th prime attention issue at time t is assumed to be cointegrated with its k number of attention search moments MA_{ikt} along with the other j-number of secondary attention issues A_{jt}. The equation *Eq-SLF* is a static long-run relationship. Its unrestricted short-run ARDL regression model specification is in *Eq-USF*. Besides, the conditional long-run and conditional error correction forms are respectively laid out in the conditional model equations *Eq-CLF* and *Eq-ECF*. I use each of the keywords TMC, BJP, CPIM and Congress as the prime attention search variable alternatively and the rest as the secondary search keywords along with those of Tumpa Sona, Khela Hobe, Health Insurance, Sonar Bangla, NRC and CAA.

$$A_{it} = \alpha_{i0} + \sum_{k=1}^{k} \sum_{t=1}^{n} \alpha_{ik} \mathrm{MA}_{ikt} + \sum_{i \neq j, j=1}^{j} \sum_{t=1}^{n} \alpha_j \mathrm{A}_{jt} + \epsilon_{it} \ldots\ldots\ldots (Eq - SLF)$$

$$\mathrm{A}_{it} = \gamma_{i0} + T_t + \sum_{r=1}^{r} \sum_{t=1}^{n} \alpha_{ir} \mathrm{A}_{it-r} + \sum_{q=1}^{q} \sum_{k=1}^{k} \sum_{t=1}^{n} \beta_{ikq} \mathrm{MA}_{ikt-q} + \sum_{q=1}^{q} \sum_{i \neq j, j=1}^{j} \sum_{t=1}^{n} \alpha_{jq} \mathrm{A}_{jt-q} + \sum_{k=1}^{k} \sum_{t=1}^{n} \lambda_{ik} \mathrm{MA}_{ikt} + \sum_{i \neq j, j=1}^{j} \sum_{t=1}^{n} \alpha_j \mathrm{A}_{jt} + \varepsilon_{it} \ldots\ldots (Eq - USF)$$

$$\Delta A_{it} = \beta_{i0} + T_t + \sum_{r=1}^{r} \sum_{t=1}^{n} \beta_{ir} \Delta A_{it-r} + \sum_{q=1}^{q} \sum_{k=1}^{k} \sum_{t=1}^{n} \gamma_{ikq} \Delta \mathrm{MA}_{ikt-q} + \sum_{q=1}^{q} \sum_{i \neq j, j=1}^{j} \sum_{t=1}^{n} \gamma_{jq} \Delta \mathrm{A}_{jt-q} + \sum_{r=1}^{r} \sum_{t=1}^{n} \delta_{ir} \mathrm{A}_{it-r} + [\sum_{q=1}^{q} \sum_{k=1}^{k} \sum_{t=1}^{n} \lambda_{ikq} \mathrm{MA}_{ikt-q} + \sum_{q=1}^{q} \sum_{i \neq j, j=1}^{j} \sum_{t=1}^{n} \lambda_{jq} \mathrm{A}_{jt-q}] + \xi_{it} \ldots\ldots (Eq - CLF)$$

$$\Delta A_{it} = \beta_{i0} + T_t + \sum_{r=1}^{r} \sum_{t=1}^{n} \beta_{ir} \Delta A_{it-r} + \sum_{q=1}^{q} \sum_{k=1}^{k} \sum_{t=1}^{n} \gamma_{ikq} \Delta \mathrm{MA}_{ikt-q} + \sum_{q=1}^{q} \sum_{i \neq j, j=1}^{j} \sum_{t=1}^{n} \gamma_{jq} \Delta \mathrm{A}_{jt-q} + \omega_i ECT_{t-1} + \varsigma_{it} \ldots\ldots (Eq - ECF)$$

In the above ARDL models, the endogenous dependent variables A_{it} has r lags, the exogenous independent variables MA_{ikt} and A_{jt} have q lags, and T_t is the trend variable. In the regression model *Eq-USF*, the lagged variables represent the long-run attention impacts while the non-lagged ones represent their short-run impacts. In *Eq-CLR*, a variable with (without) the notation Δ in prefix represent the short-run (long-run) attention impact. In *Eq-ECF*, the variable *ECT* with a one-day lag period represents the combined long-run level-effect of the exploratory variables in *Eq-SLF*. Besides, ϵ_{it}, ε_{it}, ξ_{it} and ς_{it} are the residual terms in the models.

In operating the regressions in EViews 10, firstly, the optimal lag-length r is identified with the method of Alkaline Information Criterion (AIC) for endogenous dependent variable A_{it-r}, then, a max limit of q lags for the exogenous variables MA_{ikt-q} and A_{jt-q} at *constant and Trend* are specified and finally, "automatic selection" of variables at AIC is set instead of "fixed" selection. I regress the *i*-th attention variable as the dependent variable and run the sets of ARDL models separately for the dependent variables *TMC*, *BJP*, *CPIM* and

Congress. The ARDL regression system has a maximum limit for the size of variables to be entered in EViews 10. For each prime search variable, the explanatory variables' set has endogenous variables at r lag-length, the four moments of the prime search variable and the other nine search variables along with their respective lags at q lag-length. Here, r is the optimal lag length determined in *Variance Analysis* and q is the maximum lag length until a system crash is faced. Hence, the size of Google search keywords is kept limited to ten keywords only. An absence of persistency in the Google searches has also restricted us from using some other keywords like the names of regional leaders in West Bengal. It is expected that voters focus on the state issues only and this limits their online search attention. So, the names of political leaders like Narendra Modi, Amit Shah, Jashwant Sinha and Jogi Adityanath etc. are not used here.

On revealing the persistency issue of the ARDL models, I explore the possible presence of significant heteroscedasticity problems in the ARDL models at 5% level of significance and augment the results of the ARDL model/s in *Eq-USF* within the following GARCH-X (v,u) framework. Here, θ is the GARCH constant, α_u is the ARCH (-u) impact and β_v is the GARCH (-v) impact. We have the following empirical testing procedure.

$$\begin{aligned}\mathrm{A}_{it} = \gamma_{i0} + T_t + \sum_{r=1}^{r}\sum_{t=1}^{n}\alpha_{ir}\,\mathrm{A}_{it-r} + \sum_{q=1}^{q}\sum_{k=1}^{k}\sum_{t=1}^{n}\beta_{ikq}\mathrm{MA}_{ikt-q} \\ + \sum_{q=1}^{q}\sum_{i\neq j,j=1}^{j}\sum_{t=1}^{n}\alpha_{jq}\mathrm{A}_{jt-q} + \sum_{k=1}^{k}\sum_{t=1}^{n}\lambda_{ik}\mathrm{MA}_{ikt} + \sum_{i\neq j,j=1}^{j}\sum_{t=1}^{n}\alpha_{j}\mathrm{A}_{jt} \\ + [\,\theta + \sum_{u=1}^{u}\sum_{t=1}^{n}\alpha_u\,\epsilon_{it-u}^2 + \sum_{v=1}^{v}\sum_{t=1}^{n}\beta_v\sigma_{t-v}^2\,] \dots\dots (Eq - GARCH - X)\end{aligned}$$

Hypothesis testing

With the regression models, I empirically explore the presence of lower-order and higher-order beliefs in voters' online search attention. I analyse the following null hypothesis H_0 against the relevant alternative hypothesis H_1.

***H₀*:** Voters' online search attention does not show lower-order and higher-order beliefs.

***H₁*:** Voters' online search-attention shows cointegrating attention impacts of their lower-order and higher-order beliefs.

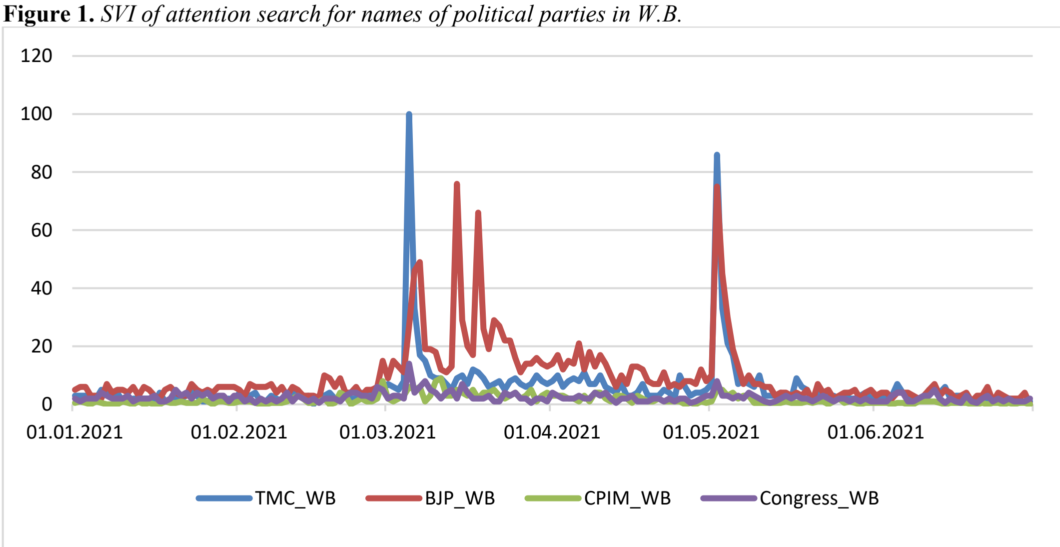
3. Results and findings

The results of the descriptive empirical analysis are given in figures and those of inferential empirical analysis are produced in the tables. In Figures 1-3, it shows the google SVI trends data for the keywords of "TMC", "BJP", "CPIM" and "Congress", for those of "Tumpa Sona" and "Khela Hobe", and of "Health Insurance", "Sonar Bangla", "NRC" and "CAA". These show popularity in attention searches. On the lower-order beliefs, it depicts progressions of the sample mean and variance for the keywords: the names of political parties, election songs and election promise in Figures 4-5, Figures 6-7 and Figures 8-9 respectively. On the higher-order beliefs, it shows their respective skewness and kurtosis in Figures 10-11, Figures 12-13 and Figures 14-15 respectively. The inferential empirical results with the ARDL model and its augmented GARCH-X model are depicted in Tables 1-4. It shows GARCH graphs for the conditional standard deviations with *TMC*, *BJP*, *CPIM* and *Congress* in Figure 16-19, and their conditional variances in Figures 20-23 as well. Hereinafter, the study interchangeably uses the search keywords and their variable-acronyms given in Annexures 1-4.

Attention search trends

Figure 1 shows that there is an exponential sudden rise in attention search for the keyword "TMC" on 5 March 2021 – a date on which the Left Front announced its candidates' list for the first two phases, followed by three sudden rises in attention search for "BJP" on 6 March 2021 – a date when the Indian National Congress announced its list of candidates for the first two phases, 14 March 2021- the congress revealed its second list and 18 March 2021 – a date when COVID-19 cases spiked in West Bengal. A repeat of such surge in attention interest is also found on 2 May 2021, the vote-counting date. Apart from the said enthusiasms in attention search, the rest of the study periods shows moderately low to very low attention interest.

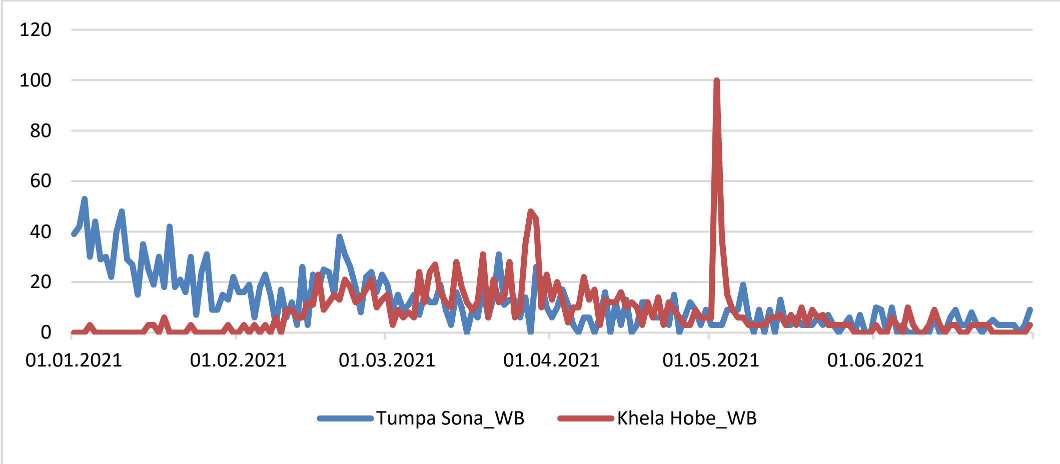
Figure 1. *SVI of attention search for names of political parties in W.B.*



Source: Prepared by the author. Note: "WB" in the variable's legend shows the search location.

Figure 2 shows that individuals' attraction to the song "Tumpa Sona" has received a lot of small spikes but eventually faded persistently while that to "Khela Hobe" has started a bit dimmed off but the same has gained its momentum in the middle of the study period and has received two exponential bursts on 29 March 2021, a date when the BJP changed its candidates just before filing the nomination and on 2 May 2021, the counting date.

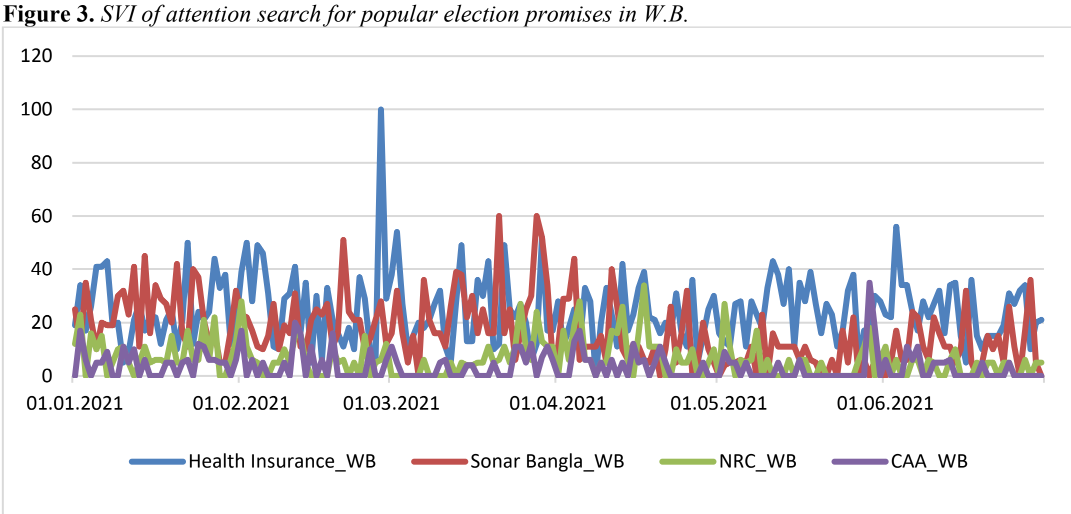
Figure 2. *SVI of attention search for popular election songs in W.B.*



Source: Prepared by the author. Note: "WB" in the variable's legend shows the search location.

In Figure 3, it is found that search keywords representing different election promises has received moderately high attention over the study period while "Health Insurance", out of the competing four election promises, has received a massive attention boost on 27 February 2021 – a date when the West Bengal government published COVID-19 health bulletin[(2)] and the ABP News published its C-Voters' opinion-poll prediction of a win for the AITMC in West Bengal[(3)] – just following the election schedule announcement on 26 February 2021.

Figure 3. *SVI of attention search for popular election promises in W.B.*



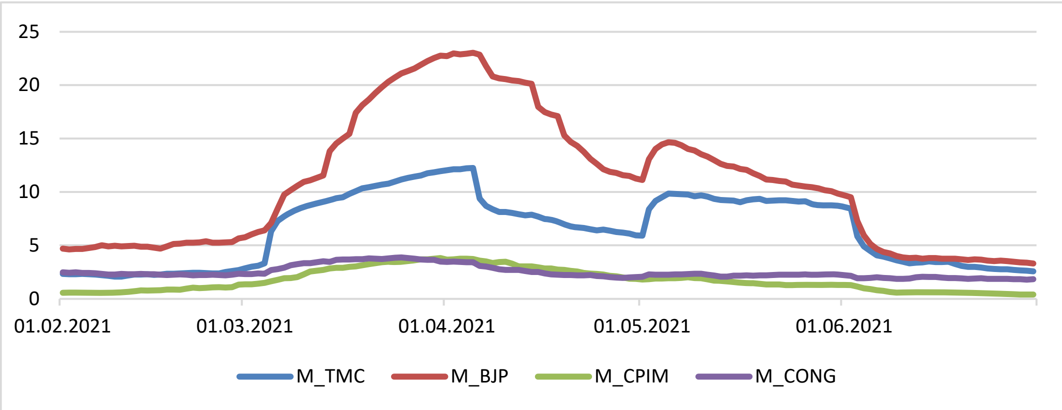
Source: Prepared by the author. Note: "WB" in the variable's legend shows the search location.

The above observations suggest that google trends SVI data have information contents and these can be used to explore the nature of the voters' beliefs – lower order beliefs vis-à-vis higher-order beliefs.

Lower-order beliefs

Amongst the said two measures for lower-order beliefs, the mean of the SVI data can suggest for the voters' craziness in search-attention while the variance measure of SVI data can show the persistency of such craziness.

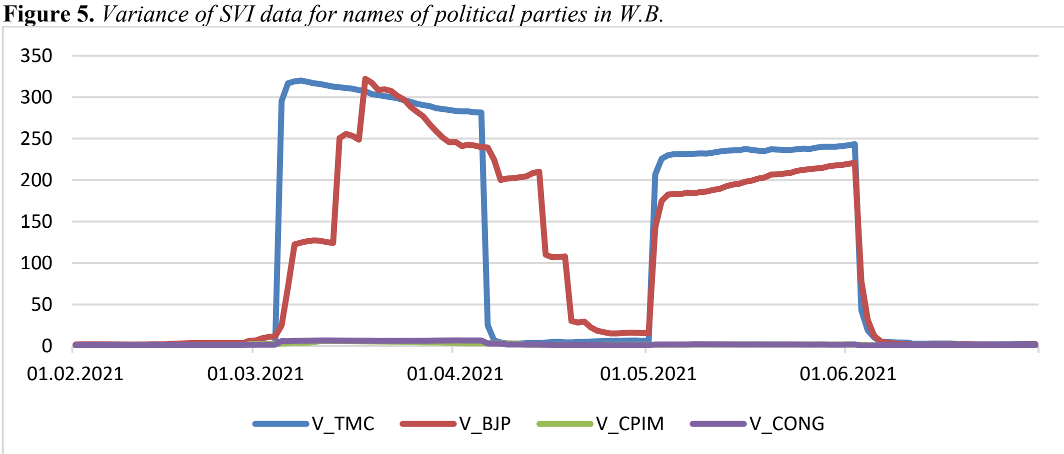
Figure 4. *Mean of SVI for names political parties in W.B.*



Source: Prepared by the author.

Now, Figure 4 depicts that the mean of attention search keywords viz., "TMC", "BJP", "CPIM" and "Congress", that is, magnitudes of variables M_TMC, M_BJP, M_CPIM and M_CONG respectively – all have set in to gain public attention on 5 March 2021 – the date of issue of notification for the 2nd phase of the election, both M_TMC and M_BJP reached their maximum on 5 April 2021 – the date of scrutineer of nominations for the 6th phase of the election while M_CPIM and M_CONG have reached their respective picks on 2 April 2021 and 31 March 2021. The public craze for "BJP" can be viewed with its mostly higher mean values than those for "TMC" over the progressions of M_BJP and M_TMC. The said public crazes in terms of M_CPIM and M_CONG were limited and constrained as well.

Figure 5. *Variance of SVI data for names of political parties in W.B.*

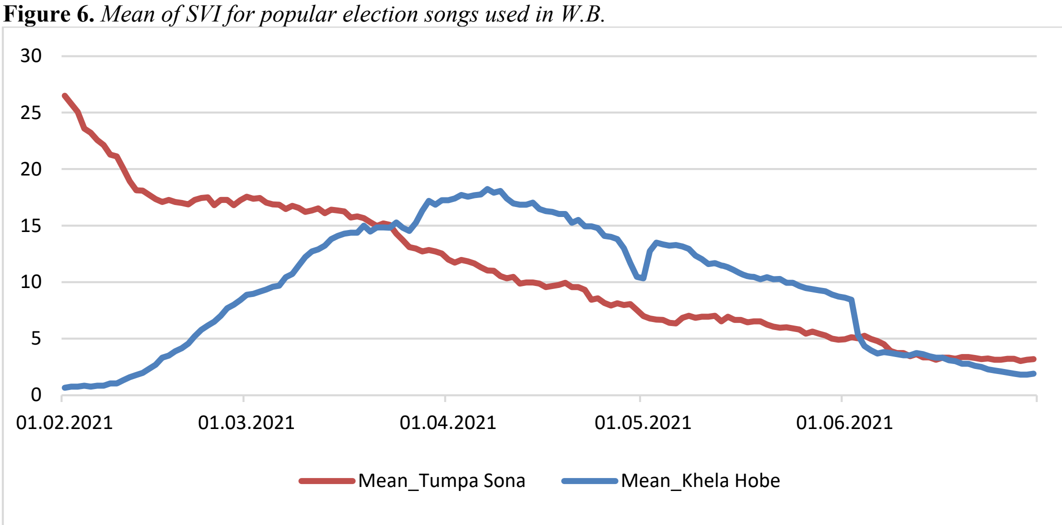


Source: Prepared by the author.

In Figure 5, with the variance measures of the SVI data viz., V_TMC, V_BJP, V_CPIM and V_CONG, I demonstrate that the above-stated attention craze for "TMC" i.e., V_TMC has received steady persistency during both the voting days – 6 March and 4 April 2021 and the post-election period – 3 May and 2 June 2021. Interestingly, it is found that the said craziness for "BJP" i.e., V_BJP has first received a step-wise increase and then similar step-wise fall during the voting days while that remained steady during the post-election period. The other two attention measures viz., V_CPIM and V_CONG have laid flat in terms of persistency in their attention craziness over the study period.

Now, I explore the craziness of individuals' search attention on the popular election songs in Figure 6 and its persistency in Figure 7.

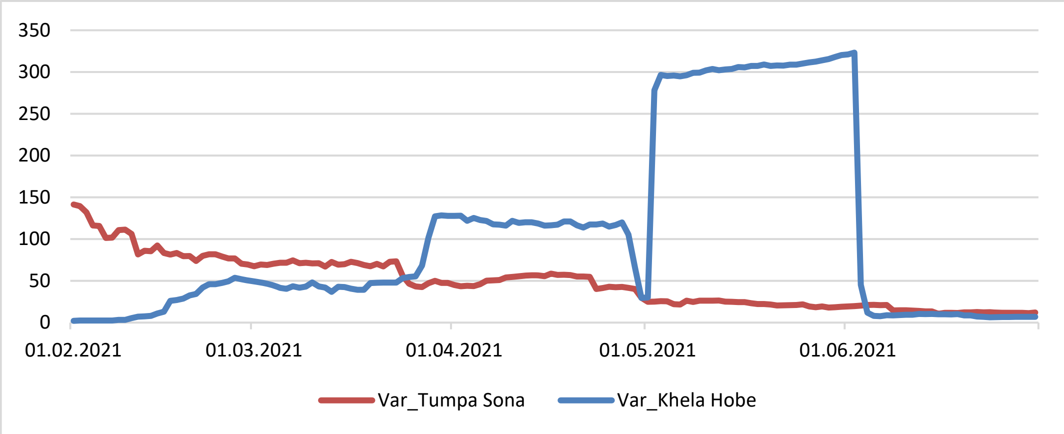
Figure 6. *Mean of SVI for popular election songs used in W.B.*



Source: Prepared by the author.

In Figure 6, it is showed that "Tumpa Sona" has started with a stormy craze of attention but received a sustained decline over the progress of the election days while, on the other hand, "Khela Hobe" has gained momentum in the attention craze till 9 April 2021 – just before the fourth phase of election and thereafter, the same has set in to decline. Interestingly, the latter election song has received a decisive spike in attention craziness on 2 May 2021, the counting date. I also find confirmation in terms of the said observations in Figure 7 below as well. Here, it can be identified that there exist persistent falls in craziness for "Tumpa Sona" while, in contrast to that, there are two persistent boosts in the attention flow for "Khela Hobe" from 31 March to 28 April 2021 and from 5 April to 1 June 2021.

Figure 7. *Variance of SVI for popular election songs used in W.B.*

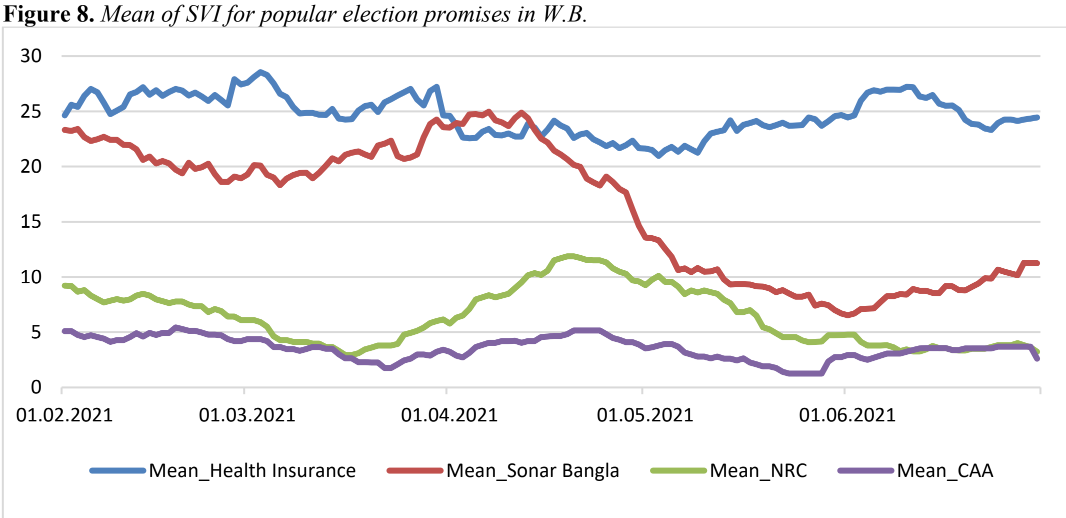


Source: Prepared by the author.

Besides the above, the study also explores voters' attention craziness and its persistency thereof for the election promises viz., "Health Insurance", "Sonar Bangla", "NRC" and "CAA" offered by the leading as well as aspiring political parties in West Bengal.

Here, in the following, Figure 8 shows that the voters' attention craziness for the first election promise has remained living at the top mostly over the whole study period while that for the second one has remained energetic and living till 13 April 2021 and thereafter, the same has showed a short-fall in its vitality. On the rest two election promises, I identify that voters' attention has showed the least vitality till the third week of March 2021, thereafter, the same depicts a boost in voters' attention craziness till the third week of April 2021 as the election season enters into its sixth phase, and finally, the craziness for the same declined steadily.

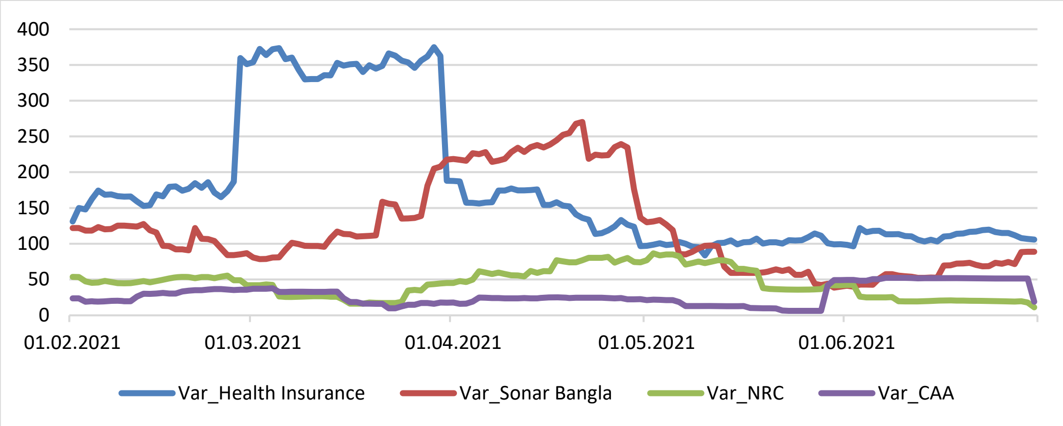
Figure 8. *Mean of SVI for popular election promises in W.B.*



Source: Prepared by the author.

On the persistency of craziness, Figure 9 identifies that "Health Insurance" has picked up a sustained craziness on 28 February 2021 and persistently maintained till the end of March 2021 when the same for "Sonar Bangla" just gained persistency. That is, the persistency in the latter came once that for the former just reaped its attention utility. However, voters' craziness on the other two election promises just received the left-over in terms of persistence in attention craziness – "NRC" received its most persistency on 5 May 2021, long after the counting date and interestingly, it is lower than the least persistency of "Health Insurance" as well.

Figure 9. *Variance of SVI for popular election promises in W.B.*



Source: Prepared by the author.

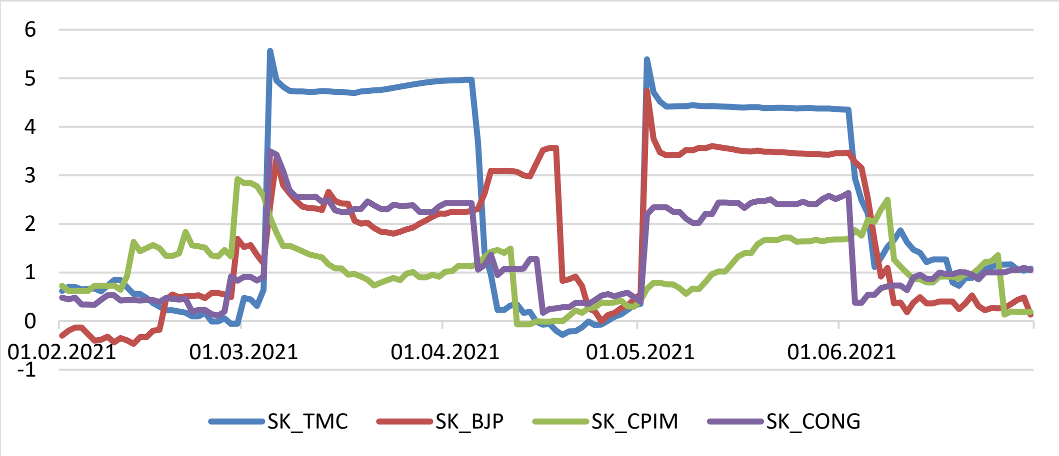
The stated observations suggest that even if voters' first-order search-attention infers a presence of limited information in voters' decision choices during the recently held assembly election in West Bengal, the same leads us exploring into their attention spectrum.

Higher-order beliefs

Amongst the said two measures of higher-order beliefs, the skewness of the SVI data suggest for the presence of right-tail or left-tail extremity in search-attentions while the kurtosis measure of the same shows the degree or persistency of such tail-extremity – the "propensity to produce outlier" (Westfall, 2014, p. 191).

Now, Figure 10 shows that the skewness measure of the SVI data for search keyword "TMC" locates in the right-hand side (i.e., positive side) of the data distribution over the whole period except for two short event windows over 24 February to 28 February 2021 and 15 April to 25 April 2021. In the former window(4), *Democracy Times Network*, a twitter handler re-twits a pre-poll survey made by the twitter-based opinion poll agency *Asia Effects @AsiaEffects* and projects a hung assembly result (read with the Wikipedia page mentioned earlier). In the second window(5), *NK Digital Magazine* (in Bengali) has published a public survey report online in the *YouTube* projecting a contrary view of the earlier one. Nonetheless, the skewness measure confirms presence of a right-tail attention concentration in favour of "TMC" during the election period and post-election period as well. Such concentration for the other three attention search keywords was mostly at the halfway mark of “TMC” or below during the election days while the same enhanced during the post-election period only for “BJP”.

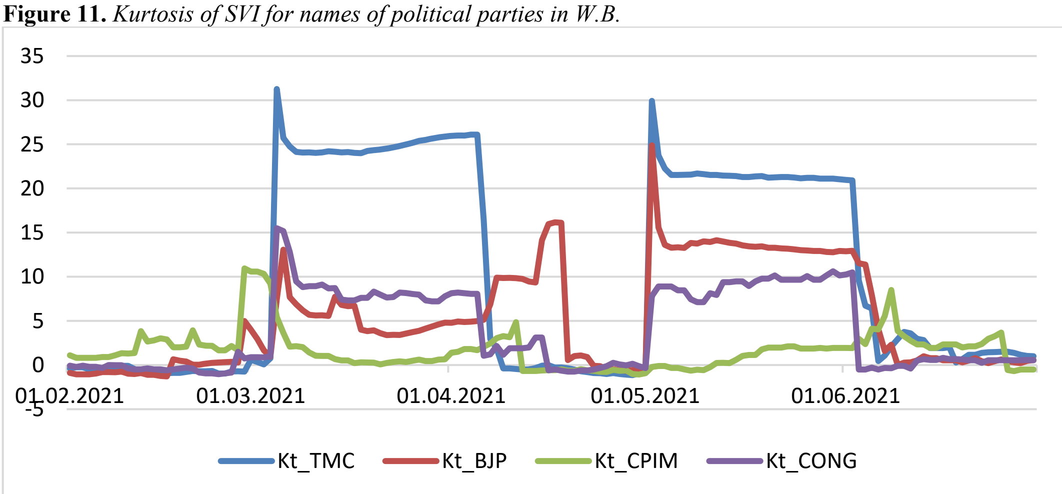
Figure 10. *Skewness of SVI for names of political parties in W.B.*



Source: Prepared by the author.

The above observations pave us to ponder on the attention utility of keyword searches at election days and post-election periods as well. In Figure 11, the magnitudes of the kurtosis measure confirm the aforementioned observations. The attention searches for “TMC” show the highest persistency of right-tail attention extremity amongst the search keywords and illustrate the propensity of attention outlier effects during the election days and post-election period as well. That is, there exist tremendous extents of higher-order beliefs for “TMC” at both the periods – during the election days and the post-election period while “BJP” gained during the post-poll period and that for “Congress” remained unchanged during the two-time spans.

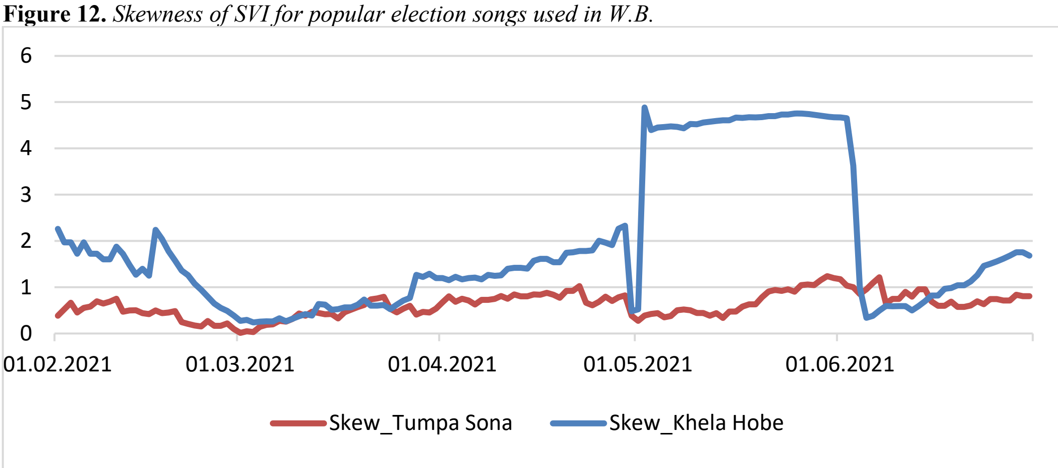
Figure 11. *Kurtosis of SVI for names of political parties in W.B.*



Source: Prepared by the author.

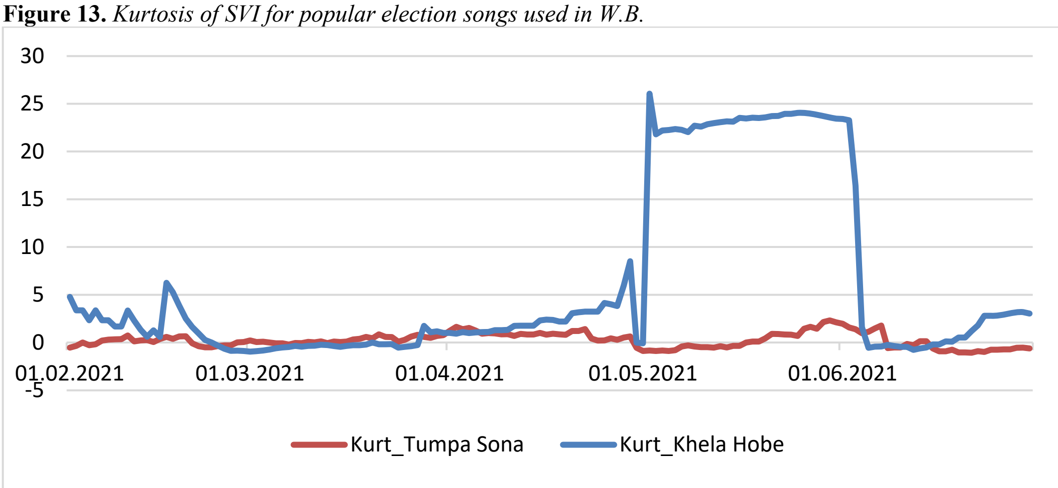
Figure 12 depicts that the skewness measure for the political song "Khela Hobe" has remained higher at the right-tail region of the data distribution than that for "Tumpa Sona" during the entire election period, and surprisingly, the former has experienced a dramatic fall in its magnitude on 1 May 2021 just before the counting day but eventually has risen on 3 May 2021 after the publication of election results. These results show that the tail-measure of the SVI data has intriguing messages within it and one needs to dive into it. In doing so, in Figure 13, a persistency is found in the presence of right-tail extremity for SVI search keyword "Khela Hobe" during the post-poll periods while the same competed neck and neck with "Tuma Sona" during the election season. Nonetheless, in both the figures, it is also demonstrated that "Khela Hobe" has regained the "sport-sprit" even in June 2021 long after the publication of election results. A possible explanation of the same, however, can lead us towards further exploration and ingenious insights in attention economy may justify the same.

Figure 12. *Skewness of SVI for popular election songs used in W.B.*



Source: Prepared by the author.

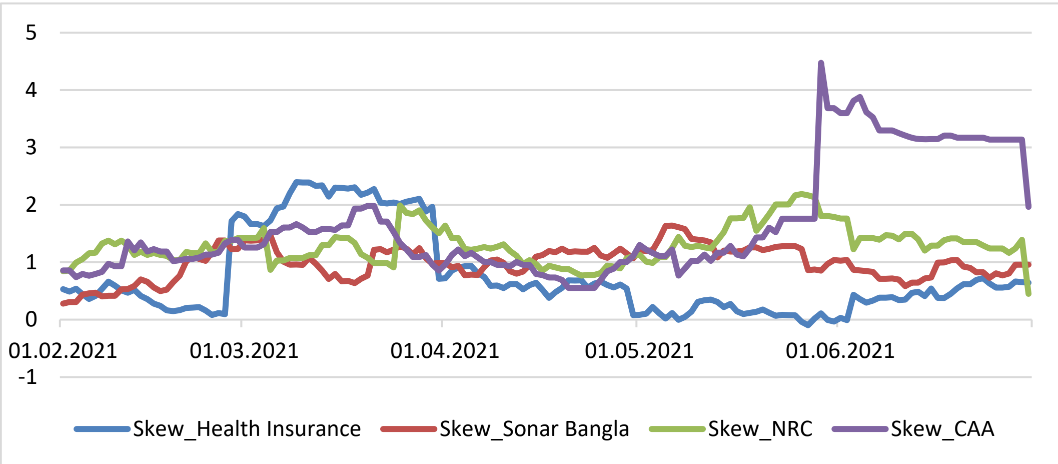
Figure 13. *Kurtosis of SVI for popular election songs used in W.B.*



Source: Prepared by the author.

Now, I explore the presence of higher-order beliefs towards the election promises. Here, Figure 14 shows their magnitudes of skewness. It demonstrates that “Health Insurance” has out-performed the other promises in terms of its presence in the right-tail of the data distribution during March 2021 entirely while in the next month, the same fall short to the others just after the end of the second phase of the election. The other search keywords have remained energetic in terms of their right-tail presence in the SVI data distribution. Besides, in the post-poll period, particularly in June 2021, the keyword “CAA” appears to be the major right-tail contributor.

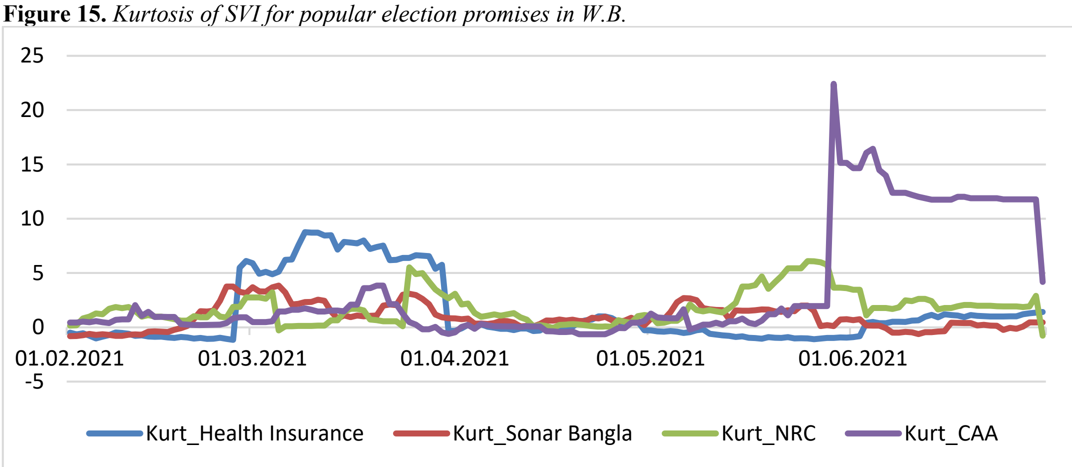
Figure 14. *Skewness of SVI for popular election promises in W.B.*



Source: Prepared by the author.

Nonetheless, in Figure 15 – with the magnitudes of kurtosis measure for the respective election promises, it shows corroborative results to those mentioned earlier: “Health Insurance” has persistently remained the outlier attention contributor from 1 March to 1 April 2021 while “CAA” has appeared as the new outlier attention impetus in June 2021.

Figure 15. *Kurtosis of SVI for popular election promises in W.B.*



Source: Prepared by the author.

Attention cointegration at different beliefs: To focus on the research hypothesis, I report the effects of lower-order and higher-order beliefs on search attention. It depicts the results with the unrestricted ARDL models, their conditional long-run forms (CLFs), the conditional error correction forms (ECFs) and the GARCH-X models in Tables 1-4.

In Table 1, it is showed that voters' online search-attention for keywords "TMC" and "CPIM" are significantly influenced by its all four measures of lower-order and higher-order beliefs measures at 5% level of significance while that for "BJP" shows only the effects of the two lower-order beliefs measures and "Congress" lacks that for the kurtosis measure only. It shows dynamic swings in signs of the coefficient-values over different lags of both beliefs-measures. Interestingly, it shows that attention to "TMC" has received multi-front cointegrating positive attention impacts of "BJP", "CONG" and "CPIM" while the same to "BJP", "CPIM" or "CONG" has received cointegrating positive attention impacts of "TMC" only. These results show a good fit of the models with voters' synergetic cointegrating attention impacts in favour of "TMC" while the others lack such impacts. Here across the attention spectrum, attention to "TMC" only shows presence of heteroskedasticity and there are no residual serial correlations. With "TMC", "BJP" and "CPIM", the model's instability can be found at CUSUM test of squared residuals. In brief, the voters' political search-attention shows effects of different order beliefs. However, I specify the other dimensions of its nature in the following.

With the conditional long-run form (CLF) of the ARDL model, it shows short-run and long-run attention impacts in Table 2. It demonstrates that voters' search attention to "TMC" is influenced by the presence of long-run and short-run impacts at both higher-order and lower-order beliefs for attention to "TMC". In contrast, attention to "BJP" shows long-run and short-run impacts at lower-order beliefs, attention to "CPIM" shows short-run impacts at both higher-order and lower-order beliefs, and attention to "CONH" shows short-run lower-order beliefs only. Besides, it is found that attention to "BJP", "CPIM" and "CONG" shows both short-run and long-run attention impacts of TMC" while attention to "TMC" shows only that aggregate cointegrating attention impacts from "BJP", "CPIM" and "CONG" as well. These illustrate that attention to "TMC" is pitched at the decibels of voters' different order beliefs and attention search pulses as well. The presence of significant F-bound F-test statistics also confirms the persistency of the stated cointegrating relationships.

Table 3 shows the results for the conditional error correction forms (ECF) of the ARDL models. It shows that the cointegration multiplier is -0.6143 for attention to "TMC" while that to "BJP", "CPIM" and "CONG" is respectively -0.62538, -0.84679 and -0.81414. Besides, the table shows their individual short-run cointegration effects. Out of the short-run effects, it finds that voters' attention to "TMC", "BJP" and "CONG" ("CPIM") has noisy dynamic effects in terms of both positive and negative values of the coefficients for lower-order (higher-order) belief measure/s while that to "TMC" ("CONG") has a deterministic positive (negative) effect at the higher-order belief measure. Interestingly, in a competitive depiction of voters' attention economy, attention to "BJP" ("CPIM" and "CONG") shows deterministic positive (noisy dynamic) short-run effect of attention to "TMC" while attention to "TMC" had not showed any impulse of attention to "BJP", "CPIM" and "CONG". Amongst all, voters' attention to "TMC" experiences the highest explanatory power as well.

In Table 4, ARCH and GARCH effects in GARCH-X augmentation as showed. To save space, I avoid reiterating the results on ARDL specification in the GARCH-X model and these are mostly similar to those in Table 1. However, attention to "TMC" and "CPIM" shows significant ARCH and GARCH effects while attention to "TMC" shows the heteroscedasticity problem only. This confirms that heterogeneity in attention cointegration does not refute the persistency in the ARDL models. Figure 16 and Figure 17 also settle such apprehension.

4. Conclusion

Voters' attention spectrum, if initiated by voters' online self-information search or positioned by the political parties as promotion tactics – both contribute to the formation of voters' beliefs in decision choices. Such beliefs pose lower-order beliefs once self-confirmation is formed by one's own-rationale while the same poses higher-order beliefs once it is formed by the others' rationale. On the context of the 2021 assembly election in W.B., India, this study ingeniously enumerates that even if the voters were mostly attentive to both "TMC" and "BJP", "Health Insurance" has appeared as the search champion during the election season while "Khela Hobe" has trumped at the post-election times. In brief – in terms of lower order beliefs, "BJP", "Khela Hobe" and "Health Insurance" have received voters' higher average persuasions at a varied level of distortion while their competitors have received lesser average persuasions at a constant level of distortion. On the higher-order beliefs, "TMC" has outperformed others at both the election days and the post-election period while "Health Insurance" and "Khela Hobe" outperform their competitors during the election days and the post-election period respectively. Nonetheless, it shows that voters' search attention to a particular political party demonstrates cointegrating relationships in terms of different order beliefs. While a presence of multi-order beliefs – both higher-order and lower-order beliefs, is most likely to contribute robustness in voters' attention search, the presence of confirmation in voters' decision choice comes only with the presence of positive effects of their higher-order beliefs.

Therefore, the marketers of political campaigns should pay attention to the presence of cointegrating impacts of voters' higher-order beliefs that predominantly exist in the attention economy during the election seasons. I corroborate the importance of strategic positioning by the political parties in their election managements in general and their campaign marketing in particular and ingeniously contribute to the literature with original findings.

In a policy implication of the present study, the election agencies may step up towards public education on voters' attention management during election periods and thereby, curbing possible political violence in the locality. The governments can utilize this study in nudging the public behaviours towards their desired behaviours at hygiene and safety protocols during COVID-19. The study used a limited number of search keywords and any generalization of the observations in the study is strictly cautioned and for a replication of the results, it needs similarity in the use of the data sets and the use of equivalent methodology as well. The present endeavour is purely academic and the readers should avoid digging into any political favouritism by the author towards any political party at all. Future works, however, may extend the present work towards the inclusion of attention search keywords for the names of national and regional political leaders vis-à-vis their political speeches.

Notes

(1) https://en.wikipedia.org/wiki/2021_West_Bengal_Legislative_Assembly_election
(2) https://www.wbhealth.gov.in/uploaded_files/corona/WB_DHFW_Bulletin_27th_ FEBRUARY_REPORT_FINAL.pdf
(3) https://www.youtube.com/watch?v=kqBtqlzmyY8
(4) https://publish.twitter.com/?query=https%3A%2F%2Ftwitter.com%2FAsiaElects%2 Fstatus%2F1364579209700667393&widget=Tweet; https://www.oneindia.com/west-bengal-election-2021-opinion-poll-and-exit-poll/; https://www.crowdwisdom360.com/blog/detail/580
(5) https://www.youtube.com/watch?v=p55PWgCWWMI

References

Angeletos, G.-M. and La'O, J., 2009. Incomplete information, higher-order beliefs and price inertia. *Journal of Monetary Economics, 56, S19-S37.* DOI: 10.1016/j.jmoneco.2009.07.001

Black, F., 1986. Noise. *The journal of finance*, *41*(3), pp. 528-543. DOI: 10.1111/j.1540-6261.1986.tb04513.x

Bosworth, S.J., 2017. The importance of higher-order beliefs to successful coordination. *Experimental Economics*, *20*(1), pp. 237-258. DOI: 10.1007/s10683-016-9483-2

Chabi-Yo, F., Ghysels, E. and Renault, E., 2008. *On portfolio separation theorems with heterogeneous beliefs and attitudes towards risk* (WP. No. 2008-16). Bank of Canada.

Da, Z., Engelberg, J. and Gao, P., 2011. In search of attention. *The Journal of Finance*, *66*(5), pp. 1461-1499. <https://doi.org/10.1111/j.1540-6261.2011.01679.x>

Da, Z., Engelberg, J. and Gao, P., 2015. The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies*, *28*(1), 1-32. <https://doi.org/10.1093/rfs/hhu072>

Dolgin, A., 2012. *Manifesto of the new economy: Institutions and business models of the digital society*. Springer.

Figueira, Á. and Oliveira, L., 2017. The current state of fake news: challenges and opportunities. *Procedia Computer Science*, *121*, pp. 817-825.

Franck, G., 2019. The economy of attention. *Journal of sociology*, *55*(1), pp. 8-19. DOI: 10.1177/1440783318811778

Hambrick, D.C. and Mason, P.A., 1984. Upper Echelons: The Organization as a Reflection of Its Top Managers. *Academy of Management Review, 9*(2), pp. 193-206. DOI: 10.5465/amr.1984.4277628

Hendricks, V.F. and Vestergaard, M., 2019. *Reality lost: Markets of attention, misinformation and manipulation*. Springer Nature.

Hofstetter, C.R., Barker, D., Smith, J.T., Zari, G.M. and Ingrassia, T.A., 1999. Information, misinformation, and political talk radio. *Political Research Quarterly*, *52*(2), pp. 353-369. DOI: 10.1177/106591299905200205

Font, J.P.P., Pere, J. and Régis, D., 2006. Chaos theory and its application in political science. In *IPSA-AISP World Congress, Session "Beyond Linearity: Research Methods and Complex Social Phenomena",* Fukuoka, Japan (9-13 July 2006).

Kajii, A. and Morris, S., 2020. Refinements and higher-order beliefs: a unified survey. *The Japanese Economic Review*, *71*(1), pp. 7-34. <https://doi.org/10.1007/s42973-019-00006-x>

Van Leeuwen, E.S. and Vega, S.H., 2021. Voting and the rise of populism: Spatial perspectives and applications across Europe. *Regional Science Policy & Practice*, *13*(2), pp. 209-219. DOI: 10.1111/rsp3.12411

Lewis-Beck, M.S. and Stegmaier, M., 2000. *Economic Determinants of Electoral Outcomes. Annual Review of Political Science, 3*(1), pp. 183-219. DOI: 10.1146/annurev.polisci.3.1.183

Markoczy, L., 1997. Measuring Beliefs: Accept No Substitutes*. Academy of Management Journal, 40*(5), pp. 1228-1242. DOI: 10.2307/256934

Marwick, A. and Lewis, R., 2017. Media manipulation and disinformation online. New York: Data & Society Research Institute, pp. 7-19.

Morris, S. and Shin, H.S., 2002. The social value of public information. *American Economic Review* 92(5), pp. 1521-1534.

Pesaran, M.H., Shin, Y. and Smith, R.J., 2001. Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), pp. 289-326. DOI: 10.1002/jae.616

Rustichini, A., 1992. March. Decision theory with higher order beliefs. In Proceedings of the 4th Conference on Theoretical aspects of reasoning about knowledge, pp. 118-131.

Sahlin, N.E., 1993. On higher order beliefs. In *Philosophy of probability,* pp. 13-34. Springer, Dordrecht.

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*, 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), 7-32. <http://www.rfb.ase.ro/articole/Art1_v13june.pdf>; DOI: 10.24818/rfb.21.13.01.01

Smith, P., 1982. Bennett's beliefs. *Philosophical Studies, 41*(3), pp. 431-442. DOI: 10.1007/bf00353891

Vosoughi, S., Roy, D. and Aral, S., 2018. The spread of true and false news online. *Science*, *359*(6380), pp. 1146-1151.

Westfall, P.H., 2014. Kurtosis as Peakedness, 1905-2014. RIP. *The American Statistician*, *68*(3), pp. 191-195. DOI: 10.1080/00031305.2014.917055

Table 1. *Voters' cointegrated search-attention at lower-order and higher-order beliefs in unrestricted ARDL Model*

SVI Data for TMC				
Variables	Coef.	Std. Error	t-Stat	Prob.
Constant	7.62251	3.03338	2.513	0.013
@TREND	-0.03690	0.01222	-3.019	0.003
SVI_TMC(-1)	0.38571	0.05653	6.823	0.001
M_TMC	2.90538	1.52736	1.902	0.059
M_TMC(-1)	-8.06405	1.56034	-5.168	0.001
M_TMC(-2)	4.94289	1.04988	4.708	0.001
V_TMC	-0.11446	0.01969	-5.812	0.001
SK_TMC	5.09183	2.44848	2.080	0.039
SK_TMC(-1)	-8.53742	1.21040	-7.053	0.001
KT_TMC	1.99911	0.47992	4.165	0.001
SVI_BJP	0.09709	0.03777	2.570	0.0113
SVI_CAA	-0.03088	0.05914	-0.522	0.6026
SVI_CONG	1.20569	0.22650	5.323	0.001
SVI_CPIM	0.66085	0.22718	2.909	0.0043
SVI_HEALTH	0.00040	0.02245	0.018	0.9858
SVI_HEALTH(-1)	-0.05337	0.02252	-2.370	0.0193
SVI_KHELA	-0.05649	0.03669	-1.540	0.1261
SVI_NRC	0.02095	0.05126	0.409	0.6835
SVI_NRC(-1)	-0.05279	0.04837	-1.091	0.2772
SVI_NRC(-2)	0.09483	0.04722	2.008	0.0468
SVI_SONAR	-0.00676	0.02673	-0.253	0.8009
SVI_TUMPA	-0.05711	0.04764	-1.199	0.2329
SVI_TUMPA(-1)	-0.07957	0.04827	-1.649	0.1017
SVI_TUMPA(-2)	-0.09181	0.05011	-1.832	0.0693
Summary Statistics				
R^2 (Adj. R^2)	0.93 (0.917)	DW stat.	2.099	
F-stat. (Prob.)	71.93 (0.01)	BGSC (1)	0.53 (0.466)	
B-P-G HT	3.24 (0.001)	BGSC (2)	0.92 (0.402)	
Resid-Skew	1.5794	Resid-Kurt	9.313	
Resid.- J-B Normality Test Stat. (Prob.)			307 (0.001)	
CUSUM Recursive Resid. Esti. Stable at α of 5%				
CUSUM of Sq. Recursi. Esti. Unstable at α of 5%				

SVI Data for BJP				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	-2.13386	2.77576	-0.769	0.444
@TREND	-0.00417	0.01660	-0.251	0.802
SVI_BJP(-1)	0.35539	0.08038	4.422	0.000
SVI_BJP(-2)	0.05790	0.06009	0.963	0.337
SVI_BJP(-3)	-0.10325	0.05441	-1.898	0.060
SVI_BJP(-4)	0.18719	0.05360	3.492	0.001
SVI_BJP(-5)	-0.12261	0.05063	-2.422	0.017
M_BJP	13.55730	1.54047	8.801	0.000
M_BJP(-1)	-17.50904	2.32871	-7.519	0.000
M_BJP(-2)	4.43484	1.67706	2.644	0.009
V_BJP	-0.02241	0.01489	-1.504	0.135
SK_BJP	0.70435	2.01695	0.349	0.728
KT_BJP	0.10688	0.41151	0.260	0.796
SVI_CAA	-0.04426	0.09913	-0.446	0.656
SVI_CONG	-0.47243	0.43766	-1.079	0.283
SVI_CPIM	0.46522	0.42540	1.094	0.276
SVI_HEALTH	0.10069	0.03604	2.794	0.006
SVI_KHELA	0.17960	0.05901	3.043	0.003
SVI_KHELA(-1)	-0.15754	0.06126	-2.572	0.011
SVI_KHELA(-2)	-0.08198	0.05601	-1.464	0.146
SVI_NRC	-0.08494	0.08787	-0.967	0.336
SVI_NRC(-1)	-0.12423	0.08224	-1.511	0.134
SVI_NRC(-2)	0.27396	0.09083	3.016	0.003
SVI_SONAR	0.08506	0.04518	1.883	0.062
SVI_TMC	0.18797	0.07375	2.549	0.012
SVI_TMC(-1)	0.12910	0.06166	2.094	0.038
SVI_TUMPA	-0.05423	0.07923	-0.684	0.495
Summary Statistics				
R^2 (Adj. R^2)	0.85 (0.817)	DW stat.	1.987	
F-stat. (Prob.)	25.83 (0.01)	BGSC (1)	0.015 (0.903)	
B-P-G HT	1.64 (0.04)	BGSC (2)	0.1638 (0.849)	
Resid-Skew	1.993	Resid-Kurt	10.74	
Resid.- J-B Normality Test Stat. (Prob.)			457.91 (0.001)	
CUSUM Recursive Resid. Esti. Stable at α of 5%				
CUSUM of Sq. Recursive Esti. Partially Stable at α of 5%				

SVI Data for CPIM				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	1.28525	0.63979	2.009	0.047
@TREND	-0.00685	0.00316	-2.168	0.033
SVI_CPIM(-1)	0.04101	0.06732	0.609	0.544
SVI_CPIM(-2)	-0.09049	0.06688	-1.353	0.179
SVI_CPIM(-3)	-0.02474	0.05762	-0.429	0.669
SVI_CPIM(-4)	0.16277	0.05742	2.835	0.006
SVI_CPIM(-5)	-0.01406	0.06332	-0.222	0.825
SVI_CPIM(-6)	0.02048	0.06513	0.315	0.754
SVI_CPIM(-7)	-0.04770	0.06569	-0.726	0.469
SVI_CPIM(-8)	-0.04973	0.05935	-0.838	0.404
SVI_CPIM(-9)	-0.05530	0.05963	-0.927	0.356
SVI_CPIM(-10)	0.12969	0.05796	2.238	0.027
SVI_CPIM(-11)	0.08128	0.05677	1.432	0.155
M_CPIM	12.17581	1.52648	7.976	0.000
M_CPIM(-1)	-11.61773	1.45823	-7.967	0.000
V_CPIM	0.87642	0.42915	2.042	0.044
V_CPIM(-1)	-0.94067	0.40903	-2.300	0.024
SK_CPIM	-3.71668	0.87231	-4.261	0.000
SK_CPIM(-1)	2.64569	1.30606	2.026	0.045
SK_CPIM(-2)	0.87828	0.84734	1.037	0.302
KT_CPIM	0.86675	0.18511	4.682	0.000
KT_CPIM(-1)	-0.55276	0.28567	-1.935	0.056
KT_CPIM(-2)	-0.28581	0.19795	-1.444	0.152
SVI_BJP	-0.00020	0.01090	-0.018	0.986
SVI_CAA	-0.02208	0.01421	-1.553	0.123
SVI_CONG	0.04431	0.05914	0.749	0.455
SVI_HEALTH	-0.00003	0.00519	-0.006	0.995
SVI_KHELA	0.00283	0.00859	0.329	0.743
SVI_NRC	0.00867	0.01249	0.694	0.490
SVI_NRC(-1)	-0.01091	0.01156	-0.944	0.348
SVI_SONAR	0.00028	0.00638	0.043	0.966
SVI_SONAR(-1)	-0.00757	0.00656	-1.155	0.251
SVI_SONAR(-2)	-0.01225	0.00632	-1.938	0.055
SVI_TMC	0.03059	0.01199	2.551	0.012
SVI_TMC(-1)	0.01527	0.00906	1.686	0.095
SVI_TMC(-2)	0.01400	0.00731	1.915	0.058
SVI_TUMPA	-0.01084	0.01181	-0.917	0.361
Summary Statistics				
R^2 (Adj. R^2)	0.887 (0.85)	DW stat.	1.8311	
F-stat. (Prob.)	22.13 (0.01)	BGSC (1)	0.763 (0.385)	
B-P-G HT	1.14 (0.303)	BGSC (2)	0.409 (0.666)	
Resid-Skew	0.2219	Resid-Kurt	3.125	
Resid.- J-B Normality Test Stat. (Prob.)			1.2316 (0.540)	
CUSUM Recursive Resid. Esti. Stable at α of 5%				
CUSUM of Sq. Recursive Esti. Not-Stable at α of 5%				

SVI Data for CONG				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	-0.10003	1.31267	-0.076	0.939
@TREND	0.00243	0.00410	0.593	0.554
SVI_CONG(-1)	0.18587	0.07675	2.422	0.017
M_CONG	14.71058	1.53346	9.593	0.000
M_CONG(-1)	-18.70394	2.18875	-8.545	0.000
M_CONG(-2)	4.57466	1.48066	3.090	0.003
V_CONG	-0.74263	0.30794	-2.412	0.017
V_CONG(-1)	0.68021	0.32085	2.120	0.036
SK_CONG	-1.12848	0.72850	-1.549	0.124
SK_CONG(-1)	0.77824	0.39265	1.982	0.050
KT_CONG	0.03533	0.14008	0.252	0.801
SVI_BJP	-0.01921	0.01064	-1.806	0.074
SVI_CAA	0.00008	0.01537	0.005	0.996
SVI_CPIM	0.06607	0.06221	1.062	0.290
SVI_HEALTH	0.01122	0.00583	1.924	0.057
SVI_KHELA	-0.01081	0.00921	-1.174	0.243
SVI_NRC	-0.02686	0.01327	-2.024	0.045
SVI_NRC(-1)	0.01395	0.01278	1.092	0.277
SVI_NRC(-2)	-0.03323	0.01218	-2.728	0.007
SVI_SONAR	0.00696	0.00741	0.939	0.349
SVI_SONAR(-1)	-0.00613	0.00770	-0.796	0.428
SVI_SONAR(-2)	0.01580	0.00756	2.090	0.039
SVI_TMC	0.11364	0.01243	9.141	0.000
SVI_TMC(-1)	-0.01779	0.01067	-1.667	0.098
SVI_TMC(-2)	0.01328	0.00788	1.686	0.094
SVI_TUMPA	-0.01396	0.01238	-1.127	0.262
SVI_TUMPA(-1)	0.01860	0.01250	1.488	0.139
SVI_TUMPA(-2)	0.01851	0.01226	1.510	0.134
Summary Statistics				
R^2 (Adj. R^2)	0.803 (0.76)	DW stat.	2.0169	
F-stat. (Prob.)	18.15 (0.01)	BGSC (1)	0.04 (0.852)	
B-P-G HT	1.32 (0.158)	BGSC (2)	0.018 (0.98)	
Resid-Skew	0.3303	Resid-Kurt	2.755	
Resid.- J-B Normality Test Stat. (Prob.)			3.060 (0.216)	
CUSUM Recursive Resid. Esti. Stable at α of 5%				
CUSUM of Sq. Recursi. Esti. Stable at α of 5%				

Note: "Prob." refers level of significance, "B-P-G HT" is Breusch-Pagan-Godfrey Heteroskedasticity Test, "BGSC" is Breusch-Godfrey serial correlation Test.
Source: Prepared by the author.

Table 2. *Voters' cointegrated search-attention at lower-order and higher-order beliefs in conditional long-run ARDL Model and bound test*

SVI Data for TMC					SVI Data for BJP					SVI Data for CPIM					SVI Data for CONG				
Variables	Coef.	Std. Error	t-Stat	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	7.62251	3.03338	2.513	0.013	Constant	-2.13386	2.77576	-0.769	0.444	Constant	1.28525	0.63979	2.009	0.047	Constant	-0.10003	1.31267	-0.076	0.939
@TREND	-0.03690	0.01222	-3.019	0.003	@TREND	-0.00417	0.01660	-0.251	0.802	@TREND	-0.00685	0.00316	-2.168	0.033	@TREND	0.00243	0.00410	0.593	0.554
SVI_TMC(-1)*	-0.61430	0.05653	-10.867	0.000	SVI_BJP(-1)*	-0.62538	0.09329	-6.703	0.000	SVI_CPIM(-1)*	-0.84679	0.22189	-3.816	0.000	SVI_CONG(-1)*	-0.81414	0.07675	-10.607	0.000
M_TMC(-1)	-0.21578	0.29392	-0.734	0.464	M_BJP(-1)	0.48310	0.22686	2.130	0.035	M_CPIM(-1)	0.55809	0.16887	3.305	0.001	M_CONG(-1)	0.58130	0.56648	1.026	0.307
V_TMC**	-0.11446	0.01969	-5.812	0.000	V_BJP**	-0.02241	0.01489	-1.504	0.135	V_CPIM(-1)	-0.06425	0.18432	-0.349	0.728	V_CONG(-1)	-0.06242	0.16794	-0.372	0.711
SK_TMC(-1)	-3.44559	1.85040	-1.862	0.065	SK_BJP**	0.70435	2.01695	0.349	0.728	SK_CPIM(-1)	-0.19271	0.34174	-0.564	0.574	SK_CONG(-1)	-0.35024	0.77912	-0.450	0.654
KT_TMC**	1.99911	0.47992	4.165	0.000	KT_BJP**	0.10688	0.41151	0.260	0.796	KT_CPIM(-1)	0.02818	0.08216	0.343	0.732	KT_CONG**	0.03533	0.14008	0.252	0.801
SVI_BJP**	0.09709	0.03777	2.570	0.011	SVI_CAA**	-0.04426	0.09913	-0.446	0.656	SVI_BJP**	-0.00020	0.01090	-0.018	0.986	SVI_BJP**	-0.01921	0.01064	-1.806	0.074
SVI_CAA**	-0.03088	0.05914	-0.522	0.603	SVI_CONG**	-0.47243	0.43766	-1.079	0.283	SVI_CAA**	-0.02208	0.01421	-1.553	0.123	SVI_CAA**	0.00008	0.01537	0.005	0.996
SVI_CONG**	1.20569	0.22650	5.323	0.000	SVI_CPIM**	0.46522	0.42540	1.094	0.276	SVI_CONG**	0.04431	0.05914	0.749	0.455	SVI_CPIM**	0.06607	0.06221	1.062	0.290
SVI_CPIM**	0.66085	0.22718	2.909	0.004	SVI_HEALTH**	0.10069	0.03604	2.794	0.006	SVI_HEALTH**	-0.00003	0.00519	-0.006	0.995	SVI_HEALTH**	0.01122	0.00583	1.924	0.057
SVI_HEALTH(-1)	-0.05297	0.03221	-1.645	0.103	SVI_KHELA(-1)	-0.05992	0.08444	-0.710	0.479	SVI_KHELA**	0.00283	0.00859	0.329	0.743	SVI_KHELA**	-0.01081	0.00921	-1.174	0.243
SVI_KHELA**	-0.05649	0.03669	-1.540	0.126	SVI_NRC(-1)	0.06479	0.15139	0.428	0.669	SVI_NRC(-1)	-0.00225	0.01696	-0.132	0.895	SVI_NRC(-1)	-0.04614	0.02119	-2.178	0.031
SVI_NRC(-1)	0.06299	0.08365	0.753	0.453	SVI_SONAR**	0.08506	0.04518	1.883	0.062	SVI_SONAR(-1)	-0.01955	0.01029	-1.900	0.060	SVI_SONAR(-1)	0.01663	0.01427	1.165	0.246
SVI_SONAR**	-0.00676	0.02673	-0.253	0.801	SVI_TMC(-1)	0.31707	0.08773	3.614	0.000	SVI_TMC(-1)	0.05986	0.01612	3.713	0.000	SVI_TMC(-1)	0.10914	0.01720	6.347	0.000
SVI_TUMPA(-1)	-0.22849	0.08353	-2.735	0.007	SVI_TUMPA**	-0.05423	0.07923	-0.684	0.495	SVI_TUMPA**	-0.01084	0.01181	-0.917	0.361	SVI_TUMPA(-1)	0.02315	0.02066	1.120	0.265
D(M_TMC)	2.90538	1.52736	1.902	0.060	D(SVI_BJP(-1))	-0.01923	0.07984	-0.241	0.810	D(SVI_CPIM(-1))	-0.11219	0.20134	-0.557	0.579	D(M_CONG)	14.71058	1.53346	9.593	0.000
D(M_TMC(-1))	-4.94289	1.04988	-4.708	0.000	D(SVI_BJP(-2))	0.03867	0.07307	0.529	0.598	D(SVI_CPIM(-2))	-0.20268	0.17557	-1.154	0.251	D(M_CONG(-1))	-4.57466	1.48066	-3.090	0.003
D(SK_TMC)	5.09183	2.44848	2.080	0.040	D(SVI_BJP(-3))	-0.06458	0.05952	-1.085	0.280	D(SVI_CPIM(-3))	-0.22743	0.16266	-1.398	0.165	D(V_CONG)	-0.74263	0.30794	-2.412	0.017
D(SVI_HEALTH)	0.00040	0.02245	0.018	0.986	D(SVI_BJP(-4))	0.12261	0.05063	2.422	0.017	D(SVI_CPIM(-4))	-0.06466	0.14875	-0.435	0.665	D(SK_CONG)	-1.12848	0.72850	-1.549	0.124
D(SVI_NRC)	0.02095	0.05126	0.409	0.684	D(M_BJP)	13.55730	1.54047	8.801	0.000	D(SVI_CPIM(-5))	-0.07872	0.14009	-0.562	0.575	D(SVI_NRC)	-0.02686	0.01327	-2.024	0.045
D(SVI_NRC(-1))	-0.09483	0.04722	-2.008	0.047	D(M_BJP(-1))	-4.43484	1.67706	-2.644	0.009	D(SVI_CPIM(-6))	-0.05824	0.13225	-0.440	0.661	D(SVI_NRC(-1))	0.03323	0.01218	2.728	0.007
D(SVI_TUMPANA)	-0.05711	0.04764	-1.199	0.233	D(SVI_KHELA)	0.17960	0.05901	3.043	0.003	D(SVI_CPIM(-7))	-0.10594	0.11321	-0.936	0.352	D(SVI_SONAR)	0.00696	0.00741	0.939	0.349
D(SVI_TUMPA(-1))	0.09181	0.05011	1.832	0.069	D(SVI_KHELA(-1))	0.08198	0.05601	1.464	0.146	D(SVI_CPIM(-8))	-0.15568	0.09449	-1.648	0.103	D(SVI_SONAR(-1))	-0.01580	0.00756	-2.090	0.039
					D(SVI_NRC)	-0.08494	0.08787	-0.967	0.336	D(SVI_CPIM(-9))	-0.21098	0.07198	-2.931	0.004	D(SVI_TMC)	0.11364	0.01243	9.141	0.000
					D(SVI_NRC(-1))	-0.27396	0.09083	-3.016	0.003	D(SVI_CPIM(-10))	-0.08128	0.05677	-1.432	0.155	D(SVI_TMC(-1))	-0.01328	0.00788	-1.686	0.094
					D(SVI_TMC)	0.18797	0.07375	2.549	0.012	D(M_CPIM)	12.17581	1.52648	7.976	0.000	D(SVI_TUMPA)	-0.01396	0.01238	-1.127	0.262
										D(V_CPIM)	0.87642	0.42915	2.042	0.044	D(SVI_TUMPA(-1))	-0.01851	0.01226	-1.510	0.134
										D(SK_CPIM)	-3.71668	0.87231	-4.261	0.000					
										D(SK_CPIM(-1))	-0.87828	0.84734	-1.037	0.302					
										D(KT_CPIM)	0.86675	0.18511	4.682	0.000					
										D(KT_CPIM(-1))	0.28581	0.19795	1.444	0.152					
										D(SVI_NRC)	0.00867	0.01249	0.694	0.490					

SVI Data for TMC					SVI Data for BJP					SVI Data for CPIM					SVI Data for CONG				
Variables	Coef.	Std. Error	t-Stat	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.
										D(SVI_SONAR)	0.00028	0.00638	0.043	0.966					
										D(SVI_SONAR(-1))	0.01225	0.00632	1.938	0.055					
										D(SVI_TMC)	0.03059	0.01199	2.551	0.012					
										D(SVI_TMC(-1))	-0.01400	0.00731	-1.915	0.058					
F-Bound F-statistics (Prob.) (Df): 12.09029 (0.01) (13)					F-Bound F-statistics (Prob.) (Df): 12.09029 (0.01) (13)					F-Bound F-statistics (Prob.) (Df): 8.340186 (0.01) (13)					F-Bound F-statistics (Prob.) (Df): 10.31817 (0.01) (13)				
F-Bound Test Table Value (Prob.) (N): 4.1 (0.01) (148)					F-Bound Test Table Value (Prob.) (N): 4.1 (0.01) (148)					F-Bound Test Table Value (Prob.) (N): 4.1 (0.01) (148)					F-Bound Test Table Value (Prob.) (N): 4.1 (0.01) (148)				
t-Bounds t-Test statistics (Prob.): -10.86725 (< -5.94; 0.01)					t-Bounds t-Test statistics (Prob.): -6.703407 (< -5.94; 0.01)					t-Bounds t-Test statistics (Prob.): -3.816355 (> - 4.96; 0.10)					t-Bounds t-Test statistics (Prob.): -10.60744 (< -5.94; 0.01)				
ECT in the ARDL model *Eq-ECF*					*ECT* in the ARDL model *Eq-ECF*					*ECT* in the ARDL model *Eq-ECF*					*ECT* in the ARDL model *Eq-ECF*				
ECT = SVI_TMC - (-0.3513*M_TMC - 0.1863*V_TMC - 5.6090*SK_TMC + 3.2543 *KT_TMC + 0.1580*SVI_BJP - 0.0503*SVI_CAA + 1.9627*SVI_CONG + 1.0758*SVI_CPIM - 0.0862*SVI_HEALTH - 0.0920 *SVI_KHELA + 0.1025*SVI_NRC - 0.0110*SVI_SONAR - 0.3720*SVI_TUMPA)					*ECT* = SVI_BJP - (0.7725*M_BJP - 0.0358*V_BJP + 1.1263*SK_BJP + 0.1709 *KT_BJP - 0.0708*SVI_CAA - 0.7554*SVI_CONG + 0.7439*SVI_CPIM + 0.1610*SVI_HEALTH - 0.0958*SVI_KHELA + 0.1036 *SVI_NRC + 0.1360*SVI_SONAR + 0.5070*SVI_TMC - 0.0867*SVI_TUMPA)					*ECT* = SVI_CPIM - (0.6591*M_CPIM -0.0759*V_CPIM - 0.2276*SK_CPIM + 0.0333*KT_CPIM - 0.0002*SVI_BJP - 0.0261*SVI_CAA + 0.0523 *SVI_CONG -0.0000*SVI_HEALTH + 0.0033*SVI_KHELA -0.0027*SVI_NRC - 0.0231*SVI_SONAR + 0.0707*SVI_TMC - 0.0128*SVI_TUMPA)					*ECT* = SVI_CONG - (0.7140*M_CONG - 0.0767*V_CONG - 0.4302*SK_CONG + 0.0434*KT_CONG - 0.0236*SVI_BJP + 0.0001*SVI_CAA + 0.0812 *SVI_CPIM + 0.0138*SVI_HEALTH - 0.0133*SVI_KHELA -0.0567*SVI_NRC + 0.0204*SVI_SONAR + 0.1341*SVI_TMC + 0.0284*SVI_TUMPA)				

Note:
"Prob." is level of significance.
"Df" is Degree of Freedom. *ECT* is Error Correction Term.
* p-value and t-stat. not with t-Bounds t-distribution rather with Dickey-Fuller test statistics.
** Variable interpreted as Z = Z(-1) + D(Z).
Source: Prepared by the author.

Table 3. *Voters' cointegrated search-attention at lower-order and higher-order beliefs in the error correction form of ARDL Model*

SVI Data for TMC				
Variables	Coef.	Std. Error	t-Stat	Prob.
Constant	7.62251	0.67996	11.210	0.000
@TREND	-0.03690	0.00622	-5.930	0.000
D(M_TMC)	2.90538	1.06487	2.728	0.007
D(M_TMC(-1))	-4.94289	0.77712	-6.361	0.000
D(SK_TMC)	5.09183	1.16835	4.358	0.000
D(SVI_HEALTH)	0.00040	0.01467	0.027	0.978
D(SVI_NRC)	0.02095	0.03614	0.580	0.563
D(SVI_NRC(-1))	-0.09483	0.03500	-2.710	0.008
D(SVI_TUMPA)	-0.05711	0.03691	-1.547	0.124
D(SVI_TUMPA(-1))	0.09181	0.03926	2.339	0.021
CointEq(-1)*	-0.61430	0.04492	-13.675	0.000
Summary Statistics				
R^2 (Adj. R^2)	0.944 (0.94)	DW stat.	2.099	
F-stat. (Prob.)		232 (0.01)		
F-Bound F-Stat. (Prob., Df, T.Value)		12.0903 (0.01, 13, 4.1)		
t-Bounds t-Test statistics (Prob.): -13.6751 (< -5.94; 0.01)				

SVI Data for BJP				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	-2.13386	0.93423	-2.284	0.024
@TREND	-0.00417	0.01075	-0.388	0.699
D(SVI_BJP(-1))	-0.01923	0.06006	-0.320	0.749
D(SVI_BJP(-2))	0.03867	0.05391	0.717	0.475
D(SVI_BJP(-3))	-0.06458	0.04810	-1.343	0.182
D(SVI_BJP(-4))	0.12261	0.04470	2.743	0.007
D(M_BJP)	13.55730	1.07789	12.578	0.000
D(M_BJP(-1))	-4.43484	1.31892	-3.362	0.001
D(SVI_KHELA)	0.17960	0.04632	3.878	0.000
D(SVI_KHELA(-1))	0.08198	0.04369	1.877	0.063
D(SVI_NRC)	-0.08494	0.06156	-1.380	0.170
D(SVI_NRC(-1))	-0.27396	0.06369	-4.302	0.000
D(SVI_TMC)	0.18797	0.04149	4.531	0.000
CointEq(-1)*	-0.62538	0.06323	-9.890	0.000
Summary Statistics				
R^2 (Adj. R^2)	0.82 (0.806)	DW stat.	1.988	
F-stat. (Prob.)		47 (0.01)		
F-Bound F-Stat. (Prob., Df, T.Value)		6.2932 (0.01, 13, 4.1)		
t-Bounds t-Test statistics (Prob.): -9.8899 (< -5.94; 0.01)				

SVI Data for CPIM				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	1.28525	0.19705	6.523	0.000
@TREND	-0.00685	0.00184	-3.727	0.000
D(SVI_CPIM(-1))	-0.11219	0.07124	-1.575	0.118
D(SVI_CPIM(-2))	-0.20268	0.06473	-3.131	0.002
D(SVI_CPIM(-3))	-0.22743	0.06539	-3.478	0.001
D(SVI_CPIM(-4))	-0.06466	0.06905	-0.936	0.351
D(SVI_CPIM(-5))	-0.07872	0.07009	-1.123	0.264
D(SVI_CPIM(-6))	-0.05824	0.07167	-0.813	0.418
D(SVI_CPIM(-7))	-0.10594	0.06806	-1.557	0.123
D(SVI_CPIM(-8))	-0.15568	0.06129	-2.540	0.013
D(SVI_CPIM(-9))	-0.21098	0.05031	-4.193	0.000
D(SVI_CPIM(-10))	-0.08128	0.04618	-1.760	0.081
D(M_CPIM)	12.17581	1.13672	10.711	0.000
D(V_CPIM)	0.87642	0.35841	2.445	0.016
D(SK_CPIM)	-3.71668	0.75108	-4.948	0.000
D(SK_CPIM(-1))	-0.87828	0.72783	-1.207	0.230
D(KT_CPIM)	0.86675	0.15898	5.452	0.000
D(KT_CPIM(-1))	0.28581	0.16592	1.723	0.088
D(SVI_NRC)	0.00867	0.00778	1.114	0.268
D(SVI_SONAR)	0.00028	0.00471	0.058	0.954
D(SVI_SONAR(-1))	0.01225	0.00479	2.558	0.012
D(SVI_TMC)	0.03059	0.00567	5.395	0.000
D(SVI_TMC(-1))	-0.01400	0.00603	-2.324	0.022
CointEq(-1)*	-0.84679	0.07380	-11.474	0.000
Summary Statistics				
R^2 (Adj. R^2)	0.863 (0.835)	DW stat.	1.831	
F-stat. (Prob.)		31.38 (0.01)		
F-Bound F-Stat. (Prob., Df, T.Value)		8.340 (0.01, 13, 4.1)		
t-Bounds t-Test statistics (Prob.): -11.4736 (< -5.94; 0.01)				

SVI Data for CONG				
Variables	Coef.	Std. Err.	t-Stat.	Prob.
Constant	-0.10003	0.13383	-0.747	0.456
@TREND	0.00243	0.00156	1.553	0.123
D(M_CONG)	14.71058	1.28743	11.426	0.000
D(M_CONG(-1))	-4.57466	1.23152	-3.715	0.000
D(V_CONG)	-0.74263	0.25389	-2.925	0.004
D(SK_CONG)	-1.12848	0.32244	-3.500	0.001
D(SVI_NRC)	-0.02686	0.00945	-2.843	0.005
D(SVI_NRC(-1))	0.03323	0.00918	3.620	0.000
D(SVI_SONAR)	0.00696	0.00525	1.325	0.188
D(SVI_SONAR(-1))	-0.01580	0.00535	-2.952	0.004
D(SVI_TMC)	0.11364	0.00815	13.937	0.000
D(SVI_TMC(-1))	-0.01328	0.00630	-2.106	0.037
D(SVI_TUMPA)	-0.01396	0.00964	-1.448	0.150
D(SVI_TUMPA(-1))	-0.01851	0.00973	-1.902	0.060
CointEq(-1)*	-0.81414	0.06434	-12.653	0.000
Summary Statistics				
R^2 (Adj. R^2)	0.858 (0.84)	DW stat.	2.017	
F-stat. (Prob.)		57.48 (0.01)		
F-Bound F-Stat. (Prob., Df, T.Value)		10.318 (0.01, 13, 4.1)		
t-Bounds t-Test statistics (Prob.): -12.6532 (< -5.94; 0.01)				

Note:
"Prob." is level of significance.
"CointEq(-1)" refers to the *ECT* at 1st lag in the *Eq-ECF* Model.
"Df" is the degree of freedom.
* p-value and t-stat. not with t-Bounds t-distribution rather with Dickey-Fuller test statistics.
Source: Prepared by the author.

Table 4. *GARCH effects in voters' cointegrated search-attention at lower-order and higher-order beliefs augmented within the unrestricted ARDL Model*

SVI Data for TMC					SVI Data for BJP					SVI Data for CPIM					SVI Data for CONG				
Variables	Coef.	Std. Error	t-Stat	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.	Variables	Coef.	Std. Err.	t-Stat.	Prob.
C	0.92805	0.59951	1.548	0.122	C	12.63416	17.73637	0.712	0.476	C	-0.00096	0.00149	-0.643	0.520	C	0.36720	1.03532	0.355	0.723
$RESID(-1)^2$	1.35685	0.37213	3.646	0.000	$RESID(-1)^2$	-0.04178	0.09002	-0.464	0.643	$RESID(-1)^2$	0.60184	0.22313	2.697	0.007	$RESID(-1)^2$	0.15000	0.35132	0.427	0.669
GARCH(-1)	-0.03853	0.04663	-0.826	0.409	GARCH(-1)	0.52672	1.79092	0.294	0.769	GARCH(-1)	0.53839	0.12315	4.372	0.000	GARCH(-1)	0.60000	1.00132	0.599	0.549
GARCH(-2)	0.05022	0.06076	0.827	0.409	GARCH(-2)	0.03803	1.44584	0.026	0.979										
GARCH(-3)	0.15692	0.07694	2.040	0.041															
Summary Statistics					Summary Statistics					Summary Statistics					Summary Statistics				
R^2 (Adj. R^2)	0.91 (0.893)	DW stat.	1.968		R^2 (Adj. R^2)	0.85 (0.817)	DW stat.	1.9902		R^2 (Adj. R^2)	0.873 (0.827)	DW stat.	1.749		R^2 (Adj. R^2)	0.803 (0.76)	DW stat.	2.0169	
Heteroskedasticity ARCH Test		0.1275 (0.7215)			Heteroskedasticity ARCH Test		0.0257 (0.8727)			Heteroskedasticity ARCH Test		0.0156 (0.901)			Heteroskedasticity ARCH Test		1.889 (0.1714)		
Resid-Skew	1.0852	Resid-Kurt	5.238		Resid-Skew	1.86687	Resid-Kurt	10.118		Resid-Skew	0.1823	Resid-Kurt	3.1002		Resid-Skew	0.3157	Resid-Kurt	2.762	
Resid.- J-B Normality Test Stat. (Prob.)			59.94 (0.001)		Resid.- J-B Normality Test Stat. (Prob.)			390.50 (0.001)		Resid.- J-B Normality Test Stat. (Prob.)			0.8277 (0.661)		Resid.- J-B Normality Test Stat. (Prob.)			2.7618 (0.2513)	

Note: "Prob." Indicates level of significance.
Source: Prepared by the author.

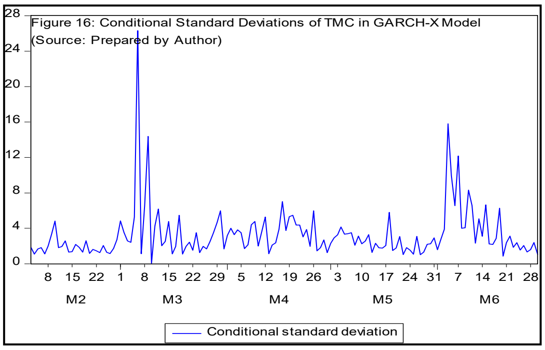


Figure 16: Conditional Standard Deviations of TMC in GARCH-X Model
(Source: Prepared by Author)

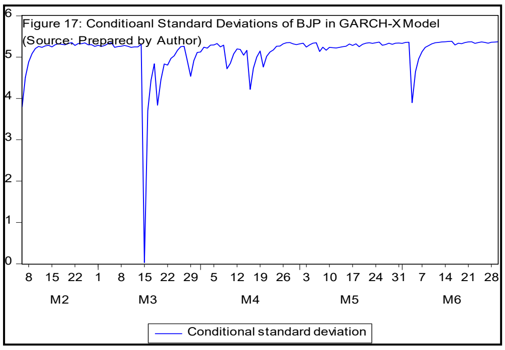


Figure 17: Conditioanl Standard Deviations of BJP in GARCH-X Model
(Source: Prepared by Author)

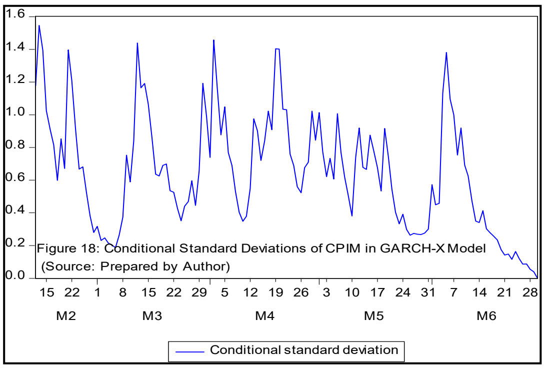


Figure 18: Conditional Standard Deviations of CPIM in GARCH-X Model
(Source: Prepared by Author)

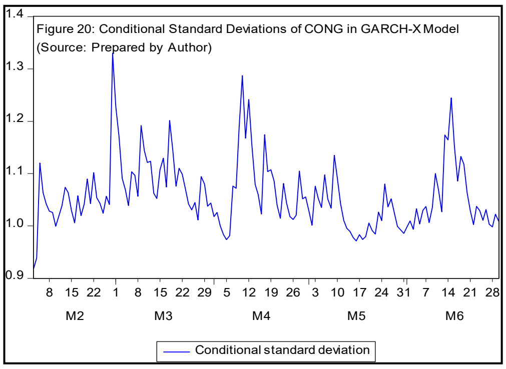


Figure 20: Conditional Standard Deviations of CONG in GARCH-X Model
(Source: Prepared by Author)

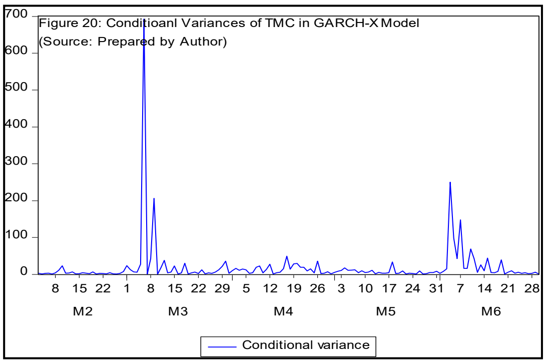


Figure 20: Conditioanl Variances of TMC in GARCH-X Model
(Source: Prepared by Author)

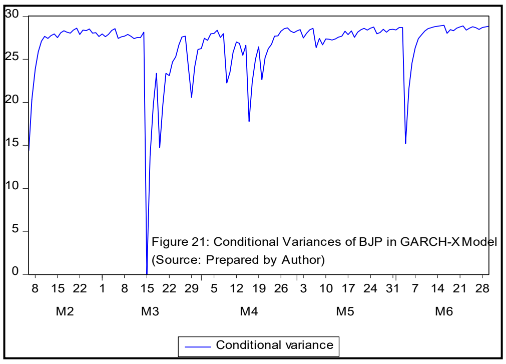


Figure 21: Conditional Variances of BJP in GARCH-X Model
(Source: Prepared by Author)

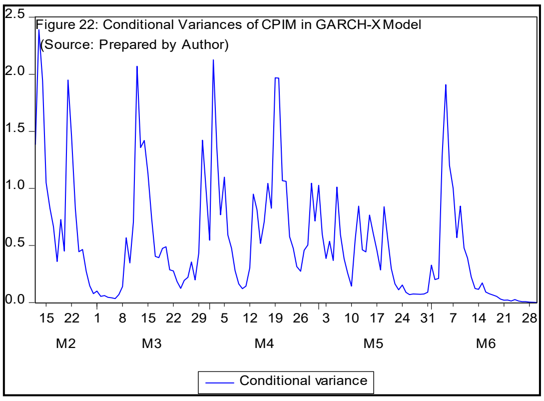


Figure 22: Conditional Variances of CPIM in GARCH-X Model
(Source: Prepared by Author)

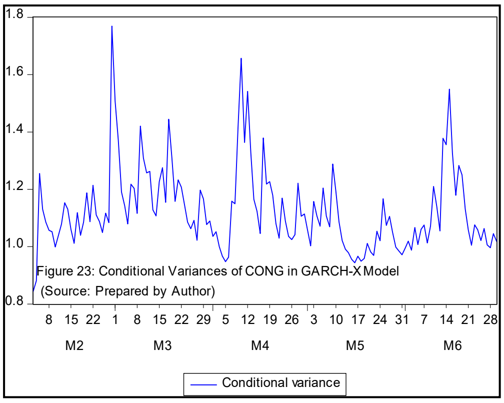


Figure 23: Conditional Variances of CONG in GARCH-X Model
(Source: Prepared by Author)

Annexure 1. *Stationarity tests for the SVI data for search keywords*
(H_0: The variable has a unit root; H_1: The variable has no unit root)

Search Keywords / Variables for SVI Data	ADF Unit Root Test Statistics			ADF Break Point Unit Root Test Statistics		
	Acronyms	t-Stat.	Prob.	t-Stat.	Prob.	Break Date
TMC	*TMC*	-8.18023	0.01	-12.2873	< 0.01	3/5/2021
BJP	*BJP*	-6.25455	0.01	-7.21056	< 0.01	3/18/2021
CPIM	*CPIM*	-2.38991	0.1464	-7.24806	< 0.01	4/14/2021
Congress	*CONG*	-5.74369	0.01	-9.61271	< 0.01	3/08/2021
Khela Hobe	*KHELA*	-7.55213	0.01	-12.7043	< 0.01	5/2/2021
Tumpa Sona	*TUMPA*	-3.24119	0.0196	-11.3028	< 0.01	4/4/2021
Health Insurance	*HEALTH*	-11.9531	0.01	-12.6198	< 0.01	2/27/2021
Sonar Bangla	*SONAR*	-8.57901	0.01	-11.0442	< 0.01	4/4/2021
NRC	*NRC*	-9.34869	0.01	-10.6092	< 0.01	4/17/2021
CAA	*CAA*	-10.1169	0.01	-11.427	< 0.01	5/29/2021

Note: "Prob." is level of significance.
Source: Prepared by the author.

Annexure 2. *Stationarity tests for moments of SVI data for name of political parties*
(H_0: The variable has a unit root; H_1: The variable has no unit root)

Mean, Variance, Skewness and Kurtosis measures of SVI Data	ADF Unit Root Test Statistics			ADF Break Point Unit Root Test Statistics		
	Acronyms	t-Stat.	Prob.	t-Stat.	Prob.	Break Date
Mean of *TMC*	*M_TMC*	-1.38947	0.5861	-2.41623	0.9228	6/02/2021
Mean of *BJP*	*M_BJP*	-1.63713	0.4611	-2.41939	0.9221	5/5/2021
Mean of *CPIM*	*M_CPIM*	-1.45653	0.5529	-2.56309	0.8825	5/8/2021
Mean of *Congress*	*M_CONG*	-1.34447	0.6078	-2.55799	0.8844	4/5/2021
Variance of *TMC*	*V_TMC*	-1.83313	0.3633	-2.52553	0.8957	6/2/2021
Variance of *BJP*	*V_BJP*	-1.63003	0.4647	-2.44654	0.9158	6/2/2021
Variance of *CPIM*	*V_CPIM*	-1.19785	0.6747	-2.07375	0.9773	4/10/2021
Variance of *Congress*	*V_CONG*	-1.46309	0.5496	-2.98714	0.6934	4/05/2021
Skewness of *TMC*	*S_TMC*	-1.99455	0.2891	-2.35841	0.9356	2/28/2021
Skewness of *BJP*	*S_BJP*	-2.21208	0.2029	-2.91938	0.7294	6/4/2021
Skewness of *CPIM*	*S_CPIM*	-2.45112	0.1297	-3.10949	0.6213	2/28/2021
Skewness of *Congress*	*S_CONG*	-2.54764	0.1064	-3.08526	0.6365	2/26/2021
Kurtosis of *TMC*	*K_TMC*	-2.18131	0.2140	-2.65045	0.85	6/2/2021
Kurtosis of *BJP*	*K_BJP*	-3.08629	0.0297	-3.56283	0.3516	6/4/2021
Kurtosis of *CPIM*	*K_CPIM*	-3.33992	0.0148	-4.4599	0.0481	2/28/2021
Kurtosis of *Congress*	*K_CONG*	-1.34447	0.6078	-2.55799	0.8844	4/05/2021

Note: "Prob." is level of significance.
Source: Prepared by the author.

Annexure 3. *Stationarity tests for moments of SVI data for popular political songs*
(H_0: The variable has a unit root; H_1: The variable has no unit root)

Mean, Variance, Skewness and Kurtosis measures of SVI Data for Election Songs	ADF Unit Root Test statistics			ADF Break Point Unit Root Test Statistics		
	Acronyms	t-Stat.	Prob.	t-Stat.	Prob.	Break Date
Mean of *Khela Hobe*	*M_KHELA*	-1.03215	0.7409	-2.64803	0.851	5/29/2021
Mean of *Tumpa Sona*	*M_TUMPA*	-4.70871	0.0001	-5.86529	< 0.01	3/23/2021
Variance of *Khela Hobe*	*V_KHELA*	-1.72814	0.415	-2.79842	0.7882	6/2/2021
Variance of *Tumpa Sona*	*V_TUMPA*	-3.37798	0.0133	-5.1204	< 0.01	4/22/2021
Skewness of *Khela Hobe*	*S_HELA*	-1.91715	0.3237	-2.70593	0.8283	5/1/2021
Skewness of *Tumpa Sona*	*S_TUMPA*	-2.66681	0.0823	-3.58381	0.3405	3/16/2021
Kurtosis of *Khela Hobe*	*K_KHELA*	-1.80213	0.3784	-2.49596	0.904	5/1/2021
Kurtosis of *Tumpa Sona*	*K_TUMPA*	-2.68209	0.0795	-4.10426	0.1243	6/7/2021

Note: "Prob." is level of significance.
Source: Prepared by the author.

Annexure 4. *Stationarity tests for moments of SVI data for political promises*
(H_0: The variable has a unit root; H_1: The variable has no unit root)

Mean, Variance, Skewness and Kurtosis measures of SVI Data for Election Promises	ADF Unit Root Test Statistics			ADF Break Point Unit Root Test Statistics		
	Acronyms	t-Stat.	Prob.	t-Stat.	Prob.	Break Date
Mean of *Health Insurance*	*M_HEALTH*	-2.02568	0.2757	-3.30765	0.4992	3/30/2021
Mean of *Sonar Bangla*	*M_SONAR*	-0.90969	0.7829	-4.45233	0.049	4/12/2021
Mean of *NRC*	*M_NRC*	-0.96474	0.7647	-2.01554	0.9816	5/10/2021
Mean of *CAA*	*M_CAA*	-1.99957	0.2869	-2.67725	0.8391	4/24/2021
Mean of *Health Insurance*	*V_HEALTH*	-1.32844	0.6155	-4.19689	0.0991	3/29/2021
Mean of *Sonar Bangla*	*V_SONAR*	-1.85802	0.3513	-2.80479	0.7852	4/27/2021
Mean of *NRC*	*V_NRC*	-0.78092	0.8212	-1.95089	0.9848	5/18/2021
Mean of *CAA*	*V_CAA*	-2.21331	0.2025	-4.0761	0.1319	5/28/2021
Mean of *Health Insurance*	*S_HEALTH*	-1.63377	0.4628	-2.93416	0.7205	3/30/2021
Mean of *Sonar Bangla*	*S_SONAR*	-3.18365	0.0229	-3.75606	0.2552	2/17/2021
Mean of *NRC*	*S_NRC*	-2.95096	0.0421	-3.17675	0.5794	5/3/2021
Mean of *CAA*	*S_CAA*	-1.854	0.3533	-5.29225	< 0.01	5/28/2021
Kurtosis of *Health Insurance*	*K_HEALTH*	-1.72117	0.4186	-2.80519	0.785	3/30/2021
Kurtosis of *Sonar Bangla*	*K_SONAR*	-2.71959	0.0731	-3.31873	0.493	5/24/2021
Kurtosis of *NRC*	*K_NRC*	-3.08335	0.03	-3.48298	0.3966	5/5/2021
Kurtosis of *CAA*	*K_CAA*	-1.70856	0.4249	-10.5303	< 0.01	5/28/2021

Note: "Prob." is level of significance.
Source: Prepared by the author.