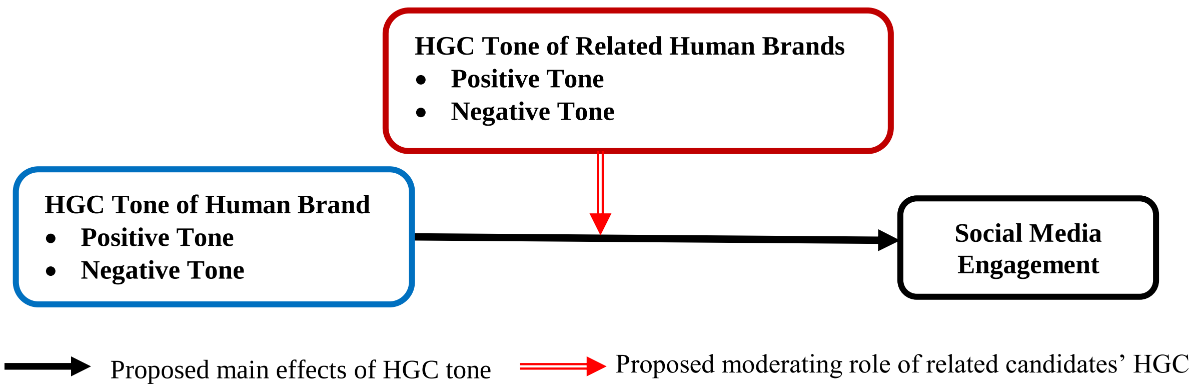
Online Supplement to
The Effects of Social Media Tone on Engagement: Evidence from Indian General Election 2014

Appendix A. Conceptual Framework

In this section, we develop and present a conceptual framework (see Figure A1) that helps in explaining the effect of the tone of HGC on audience engagement levels. We build on existing literature from the areas of psychology and marketing to explain and theorize the possible direction of the relationship between the tone of the human brand and the social media engagement. Before we do so, we first describe the operationalization of the key dependent variable, i.e., the social media engagement.

Figure A1. Conceptual Framework



A.1 Social Media Engagement

A key characteristic of social media is that it acts as a platform to facilitate direct engagement of the audience with brands. One of the primary goals of human brands on social media is to increase its engagement levels with the audience. Hence, the dependent variable for our study is the level of social media engagement. Van Doorn et al. (2010) define engagement as "*customer's behavioral manifestation towards a brand.*" Extant literature in information systems (IS) and marketing have studied the impact of social media content on sales and other economic outcomes that could represent engagement (Kumar et al. 2016). However, Van Doorn et al. (2010) argue: *"engagement is behavioral construct that goes beyond purchase behavior alone."* While there are several ways to measure engagement, Kumar et al. (2010) argue that the customers engage and create value for the brand by sharing the brand's social media content with others in their network, thereby amplifying the impact of the original content.

Retweeting is a feature on Twitter that allows a user to share the tweet of another user. By "*retweeting*" the message of human brands, the user is spreading or transmitting the message to their followers and thus increasing the reach of the message beyond the followers of the human brand (Kwak et al. 2010). Brand marketers acknowledge that the number of retweets is an appropriate measure of audience engagement on Twitter (Long 2015). Accordingly, in line with prior literature and practice, we employ number of retweets of HGC as a metric to measure the social media engagement. As mentioned earlier, while prior studies have looked at the effects of user engagement of social media content on metrics such as sales (e.g., Kumar et al. 2013), we focus on the engagement of content (tweet in our context) created by human brands as measured by sharing and transmission of social media content.[1]

A.2 Tone of HGC and Engagement

The tone of content in political campaigns has been a topic of debate in the political marketing literature. However, extant literature in political science and marketing suggests conflicting views on the consequences of positive tone and negative tone in political campaigns and advertising. In this rest of this subsection, we use prior literature to explain the rationale behind the conflicting effects of different tones of social media content on audience engagement.

Positive toned content in politics, in general, is intended to propagate the message of the sponsor of the content in addition to emphasizing the strengths of the content creator. However, literature in marketing and psychology provides competing arguments on the effects of positive toned content on engagement. On the one hand, Berger and Milkman (2012) argue that the audience often share content for altruistic motives and enhancing the perception among their peers. They find that positive toned news articles are more likely to be shared online. We thus argue that the positive tone of HGC entices optimistic mood among the audience. Given the assumption that the online audience want to be perceived positively among their peers, the audience is more likely to share human brands' positive toned content, thus increasing the engagement

[1] In other words, we focus on the effect of tone of HGC on retweets and not on the consequences of retweets.

levels with the human brands that post positive toned HGC. However, on the other hand, researchers argue that the positive toned HGC does not increase the curiosity of the audience, and therefore they are less inclined to engage with positive content. Hence, positive toned HGC does not draw the attention of the audience on social media; consequently, an increase in the number of positive toned HGC may not be associated with higher engagement levels.

Negative toned advertising in politics refers to ads that are used to attack an opponent by highlighting his/her weaknesses. Although negative advertising is often associated with politics, it is quite common to see negative or comparative advertising in brand/product promotion. The impression formation literature in psychology, which studies how consumers process and integrate information, explains one of the rationales behind the positive effect of negative advertising. Within the impression formation literature, the novelty theory proposed by Fiske (1980) argues that rare and novel information is highly revealing since it distinguishes itself from other more common information and thus requires greater attention. As a result, consumers pay more attention to negative information and value it more when compared to positive information (Hamilton and Zanna 1972; Baumeister et al. 2001). This positive effect of negative information has been documented in both product evaluation and person perception (Wright 1974; Herr et al. 1991). Another reason for the positive effect of negative tone is that negative information is deemed more diagnostic when compared to positive information and hence given more weight by the audience (Maheswaran and Meyers-Levy 1990; Herr et al. 1991). Based on the aforementioned research, we argue that a candidate's negative toned HGC evokes the interest of the online community. Thus, the users of social media are more likely to engage with the human brands by retweeting more number of negative toned HGC. In contrary, a competing argument in the prior literature of psychology and marketing suggests that negative toned advertising may lead to unintentional effects (Pinkleton 1997) including backlash from the audience (Sorescu and Gelb 2000). Thus, in our context, the online audience might not be receptive to more number of candidate's negative toned HGC resulting in the lower social media engagement.

Based on the above discussion, both sides of the argument (i.e., both positive and negative toned content may be associated with either higher or lower engagement) are theoretically plausible, thus presenting a necessity to conduct an empirical analysis to understand the relationship between the tone of HGC and the number of retweets. In summary, our study builds upon the prior literature that focuses on the effects of the tone of content on the perception of audience; we extend the literature and understand the effects of negative and positive toned HGC on engagement with the audience on social media platforms.

A.3 Spillover – Individual Brands and Related Brands

We use the existing literature to explain the spillover effects in social media. Prior studies in the area of marketing suggest that individual brands cannot be isolated from exposure of information about related brands and umbrella brand (Lei et al. 2008). Similar to corporate brands, political parties are umbrella brands. For example, brands as Corn Flakes, Froot Loops, Raisin Bran, and Special K belong to the same corporate brand (i.e., Kellogg's). Likewise, political parties are an umbrella brand to several individual brands, i.e., individual political members of a political party (Singer 2002). In addition, candidates (or human brands) are appropriate representatives of their political parties (or respective groups). We define related candidates as individual political members belonging to the same political party. Similar to the spillover of perception between brands within an organization, we argue that there may be spillover of perception due to HGC from related candidates. Spillover occurs when existing perception and information about a brand influences the beliefs and opinions of another brand (Janakiraman et al. 2009). For example, spillover of perceptions can happen between players belonging to the same team, or politicians belonging to the same political party. More specifically, we expect that the effect of HGC tone on engagement may be moderated by the tone of the related brands. We now discuss the theoretical reasoning behind perception spillover.

Extant literature in psychology and behavioral economics suggest that when forming an opinion about a brand, customers may look for traits that are common between the focal brand and other similar brands (Bazerman and Moore 2009). The accessibility–diagnosticity theory helps us explain the underlying rationale behind the spillover of perceptions between human brands belonging to the same political party. Proposed by Feldman and Lynch (1988), this theory suggests that if a customer considers that brand X is informative (diagnostic) about brand Y, s/he will use the information and perceptions of brand X to form an opinion about brand Y (Roehm and Tybout 2006; Janakiraman et al. 2009). However, this is effective only if both the brands are accessible (or retrieved) in the memory of the customer at the same time (Roehm and Tybout 2006). Therefore, perception spillover between human brands exists only when the association between the brands is strong and thereby they are associated in the customer's memory. The audience often perceive all the politicians belonging to the same party as belonging to one group. For example, voters often view members and candidates of the Republican Party to be similar to each other. Given that political party members are often associated to a group, there will be spillover of perception.

Furthermore, the spreading activation framework suggests that information about brands and their attributes reside in customers' knowledge network as network nodes and network linkages between such nodes promote accessibility (Collins and Loftus 1975; Anderson 1983; Janakiraman et al. 2009). Hence, we argue that when an online user gets a message on Twitter from a human brand, the node of a focal human brand is activated; in addition, all the associated nodes (i.e., related candidates) are activated as well causing retrieval of memory of the user. Thus, the audience on social media uses all the information available in its memory when making a decision to engage. Thus, the tone of HGC of related brands may affect the relationship between the focal human brand's tone and engagement levels. In other words, the tone of related brands' HGC may moderate that relationship between the focal human brand's HGC tone and the social media engagement.

Literature on perception spillover suggests that brands belonging to the same group benefit from each other's advertising (e.g., Balachander and Ghose 2003). We define this benefit as a positive spillover effect. In our context, positive spillover refers to the positive moderation of the relationship between the focal human brand's tone and audience engagement when the tone of both the focal human brand and related brands is same. For example, if our findings to the first research question demonstrate that the negative toned HGC increases engagement, this relationship is further intensified when the tone of related brands is also negative. Similarly, if our findings suggest that the positive tone of focal human brand's HGC is associated with higher engagement levels, this association is further strengthened when the tone of the related candidate is also positive.

Alternatively, when the tone of HGC of both the focal human brand and the related brands is negative, the accessibility–diagnosticity theory suggests that the audience perceives higher number of negative toned

HGC from related brands as more negative toned HGC from the focal brand itself. This higher number of negative toned content (from the perspective of the audience) may eventually lead to backlash and hurting the focal brand. Thus, when the tone of related brands is negative and the tone of the human brand is also negative, the engagement may decrease. In addition, the positive tone of HGC of both the focal and related human brands may not generate curiosity in the minds of the audience, and hence may have a negative impact on engagement levels. Thus, a theoretical argument for the presence of negative spillover can be made.

The positive (resp., negative) toned HGC of related brands could moderate the relationship between the negative (resp., positive) tone of HGC of focal human brand and audience engagement levels. The proposed multi-level mixed effects model, which we employ to answer our research questions, allows us to explore the impact of positive (resp., negative) tone of related brands on the relationship between the negative (resp., positive) tone of focal human brand's HGC and audience engagement. To the best of our knowledge, our study is the first to systematically analyze this moderating effect.

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Appendix B. Discussion on Key Variables of Interest

In the following subsections, we discuss the operationalization of the variables we use.

B.1 Dependent Variable: Number of Retweets

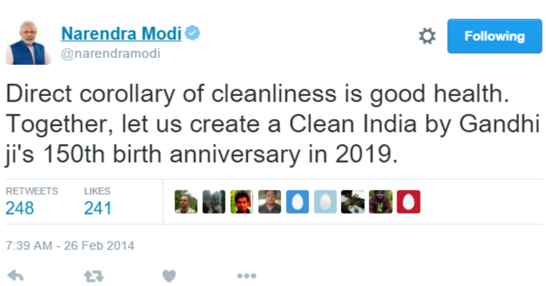
The dependent variable in our study is the number of retweets (denoted by RT_{ipt}) received in week t by candidate i belonging to the political party p. When a human brand tweets a message, it reaches the Twitter home page of all the followers of that particular human brand. The home page of a Twitter user A is often updated will all the tweets from users that user A is following. When user A opens his/her Twitter account, he will see the recent tweets from the human brands that he/she is following. However, if user A is not very active on Twitter (for example, he/she opens the Twitter once a month), he/she will generally see only the most recent tweets. Thus, we assume that a user generally retweets recent tweets. That is, we assume that the tweets by the candidates are retweeted in the same week. We identify the number of retweets for each of the 16,471 distinct tweets posted by 63 candidates contesting the general elections.

B.2 Independent and Control Variables

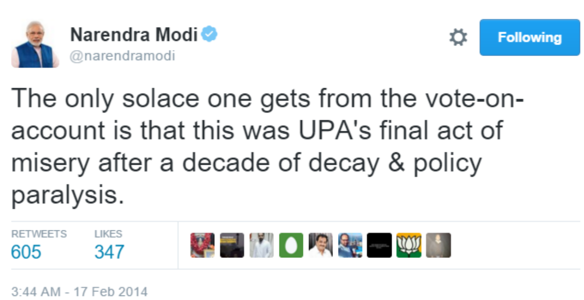
Our main explanatory variables deal with the sentiment of tweets by the individual candidates. Following recent studies, we employ a commonly used sentiment classification algorithm - Naïve Bayes algorithm (Antweiler and Frank 2004; Gu et al. 2014) to classify tweets into three categories: positive sentiment, negative sentiment, and mixed sentiment. This technique is proven to be highly reliable and has been widely used in prior studies in the area of IS and management science (e.g., Das and Chen 2007; Gu et al. 2014). As the name suggests, this algorithm is based on the Bayes theorem. The Naïve Bayes model is based upon the following principles: words in a tweet are independent to each other, each word has a pre-determined tone or sentiment, and the overall sentiment or tone of a sentence (or a tweet) is the collective sentiment of all the words in the tweet (Antweiler and Frank 2004).[2]

Figure B1. Example HGC

Panel A: Positive toned HGC



Panel B: Negative toned HGC



[2] Please refer to Antweiler and Frank (2004) for detailed discussion on the Naïve Bayes sentiment classifier.

Figure B1 illustrates an example of positive and negative toned tweets (see panel A and panel B, respectively). In addition to classifying the tweets into positive tone and negative tone, the sentiment classification algorithm categorizes tweets into mixed or neutral tone. We define mixed or neutral tone tweets as those that contain either both positive and negative tone or neither of these tones. Among the 16,471 tweets by candidates contesting the elections, our classification algorithm classified 3,965 tweets as positive toned, 1,710 tweets as negative toned, and the remaining tweets as mixed or neutral toned. The number of positive toned tweets in week t posted by candidate i belonging to political party p is denoted by $PosT_{ipt}$. $NegT_{ipt}$ represents the number of negative toned tweets by candidate i belonging to political party p during week t. Finally, $MixT_{ipt}$ represents the number of mixed or neutral toned tweets by candidate i belonging to political party p during week t.

Next, we capture the number of tweets of different tones of all the related candidates. The related candidates of the human brand i of the political party p consist of: (i) all the candidates of the political party p, (ii) the prominent members of the political party p who are not participating in the elections, and (iii) the official Twitter accounts of the political party p at the state level and the national level. The number of positive toned tweets by the related candidates (denoted by $PartyPosT_{ipt}$) is the sum of all the positive toned tweets by the candidates belonging to party p not including the positive toned tweets of the focal candidate during week t. Likewise, $PartyNegT_{ipt}$ and $PartyMixT_{ipt}$ represent the number of negative and mixed/neutral toned tweets by related candidates. Among the 98,237 tweets by related candidates, the Naïve Bayes algorithm classified 19,933 tweets as positive toned, 9,729 tweets as negative toned, and the rest as mixed or neutral toned.

We conceptualize the spillover effect as the interaction between the number of positive (and negative) toned tweets of candidate i and the number of positive (and negative) toned tweets of related candidates of i. We thus have four interaction terms to measure the spillover effect as follows: (i) $PartyPosT_{ipt}$ x $PosT_{ipt}$, (ii) $PartyNegT_{ipt}$ x $NegT_{ipt}$, (iii) $PartyPosT_{ipt}$ x $NegT_{ipt}$, and (iv) $PartyNegT_{ipt}$ x $PosT_{ipt}$. The signs of the coefficients of these interaction terms will provide us with the direction of the spillover effects. For example, if the sign associated with the interaction term $PartyPosT_{ipt}$ x $PosT_{ipt}$ is positive, there is a positive spillover effect. That is, the audience transfers positive perception of related brands onto the focal human brand.

In addition to the main independent variables and the interaction terms, we include several variables in our model to improve the precision of our estimates and to control for heterogeneity at the candidate level. Age_i is the actual age of the candidate in years. The age of the candidate is a broad indicator for the experience of the candidate. $Male_i$ is a dummy variable set equal to 1 if the candidate is male. In addition, we control for the candidate's spending power measured by candidate's net worth in logarithmic scale (log_assets_i). We also control the level of education through three dummy variables (i.e., high school or below, college degree, and higher degree). Further, we control for the candidate's geographical area through the dummy variables *Region*$_i$ (i.e., North India, East India, West India, and South India). We also control for the election result of the candidate through the dummy variable *Result*$_i$. We obtain the data on candidate-specific time-invariant control variables from the website of the election commission of India.

In addition to the personal attributes, we control for candidate's popularity on Twitter. We use number of followers (denoted by Fol_{ipt}) as a measure of the candidate's popularity among users of the social media platform. For example, a candidate with more number of followers may have greater levels of engagement as the candidate's HGC is reaching more number of users on Twitter. We note that the number of followers is dynamic (i.e., it could increase or decrease over a period). Therefore, we operationalize this variable by calculating the number of followers on a weekly basis. Furthermore, Berger and Schwartz (2012) suggest that the visibility of the candidate on social media platform stimulates interest in the candidate, and it is positively correlated with engagement. Therefore, we control for the visibility of the candidate through the variable $Mentions_{ipt}$, which represents number of mentions of a candidate in tweets by all the users on Twitter during that particular week. Our data consists of entire Twitter activity on the topic of elections. Hence, mention of a candidate by their Twitter username and the number of followers of a candidate are good proxies for his/her visibility and popularity, respectively.[3]

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[3] We note that the users may use the first or last name of the candidate in their tweet rather than using their Twitter username. We do not consider tweets that do not use the official Twitter username in a tweet. One reason is because several Indian names are quite common and hence it would not be possible to differentiate the candidates from non-candidates.

Appendix C. Details of Supplementary Analysis

To benchmark and validate the statistical fit of our proposed model, we conduct a series of robustness tests using alternative specifications and samples. In addition, to understand the performance of our empirical strategy, we estimate our model using the conventional random effects and fixed effects model. We find that our key results are substantively robust to these alternative specifications.

C.1 Robustness to Temporal Changes

We first include the time fixed effects in our main model (see Table C1, Column R1) to control for any temporal changes. In particular, as the elections are closer, the candidate's tone might change. Hence, to control for any change in the candidate's social media strategy and any unobserved time-specific shocks, we include the time fixed effects (i.e., an indicator variable for each week) in our model. Our results indicate that the time fixed effects are not statistically significant, and our key results are robust even with the time fixed effects.

C.2 Robustness with Alternative Specifications

Recall that, in the proposed model (i.e., Model 5 in the main paper), the coefficients for $PosT_{ipt}$ *and* $NegT_{ipt}$ were modeled as a function of party specific factors to ensure that the group stimuli do not affect the estimation of our model. We now assess the robustness of our model by making the coefficients of $Mentions_{ipt}$, Fol_{ipt}, and $MixT_{ipt}$ to be random across party level. Hence, to control for party-specific unobserved heterogeneity that may affect the variables $Mentions_{ipt}$, Fol_{ipt}, and $MixT_{ipt}$, we re-estimate our model treating the coefficients of $Mentions_{ipt}$, Fol_{ipt}, and $MixT_{ipt}$ to be random. Specifically, the coefficients of $Mentions_{ipt}$ (denoted by δ_{1pt}), Fol_{ipt} (denoted by δ_{2pt}), and $MixT_{ipt}$ (denoted by β_{3pt}) are as follows: $\delta_{1pt} = \lambda_{10} + \upsilon_{1pt}$, $\delta_{2pt} = \lambda_{20} + \upsilon_{2pt}$, and $\beta_{3pt} = \lambda_{30} + \upsilon_{3pt}$. The party specific random error terms, υ_{1pt}, υ_{2pt}, and υ_{3pt} capture the unobserved party level variance of $Mentions_{ipt}$, Fol_{ipt}, and $MixT_{ipt}$. The results, shown in Table C1, Column R2, with this alternative specification are qualitatively very similar to those in the main model.

--INSERT TABLE C1 HERE—

C.3 Robustness with Alternate Sample

Next, we re-estimate our full model with an alternative sample. As the focus of our study is to understand the drivers of engagement based on human brand's social media activity, we had previously employed twenty-six tweets per candidate (i.e., on average at least one tweet per week) as a cut-off for our main model. In order to examine the consistency of our results, we re-estimated our model by including candidates with lower levels of activity on Twitter. Specifically, we lower the number of tweets to six tweets for the 6-month period instead of twenty-six tweets (i.e., on average at least one tweet per month). The results, shown in Table C2 (column R3), are consistent with the key findings regardless of different levels of activity on social media platforms.

--INSERT TABLE C2 HERE—

C.4 Disaggregate Model of Tones of HGC

One might argue that the aggregation of retweets of positive, negative, and mixed toned HGC in the main model (Equation 5 in the main paper) might lead to biased estimates. To address this, we ran separate regression models for negative toned HGC, positive toned HGC, and mixed toned HGC (see Table C3, Columns R4, R5, and R6, respectively). In the model specified for positive (resp., negative) toned HGC, the dependent variable of interest is the engagement levels of the positive (resp., negative) toned HGC with the number of positive (resp., negative) toned HGC being the main independent variable of interest. In the case of our main model, we assume random coefficients for the main independent variable to account for unobserved heterogeneity at the political party level. The results for the separate models are shown in Table C3.

In the case of negative sentiment model (Column R4 in Table C3), the findings are consistent with the results from the full model. That is, we find that the negative toned HGC are associated with greater levels of consumer engagement, and this result is statistically significant. Further, the interaction between the candidate and party negative toned HGC is negative and significant. These results are qualitatively similar to our findings in the main model, providing further evidence to the premise that the negative toned HGC has a positive effect on the number of retweets, whereas the negative tone of related brands reduces this positive impact. However, in case of the positive sentiment model (Column R5 in Table C3); we do not find statistical significance for the coefficient of the number of positive toned tweets.

--INSERT TABLE C3 HERE --

C.5 Robustness Check: Conventional Models

Finally, we compare the estimates of our proposed estimation procedure for our model in Equation 5 (of the main paper) to the conventional estimation procedures (fixed effects and random effects). As discussed earlier, the past literature suggests that the mixed effects model provides efficient estimates. In other words, if the estimates of the conventional model are consistent (even with not so efficient estimators), it suggests that our qualitative results are robust. Further, it would be interesting to compare the estimates when accounting for heterogeneity at party level. We present the results of both the conventional models (i.e., random and fixed effects) and the random coefficients model in Table C4. Results suggest that most of the results are consistent qualitatively. Furthermore, as seen in Table C4, the estimates from mixed effects estimation procedure tend to provide more efficient estimates.

--INSERT TABLE C4 HERE –

Tables for Appendix C

Table C1. Results for Models with Time Fixed Effects and Other Random Coefficients

	R1	R2
DV	**RT**	**RT**
Main Effect of HGC		
$PosT_{ipt}$	-68.70***	-44.73*
	(13.35)	(18.81)
$NegT_{ipt}$	52.15*	43.28***
	(20.5)	(10.72)
$MixT_{ipt}$	44.86***	22.83*
	(3.079)	(9.775)
$PartyPosT_{ipt}$	-0.257	0.165
	(0.202)	(0.204)
$PartyNegT_{ipt}$	0.646	-0.0629
	(0.464)	(0.329)
$PartyMixT_{ipt}$	0.0333	-0.0592
	(0.0268)	(0.0327)
Moderating Effects		
$PosT_{ipt}$ x $PartyPosT_{ipt}$	0.0661**	0.0213
	(0.0208)	(0.031)
$NegT_{ipt}$ x $PartyNegT_{ipt}$	-0.612***	-0.498***
	(0.139)	(0.124)
$NegT_{ipt}$ x $PartyPosT_{ipt}$	0.155***	0.142**
	(0.0461)	(0.0469)
$PosT_{ipt}$ x $PartyNegT_{ipt}$	0.0347	0.11
	(0.0642)	(0.0656)
Controls		
$Mentions_{ipt}$	0.276***	0.268***
	(0.032)	(0.0413)
Fol_{ipt}	-2.30E-04***	-2.85E-04***
	(2.99E-05)	(5.02E-05)
log_assets_i	7.341	11.25
	(12.43)	(9.029)
Age_i	3.396*	0.195
	(1.336)	(1.204)
$Male_i$	-97.02*	-11.76
	(38.24)	(7.567)
$Result_i$	3.388	-81.15**
	(38.53)	(28.23)
Region Controls	Yes	Yes
Education Controls	Yes	Yes
Time Fixed Effects	Yes	No
Intercept	-514.9**	-223.6
	(196.6)	(180.8)
N	1376	1376
Log-likelihood	-10700.123	-10628.632

Robust standard errors clustered at party level are in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table C2. Results with Alternative Sample

	R3
DV	**RT**
Main Effect of HGC	
$PosT_{ipt}$	-75.74***
	(12.990)
$NegT_{ipt}$	64.14*
	(27.340)
$MixT_{ipt}$	42.66***
	(3.630)
$PartyPosT_{ipt}$	0.0658
	(0.189)
$PartyNegT_{ipt}$	0.146
	(0.361)
$PartyMixT_{ipt}$	-0.0452*
	(0.0193)
Moderating Effects	
$PosT_{ipt}$ x $PartyPosT_{ipt}$	0.0696***
	(0.0146)
$NegT_{ipt}$ x $PartyNegT_{ipt}$	-0.647***
	(0.136)
$NegT_{ipt}$ x $PartyPosT_{ipt}$	0.146***
	(0.0376)
$PosT_{ipt}$ x $PartyNegT_{ipt}$	0.0534
	(0.0478)
Controls	
$Mentions_{ipt}$	0.281***
	(0.0302)
Fol_{ipt}	-2.27E-04***
	(2.83E-05)
log_assets_i	9.893
	(10.290)
Age_i	1.817**
	(0.705)
$Male_i$	-76.18**
	(26.45)
$Result_i$	16.22
	(32.85)
Region Controls	Yes
Education Controls	Yes
Intercept	-344.2
	(206.3)
N	1939
Log-likelihood	-14791.435

Robust standard errors clustered at party level are in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table C3. Results for Separate Models for Each Tone

	R4	R5	R6
DV	RT - Neg	RT - Pos	RT - Mix
Main Effects of HGC			
$PosT_{ipt}$	-	2.758	-
	-	(6.534)	-
$NegT_{ipt}$	21.08*	-	-
	(8.893)	-	-
$MixT_{ipt}$	-	-	22.82**
	-	-	(8.813)
$PartyPosT_{ipt}$	-0.0678***	-0.0246	-0.124
	(0.0107)	(0.114)	(0.203)
$PartyNegT_{ipt}$	0.0907***	0.0188	0.575*
	(0.0115)	(0.19)	(0.275)
$PartyMixT_{ipt}$	0.0111***	-0.0156*	-0.0269
	(0.0019)	(0.00644)	(0.032)
Moderating Effects			
$PosT_{ipt}$ x $PartyPosT_{ipt}$	-	-0.0649	-
	-	(0.0451)	-
$NegT_{ipt}$ x $PartyNegT_{ipt}$	-0.0816***	-	-
	(0.0212)	-	-
$NegT_{ipt}$ x $PartyPosT_{ipt}$	0.0453***	-	-
	(0.00191)	-	-
$PosT_{ipt}$ x $PartyNegT_{ipt}$	-	0.0554***	-
	-	(0.0156)	-
$MixT_{ipt}$ x $PartyNegT_{ipt}$	-	-	-0.174***
	-	-	(0.00838)
$MixT_{ipt}$ x $PartyPosT_{ipt}$	-	-	0.0249***
	-	-	(0.00393)
Controls			
$Mentions_{ipt}$	0.00908***	0.0574***	0.209***
	(5.23E-04)	(0.0108)	(0.0173)
Fol_{ipt}	2.7E-05	6.13E-05	-5.08E-04***
	(3.83E-05)	(4.16E-05)	(1.3E-04)
log_assets_i	-0.0999	-3.886*	6.406
	(1.863)	(1.734)	(8.128)
Age_i	0.841***	1.035***	-0.878
	(0.153)	(0.268)	(1.032)
$Male_i$	1.713	-7.559	-37.39**
	(10.1)	(10.94)	(12.51)
$Result_i$	-4.554	-19.82***	-88.44*
	(4.586)	(1.953)	(44.26)
Region Controls	Yes	Yes	Yes
Education Controls	Yes	Yes	Yes
Intercept	-57.71	24.40	-96.70
	(53.29)	(71.75)	(156.20)
N	1376	1376	1376
Log-likelihood	-8403.455	-9086.65	-10421.682

Robust standard errors clustered at party level are in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table C4. Conventional Models vs Random Coefficients Model

	Random Effects	Fixed Effects	Proposed Model
DV	**RT**	**RT**	**RT**
Main Effect of HGC			
$PosT_{ipt}$	**-65.892***	**-60.995**	**-72.82***
	(13.817)	(13.799)	(11.9)
$NegT_{ipt}$	**44.856**	**39.685**$^{+}$	**61.49**
	(18.104)	(21.092)	(22.35)
$MixT_{ipt}$	42.698***	41.649***	43.89***
	(4.098)	(6.562)	(3.438)
$PartyPosT_{ipt}$	0.126	0.1006	0.141
	(0.263)	(0.219)	(0.27)
$PartyNegT_{ipt}$	0.196	0.114	0.211
	(0.573)	(0.661)	(0.558)
$PartyMixT_{ipt}$	-0.0644***	-0.0689**	-0.0670**
	(0.0236)	(0.0148)	(0.0208)
Moderating Effects			
$PosT_{ipt}$ x $PartyPosT_{ipt}$	**0.0551***	**0.0537**	**0.0701***
	(0.013)	(0.0195)	(0.0155)
$NegT_{ipt}$ x $PartyNegT_{ipt}$	**-0.543***	**-0.4867***	**-0.598***
	(0.135)	(0.203)	(0.138)
$NegT_{ipt}$ x $PartyPosT_{ipt}$	**0.155**	**0.1355**$^{+}$	**0.136**
	(0.082)	(0.0699)	(0.0425)
$PosT_{ipt}$ x $PartyNegT_{ipt}$	**0.0515***	**0.0435**	**0.0409**
	(0.024)	(0.0283)	(0.0527)
Controls			
$Mentions_{ipt}$	0.287***	0.292***	0.279***
	(0.023)	(0.0443)	(0.0319)
Fol_{ipt}	-2E-04	-4.00E-05	-2.22E-04***
	(1.06E-04)	(2.49E-03)	(3.02E-05)
Controls	(Yes)	-	(Yes)
Intercept	-528.6*	-81.455	-486.0*
	(241.5)	(64.0136)	(246.3)
N	1376	1376	1376
Log-likelihood	-	-	-10723.76
R-Squared (Overall)	0.9112	0.9087	-

Robust standard errors clustered at party level are in parentheses
$^{+}$ p<0.12, * p<0.05, ** p<0.01, *** p<0.001