Measuring Agenda-Setting Power in Political Discourse*

Erin Rossiter

Department of Political Science

Washington University in St. Louis

February 15, 2019

ABSTRACT

How can we determine who holds the power in a political exchange? In an interactive communication (i.e., a debate, deliberation, or discussion), I argue power is exercised by controlling the conversational agenda. Since agenda-setting power is not directly observable, I measure this trait using the texts from communications as data and a topic model equipped to measure when changes in topic occur (Nguyen et al. 2014). Importantly, the model measures agenda-setting by attributing topic changes to the behavior of speakers. I use simulation studies to show the model performs as expected and provides a methodological contribution to the discipline as standard text methods fail at identifying agenda-setting behavior. I further validate the agenda-setting measure with experimental deliberation data to show it captures a form of strategic participation. Lastly, I analyze the highly strategic setting of electoral debates to not only measure candidates' agenda-setting abilities, but to also describe the agendas candidates use their power to promote using the latent topics estimated by the model. Taken together, these applications of the model provide evidence for its validity and usefulness to the text analysis and political communication literatures.

*I am grateful to Christopher Karpowitz and Hans Hassell for generously sharing data. I appreciate any comments or suggestions. Please do not cite or distribute without permission.

1 INTRODUCTION

Who holds the upper-hand, the control, or the *power* in a political exchange is fundamental to the study of political discourse but remains an elusive concept to quantify. While observing the exercise of power is more straightforward in the formal political arena (e.g., a president vetoes a bill), we lack a systematic way to study power in the countless communications among actors that are important and pervasive pre-cursors to any formal display of power we might observe.

In this paper, I propose an approach for measuring the power of actors in an interactive political communication. This approach is general so to be applicable to any written or spoken interaction, whether it be a debate or deliberation, in public or private, with or without formal rules, etc. I posit that in an interactive communication, power is exercised by controlling what is (and what is not) discussed. In other words, *agenda-setting* is power. Specifically, agenda-setting is the ability to effectively change the topic of conversation to one's own agenda, thereby excluding others' agendas from being heard. Since agenda-setting in a social interaction is not directly observable, I propose using the text of the interaction as data to measure this latent ability of actors.

My measurement strategy is to build upon existing topic modeling methods since topics of conversation are key to agenda-setting. Specifically, I use a model called Speaker Identity for Topic Segmentation (SITS) from the computer science topic segmentation literature (Nguyen et al. 2014; Nguyen, Boyd-Graber and Resnik 2012). This model endows a parametric topic model with additional latent variables to estimate (1) when topic changes occur and (2) each speakers' propensity to change the topic, or each speakers' agenda-setting power.

I proceed by first reviewing theories of power and agenda-setting in interpersonal communication to inform my measurement strategy of these concepts. Next, I review how previous work has quantified political interactions to measure participant-level traits and outline my proposed approach to measuring on such trait—agenda-setting power. I then explain the data-generating process of a text under this approach and the estimatin strategy of the model. To validate the model, I use simulation studies to provide evidence that the model recovers quantities of interest even with sparse interactions which typify discussions. I also show that standard text methods do not perform well when adapted to the task of identifying the topic changes that underly agenda-setting behavior. I then provide evidence that the agenda-setting measure captures *strategic* behavior, showing agenda-setters display less attitude change regarding the topic of discussion than others in laboratory-generated deliberation texts. Lastly, I apply the model to the highly strategic setting of electoral debates to not only to challenge the model to measure candidates' relative power in observational data, but to also describe the agendas for which the candidates wield their power using the latent topics estimated by the model. Taken together, these applications of the model provide evidence for its validity and its contribution to the text analysis and political communication literatures.

2 AGENDA-SETTING AS A FORM OF POWER

Consider one well-known typology of power offered by Steven Lukes, where power can be wielded by political actors in the form of decision-making power, agenda-setting power, or manipulation (Lukes 1974). Decision-making power is changing the behavior of others (i.e., achieving compliance) as a result of one's exercise of power (Dahl 1957; Polsby 1964). Power in this form is easily observable, such as the exercise of formal powers of institutions (e.g., a president vetoes a bill) and decision-making votes of actors. Due to its observable nature, political scientists have studied this dimension of power extensively, asking who has decision-making power and how is it used (e.g., Howell 2003; Krehbiel 2010; Segal and Spaeth 2002). Researchers have also succeeded in systematically studying power of manipulation, or the power to shape perceptions, preferences, and interests of others. Research studying this form of power includes that which explains the use of censorship (e.g., King, Pan and Roberts 2013) and propaganda (e.g., King, Pan and Roberts 2017) in shaping the perceptions and preferences of citizens.

Yet, power extends beyond institutions' decision-making and elite actors' manipulation of the public. Political actors also fight over and exercise power during social interactions that are ubiquitous in the political sphere. One way power is exercised in interpersonal communications is by setting the conversational agenda. Further, not only is agenda-control fought over when two political actors communicate, but importantly, theories of power posit that agenda-setting power moderates what decision-making power we might observe. Agenda-setting accomplishes this by preventing discussion on a given topic, or conversely, steering discussion toward a given topic (Bachrach and Baratz 1962, 1963, 1970). In other words, issues that are *not* discussed are just as consequential as those issues that are included on the agenda because what makes it to the agenda moderates the potential decision-making outcomes we might observe (Cox and McCubbins 2005). Thus, agenda-setting behavior occurs in any given political interaction, as actors seek to gain the floor and shape the scope of the discussion to their preferred issues.

To clarify, the practice of agenda-setting that is the focus of this paper is different from the mass media's role in agenda-setting (e.g., McCombs and Shaw 1972), the government's role in agenda-setting (e.g., Baumgartner and Jones 2010) or setting a formal agenda via institutions (e.g., Cox and McCubbins 2005). These forms of agenda-setting are beyond the scope of this paper as agenda-setting during political interactions is an inherently social phenomenon and thus requires a different approach to quantify.

Agenda-setting power in social settings has remained difficult for researchers to study, partly due to the often informal and private nature of political interactions among elites. For example, academics do not have access to the private conversations a president has with her advisors behind closed doors.[1] Regardless, there are plenty of interactions in the political arena that are not private and audio or textual data are disseminated publicly, as is the case with electoral debates, Supreme Court oral arguments, congressional committee hearings, White House press secretary briefings, and United Nations hearings, for example. And while the collection and analysis of large corpora of text was once too time consuming to undertake, scholars have introduced text as data methods to the discipline to aid in systematic analysis of such data (Grimmer and Stewart 2013). Therefore, the systematic study of agenda-setting power in political interactions is hindered namely by the need for a measure of this theoretical concept. In the next section I discuss ways in which scholars have quantified texts to study interactions, and building upon this literature, I introduce an approach

[1] However, sometimes such private communications become available to the public, such as President Richard Nixon's audio recordings of conversations between himself and his administration or Hillary Clinton's emails as Secretary of State.

to measure agenda-setting power in social interactions.

3 QUANTIFYING INTERACTIONS

In this paper I aim to quantify a participant-level behavior in interactive political communications: power in the form of agenda-setting. While previous researchers have sought to measure participant-level traits and behaviors in interactions, I echo the sentiment expressed by a group of these scholars that "systematic analysis of deliberators' behavior is almost nonexistent," (2012, p. 534) and I argue this holds for political interactions in general. Due to the difficulty in quantifying behavior in the interactions of individuals, there have been several different approaches to measuring such quantities, each approach with its own limitations.

3.1. *Previous Approaches to Measurement*

One approach to quantifying interactions is to hand code texts for participant behavior, such as staying on topic in an electoral debate (e.g., Boydstun, Glazier and Phillips 2013). Hand coding, while an intuitive and adaptable measurement strategy, has significant weaknesses. First, recruiting, adequately training, and compensating the work of research assistants can be prohibitively time-consuming and costly. Second, research shows that even high quality coders provide estimates that are unreliable (Mikhaylov, Laver and Benoit 2012).

Another approach taken to measure behavior in interactions has been to count easily observable and quantifiable behaviors such as the number of turns, interruptions, or words spoken by participants (e.g., Kathlene 1994; Johnson, Black and Wedeking 2009; Karpowitz, Mendelberg and Shaker 2012). This approach measures *quantity* of participation, itself an important concept in the study of representation in group deliberations. However count-based measures are limited when the goal is to study the *quality* of participation or the strategic participation of actors.

Scholars have also conducted surveys to measure concepts regarding social interactions in one's life (e.g., Huckfeldt, Johnson and Sprague 2004) or interactions that occurred in the lab (e.g., Druckman, Levendusky and McLain 2017; Gastil, Black and Moscovitz 2008; Klar 2014; Karpowitz and Mendelberg 2014; Druckman and Nelson 2003) in order to assess the effects of interactions on attitudes and behavior. Survey questions rely on self-reported behavior and perceptions, both tainted with potential bias (e.g., Prior 2009), and overlook the interactions themselves as rich sources of data.

Additionally, research has recently begun to exploit audiovisual data for additional dimensions of interactions beyond the words spoken, such as emotion via vocal pitch (e.g., Dietrich, Enos and Sen 2016). This methodology has not yet been extended to study *strategy* in interactions, which unlike emotion, is likely to be manifested in the words of the text in addition to any vocal features in the audio.

Lastly, though not the study of interpersonal interactions, text as data methods have been applied to study agenda-setting in legislative bodies (Quinn et al. 2010; Eggers and Spirling 2016). Studying how the agenda in the U.S. Senate changes over time, Quinn et al. (2010) conceptualized agenda-setting as what issues are broadly gaining attention in the political arena and which are not, but do not seek to measure the agenda-setting behavior of senators. Analyzing speeches by MPs in the House of Commons, Eggers and Spirling (2016) do indeed propose a measure of the agenda-setting abilities of political actors. Their approach differs from the focus of this paper as they do not conceptualize the issue agenda as evolving within a a social interaction, but rather, they conceptualize the agenda as the relative importance placed on issues over time (i.e., months and years). An MP's latent agenda-setting ability is then uncovered by their contribution to the growth of an issues' importance via the language used in speeches. In this paper, I focus on agenda-setting behavior of actors in *interactions*, which unlike speeches, are a social game in which power must be negotiated as the communication unfolds. Like this line of research, I propose using text as data to measure agenda-setting behavior, but the approach I detail next considers agenda-setting within the social context of political interactions.

3.2. *Proposed Approach*

I argue in Section 2 that power in an interactive political communication is manifested in one's agenda-setting ability. Agenda-setting is the ability of an actor to control what is, and importantly, what is *not* discussed. Agenda-setting is therefore a form of strategic participation whereby a

Figure 1: Generative Process of LDA

- For each topic $k \in [1, K]$, draw a topic-word distribution $\phi_k \sim \text{Dir}(\beta)$.
- For each turn $t \in [1, T_d]$, in each discussion $d \in [1, D]$:
  - Draw a topic distribution $\theta_{d,t} \sim \text{Dir}(\alpha)$.
  - For each word index $n \in [1, N_{d,t}]$:
    - Draw a topic $z_{d,t,n} \sim \text{Multinomial}(\theta_{d,t})$.
    - Draw a word $w_{d,t,n} \sim \text{Multinomial}(\phi_{z_{d,t,n}})$.

Note: The underlying data-generating process of the Latent Dirichlet Allocation (LDA) statistical model (Blei, Ng and Jordan 2003).

participant first gains control of the floor by brining up a given issue and subsequently maintains control of the floor by successfully swaying others to discuss it. Agenda-setting is a latent ability of political actors, and thus not directly observable. However, the text of an interaction is observable. Using text as data, existing methods allow for the estimation of latent topics (Blei, Ng and Jordan 2003). Since agenda-setting is defined as successfully changing the course of a discussion to preferable topics, I propose measuring latent agenda-setting abilities by identifying who brought about topic changes in a discussion. Note that this framework is general so to be applicable to any interaction, whether it be a formal debate or impromptu discussion. In the next section I formalize this approach in a statistical model of interactive political communications.

4 MODELING DISCUSSION TEXTS

This section details the Speaker Identity for Topic Segmentation (SITS) model which uses texts from political interactions as data (Nguyen, Boyd-Graber and Resnik 2012; Nguyen et al. 2014). As SITS builds upon Latent Dirichlet Allocation (LDA) (Blei, Ng and Jordan 2003), I will first review LDA, note its limitations as applied to interactive texts, and explain how SITS accounts for these limitations to measure agenda-setting behavior. For ease of exposition, I will refer to an interactive communication simply as a "discussion," each actor participating in a discussion as a "speaker," and each uninterrupted utterance by a speaker as a "speaking-turn."

4.1. *LDA*

Readers are likely familiar with Latent Dirichlet Allocation (LDA) (Blei, Ng and Jordan 2003), a topic model widely used in political science, and the model upon which the Structural Topic Model is based (Roberts et al. 2014; Roberts, Stewart and Airoldi 2016). LDA is a probabilistic topic model, where each document is a mixture over latent topics. Figure 1 presents the generative process of a document of text under LDA. Note that the notation is modified to make this data generating process applicable to a corpus of discussion texts, where discussions are a class of texts that feature multiple speakers taking turns to generate words. Specifically, what is usually referred to as a "document" in LDA is defined in Figure 1 as a single speaking turn of one participant. Formally, for each discussion $d \in [1, D]$, assume LDA treats each speaking turn $t \in [1, T_d]$ as a "document."[2]

Given this alteration to the notation, the data generating process is as follows. First topics (ϕ_k), or probability distributions over the corpus vocabulary, are drawn for each of K topics. Then for each speaking turn $t \in [1, T_d]$ in each discussion $d \in [1, D]$, a distribution over topics ($\theta_{d,t}$) is drawn. Next, for each word index $n \in [1, N_{d,t}]$ in the speaking turn, a topic ($z_{d,t,n}$) is drawn from the turn's distribution over topics and a word ($w_{d,t,n}$) is drawn from the assigned topic.

4.2. *Limitations to LDA as Applied to Discussions*

LDA is not well-suited for discussion texts as it fails to capture the temporal and social dynamics of a discussion. Note that applying LDA to a corpus of texts assumes that each "document" is a *new* mixture over topics ($\theta_{d,t}$). Therefore LDA, as applied to a discussion texts, draws a new mixture over topics for each speaking turn. This step in the data-generating process does not capture the dynamic nature of a discussion. In a discussion, the content of turn t is highly correlated with the content of $t-1$; that is, what the current speaker says is likely to be in response to the previous speaker's comments. Therefore, a new topic distribution does not need to be drawn for every speaking turn. Rather, it is more representative of a discussion text to let the distribution

[2]One must choose at what level to conceptualize a "document" when using discussion texts with extant text methods. Alternatively, it could be defined at the discussion-level, however this would disregard the interactive nature of discussions by obscuring all separate speaking turns into one instance of text.

Figure 2: Generative Process of SITS

- For each speaker $m \in [1, M]$, draw a speaker topic shift probability $\pi_m \sim \text{Beta}(\gamma)$.
- For each topic $k \in [1, K]$, draw a topic-word distribution $\phi_k \sim \text{Dir}(\beta)$.
- For each turn $t \in [1, T_d]$, in each discussion $d \in [1, D]$ (with speaker $a_{d,t}$):
  - If $t = 1$, set the topic shift $l_{d,t} = 1$, otherwise draw $l_{d,t} \sim \text{Bernoulli}(\pi_{a_{d,t}})$.
  - If $l_{d,t} = 0$, set the topic distribution $\theta_{d,t} \equiv \theta_{d,t-1}$, otherwise draw $\theta_{d,t} \sim \text{Dir}(\alpha)$.
  - For each word index $n \in [1, N_{d,t}]$:
    - Draw a topic $z_{d,t,n} \sim \text{Multinomial}(\theta_{d,t})$.
    - Draw a word $w_{d,t,n} \sim \text{Multinomial}(\phi_{z_{d,t,n}})$.

Note: The underlying data-generating process of the parametric Speaker Identity for Topic Segmentation (SITS) statistical model (Nguyen, Boyd-Graber and Resnik 2012; Nguyen et al. 2014). Colored text indicates extensions made to the Latent Dirichlet Allocation statistical model (Blei, Ng and Jordan 2003). Data generating process adapted from Nguyen et al. (2014).

over topics apply to subsequent speaking turns until we think a topic change has occurred, and only then draw a new distribution over topics.

How might we know when a topic change occurs? A discussion evolves as speakers interact with each other navigating the waters of a social setting. Some speakers will exert more power in the discussion than others; some speakers will succeed in pushing their agendas by changing the topic. Therefore, topic changes are a function of the speakers' agenda-setting abilities. The current speaker influences the probability that a topic change will occur during a given speaking turn. Allowing for speakers' agenda-setting abilities to influence the data-generating process would more accurately reflect the social dynamics inherent in a discussion.

4.3. *SITS*

SITS builds upon LDA to incorporate the temporal flow of discussion topics and social behavior of speakers into the data-generating process outlined in Figure 2. Note the data generating process is similar to that of LDA presented in Figure 1 with additions noted in green. First, for each speaker $m \in [1, M]$, a topic shift probability(π_m) is drawn. This captures the latent agenda-setting propensity of speakers. As with LDA, K topics are drawn (ϕ_k). Next, also similar to LDA, for each turn t in discussion d a topic distribution is drawn ($\theta_{d,t}$). SITS additionally notes the observed speaker of each speaking turn ($a_{d,t}$). If it is the first turn in a discussion, a topic change is considered to have occurred. This is noted with a turn-level topic shift binary variable ($l_{d,t} = 1$). If it is not the first turn, the topic shift indicator is drawn from a Bernoulli distribution parameterized by the speaker's agenda-setting measure ($\pi_{a_{d,t}}$). That is, if a speaking turn changes the topic is influenced by its speaker's latent tendency to do so. If a topic change is indicated, a new topic distribution is drawn ($\theta_{d,t}$), otherwise the turn shares the same topic distribution as the previous turn ($\theta_{d,t} \equiv \theta_{d,t-1}$). Then for each word index, topic assignments ($z_{d,t,n}$) and words ($w_{d,t,n}$) are drawn as they are with LDA.

The data generating process of SITS captures both the *dynamic* nature of conversation topics as a sequence of speaking turns on the same topic will share the same topic distribution and the *social* nature of a discussion as power in the form of agenda-setting influences the flow of topics we observe.

4.4. *Estimation*

In what follows, I estimate SITS using a collapsed Gibbs sampler written by the original model authors (Nguyen 2014). It is important to note that the sampler has similarities and differences to a collapsed Gibbs sampler for the LDA (Griffiths and Steyvers 2004). Both SITS and LDA estimate topic assignments ($z_{d,t,n}$), topic distributions ($\theta_{d,t}$), and topics (ϕ_k). SITS also estimates two additional latent variables: turn-level topic shifts ($l_{d,t}$) and speaker-level agenda-setting measures (π_m).

An iteration of the sampler first samples the topics assigned to each word in a speaking turn ($z_{d,t,n}$) as well as the topic shift indicator assigned to each turn ($l_{d,t}$)(Wallach 2008).[3] Latent topic distributions ($\theta_{d,t}$) and topics (ϕ_k) are marginalized over, as is the case with the LDA collapsed Gibbs sampler, but are easily estimated from the posteriors of topic assignments to words ($z_{d,t,n}$). For SITS, speaker agenda-setting measures (π_m) are also marginalized over but are easily estimated from the posteriors of the topic shift indicators ($l_{d,t}$).[4]

[3]Recall that $l_{d,t=1}$ is not sampled for turns that begin a discussion; it is set to 1. Likewise, I consider turns with 4 or less tokens not able to change the topic, thus $l_{d,t}$ is not sampled for such turns and is set to 0. However, the vector of topic assignments $\mathbf{z_{d,t}}$ is sampled each iteration, regardless of turn length.

[4]Additional details regarding estimation are available in the appendix.

5 APPLICATIONS

5.1. *Validating the Model: Simulation Tests*

It is important to first establish not only that the model performs as expected, but that the model provides a valuable contribution to the suite of text as data methods political scientists have at their disposal. I assess each of these concerns in turn with a simulation study. The goal of the first simulation study is to validate that the model recovers the agenda-setting and topic shift parameters and is robust to sparse data (i.e., when speaking turns feature few words). The goal of the second study is to demonstrate that standard text methods do not perform well when adapted to the task of estimating the topic shifts that underly agenda-setting behavior.

I simulated a corpus of 10 discussions sharing 5 speakers and 10 topics according to the data generating process outlined in Figure 2. Each discussion had 25 speaking turns, and each turn was randomly assigned a speaker.[5] Importantly, by simulating the corpus, I have true values for all parameters. Below I will compare estimated topic shift indicators ($l_{d,t}$) and agenda-setting measures (π_m) to the true parameters to assess model performance under different conditions.

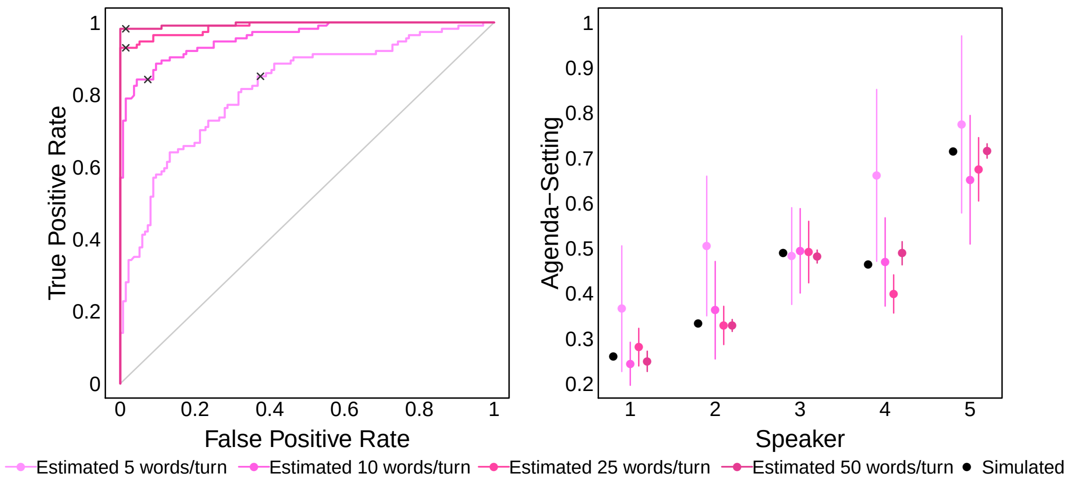
5.1.1. *Parameter Estimation with Sparse Texts*

A crucial difference between text generated in a discussion verses a non-discussion context is that discussion contexts are likely to feature few words per speaking turn. That is, each speaking turn for SITS, or equivalently, each "document" for LDA, will likely be very short. This is an important consideration when validating the SITS model, as existing topic models such as LDA do not perform well with short texts (e.g., Hong and Davison 2010). This is because the model utilizes how words co-occur at the document-level to discover latent topics, and the extremely sparse nature of short documents hinders coherent topic discovery.

Given this limitation of LDA, it is pertinent to evaluate the performance of SITS while varying

[5]The agenda-setting measure for each speaker was drawn from a Beta distribution with symmetric $\gamma = 1$. Each topic was drawn from a Dirichlet with symmetric $\beta = .1$ over a vocabulary of length 750. As per the data-generating process in Figure 2, whether or not a speaking turn changed the topic was determined by the speaker's agenda-setting measure. If a topic change was indicated, a new topic distribution over the speaking turn was drawn from a Dirichlet with symmetric $\alpha = .1$. Topic assignments for each word in the speaking turn were drawn from the turn's topic distribution, and word indices were drawn given the topic assignments.

Figure 3: Recovering Topic Shift and Agenda-Setting Parameters with Sparse Texts



Note: The left figure is ROC curves. Each line considers classification of latent turn-level topic shifts after averaging across the 10 estimated models. Crosses show diagnostics at a threshold of 0.5. The right figure plots the simulated agenda-setting measure and the estimated measures, averaged across the 10 models, for each dataset. Lines indicate one standard deviation above and below the mean.

the number of words per speaking turn (i.e., document length). To do so, I simulated four datasets, all identical but for the number of words per speaking turn ($N_{d,t}$).[6] The simulated datasets used $N_{d,t} = [5, 10, 25, 50]$ words per turn, respectively. I ran 10 models for each simulated dataset. Each model had randomly drawn hyperparameters and a randomly drawn number of topics $K \in [5, 15]$.[7] Each model ran for 25,000 iterations with 20,000 burn-in iterations and a sample lag of 10 iterations.

Results for this simulation are displayed in Figure 3. The left figure plots receiver operating characteristic (ROC) curves for the turn-level topic shift variables. Recall the topic shift variables are binary. Here I consider the average sampled topic shift across the models for each turn. ROC curves are a visualization of the diagnostic ability of a binary classifier—in this case, classifying turns as topics shifts or not—while varying the threshold at which to determine classification—in this case, varying the threshold at which a turn is considered a topic shift. Each line corresponds to the classification rate of the model (averaged across the 10 runs) for a given dataset. The x-axis

[6]As a consequence, the vector of topic assignments ($\mathbf{z_{d,t}}$) and words ($\mathbf{w_{d,t}}$) that were chosen varied, but the topic distribution ($\theta_{d,t}$) did not

[7]The hyperparameters α and β were drawn from $Beta(2, 18)$ and γ was drawn from $Uniform(0, 2)$ for each model.

is false positive rate and the y-axis is true positive rate. Crosses show diagnostics at a threshold of $\bar{l}_{d,t} = 0.5$, as this is the intuitive threshold to use to determine whether a topic change occurred. The model performs well at correctly identify whether or not a topic change occurred, even with sparse data of 5 or 10 words per speaking turn. It comes at no surprise that the model improves as it is provided more data, with almost perfect classification (regardless of chosen threshold) when the simulated data had 50 words per speaking turn.

The right figure plots the simulated agenda-setting measure (in black) and the estimated measures, averaged across the 10 models, for each speaker and for each dataset. Lines indicate one standard deviation above and below the mean of the estimates. Again it is apparent that more data allows for more accurate and precise estimation. Even so, 50 words per speaking turn or "document" in LDA is still a relatively short text, and the model proves to provide reliable and precise estimates of speaker-level parameters with sparse data.

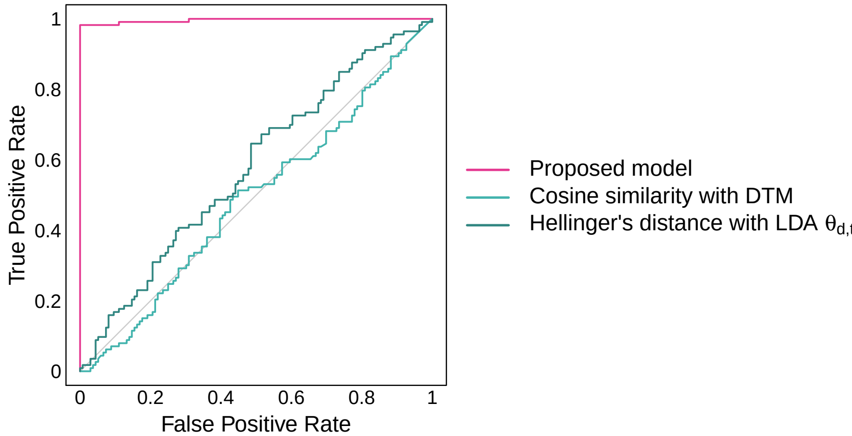
5.1.2. *Adapting Standard Methods*

The goal of the next study is to demonstrate that standard text methods do not perform well when adapted to the task of estimating the topic shifts used to measure agenda-setting, providing evidence that SITS is a meaningful methodological contribution to the literature. One might think that an easy way to detect topic shifts would be to assess similarity of consecutive speaking turns. That is, if turn t is similar to turn $t-1$ it is unlikely to have changed the topic; and conversely, if turn t is dissimilar to turn $t-1$ we might suspect the speaker shifted the topic.

Similarity could be measured with one of many metrics (e.g., cosine similarity, Kullback Leibler divergence, Hellinger's distance) depending on the representation of the document at either the word level (using vectors of words $\mathbf{w_{d,t}}$ and $\mathbf{w_{d,t-1}}$) or at the topic level (using estimated topic proportions $\theta_{d,t}$ and $\theta_{d,t-1}$ from a topic model). I assess the classification of topic shifts using cosine similarity with consecutive documents at the word-level and Hellinger's distance with consecutive document-topic proportions estimated with LDA.[8]

[8] I estimated LDA from the data using a collapsed Gibbs sampler with the same number of iterations as the SITS estimation; however, I used the true values of hyperparameters α, β, and K for the LDA estimation

Figure 4: Topic Shift Classification Across Methods



Note: Figure presents ROC curves for turn-level topic shift classification. Adapted text as data methods do hardly better or worse than random guessing (indicated by diagonal gray line), regardless of chosen threshold.

Figure 4 plots the ROC curves for the classification of topics shifts using these two methods and SITS. I use the 50 words per turn dataset, the largest simulated dataset, so to provide the methods as much data as possible to detect similarity. Since there is no intuitive value of cosine similarity or Helligner's distance to consider as a threshold for determining if a topic shift occurred or not, I use ROC plots which consider classification at any given threshold. We see neither cosine similarity with word vectors nor Hellinger's distance with topic proportions do much better than random guessing as indicated by the diagonal gray line. This simulation suggests that identifying documents that change the topic is not easily accomplished with commonly used text methods, demonstrating the usefulness of SITS for this task and thus the task of measuring agenda-setting behavior.

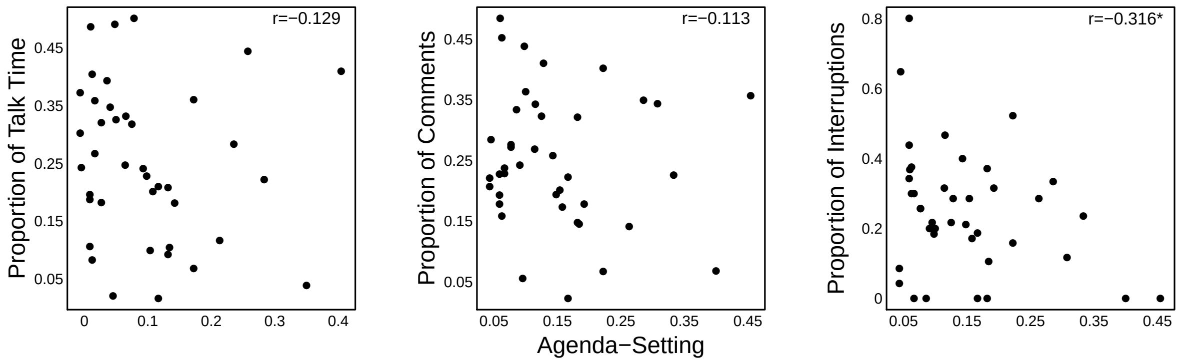
5.2. *Validating the Agenda Setting Measure: Experimental Evidence*

I next analyze discussion texts generated in a laboratory experiment to both demonstrate the wide applicability of SITS across research design settings as well as to illustrate SITS's contribution to the literature regarding political discussion's effects on attitudes and behavior.

Deliberation texts were generously shared by Christopher Karpowitz and Hans Hassell from a pilot study examining the effect of stress on discussion participation.[9] For this study, members

[9] I find no evidence of a treatment effect; therefore, I do not include the treatment as a variable in subsequent

Figure 5: Agenda Setting Correlates with Quality, not Quantity, of Participation



Note: *p<0.05. Figures report Pearson's r correlation coefficients. The y-axes are the speaker's proportion of group-level talking time, comments, and interruptions, respectively.

of the Brigham Young University (BYU) community were recruited to discuss the BYU Dressing and Grooming Standards, a specific set of rules governing the appearance of all students and staff at the university. The study included 10 discussion groups, each composed of 4 members. Participants first completed a pre-discussion survey about their attitudes regarding the Dress and Grooming Standards. Participants then engaged in a discussion in which they had 25 minutes to discuss the pros and cons of the standards and agree upon recommendations regarding changes to the standards, if any. After the discussion, participants completed a survey about their attitudes regarding the Dress and Grooming Standards and their thoughts regarding the discussion. While not a political discussion topic, the participants had to deliberate to share deeply held and sometimes conflicting perspectives, aggregate their individual preferences to two policy proposals, and vote. I estimated SITS from the data with 10 topics, and set $\alpha = .1$, and $\beta = .01$ to induce sparsity in the topic-word distributions and document-topic distributions, respectively.[10]

Without a statistical model of discussion text equipped to measure speaker behavior, researchers have resorted to measuring more easily quantifiable discussion dynamics as discussed in Section 3. Therefore, we might first ask, how does agenda-setting relate to the status quo of quantifying participation in a discussion? Figure 5 plots π_m against three commonly used participation measures in the literature, including the proportion of the group's discussion time in which a participant

analyses.

[10]Additional details pertaining to estimation and convergence are available in the appendix.

Table 1: Agenda-Setting and Attitude Change

	Dependent variable: Attitude Change
Agenda-Setting	-0.747*
	(0.371)
Constant	0.353*
	(0.068)
Observations	39
R^2	0.08

Note: *p<0.05. Coefficients from a linear regression with clustered standard errors at the discussion group level in parentheses. Dependent variable is absolute value of a participant's attitude change indicated by the difference between pre- and post-discussion survey responses.

spoke, the proportion of the group's comments made by a participation, and the number of times a participant interrupted someone. Each plot also displays the correlation coefficient, r, between the participation measure and the agenda-setting measure. First, we see no notable correlation between the first two measures of participation. These measures are based on the *quantity* of participation of the speakers, whereas π_m takes into account the *quality* of participation—was the speaker successful at changing the course of the discussion? Second, we see a negative correlation between how often a participant is interrupted and their agenda-setting tendency. That is, participants that interrupt less are also more likely to successfully push their agendas. This result provides construct validity that π_m correlates with a dimension of quality, rather than quantity, of participation.

I next examine the role of agenda-setting and one important discussion outcome—attitude change. An important question in the literature on political deliberation pertains to how deliberating affects one's attitudes, finding it can influence the formation and strength of issue attitudes (Huckfeldt, Johnson and Sprague 2004; Levendusky, Druckman and McLain 2016; Klar 2014). These studies find evidence of this effect using pre- and post-discussion surveys to measure attitude change (e.g., Levendusky, Druckman and McLain 2016). In what follows, I also use survey responses to measure attitude change, but I also use SITS to analyze discussions themselves to help explain how the dynamics of a discussion correlate with the extent to which a participant changes their attitudes.

Before and after the discussion, participants were asked to rate their agreement with several questions regarding the purpose and fairness of the Dress and Grooming Standards on a seven point scale. All questions could be coded such that 1 indicated the least critical/most supportive stance toward the standards and 7 indicated most critical/least supportive stance toward the standards. To measure attitude change, I calculated the absolute value of the mean difference between pre-discussion and post-discussion responses. Therefore, a value of .5 means the respondent changed their responses to each battery item, on average, by .5 points on the scale.

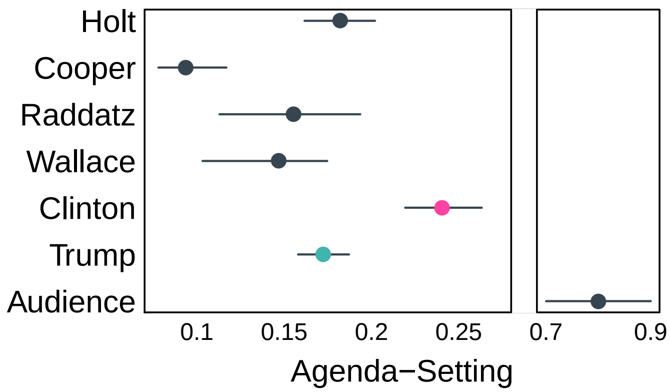
I measure each participant's agenda-setting abilities using SITS to garner insight into how a speaker's behavior *during* the discussion correlates with her change in attitude regarding the topic of discussion. Table 1 presents coefficients from a linear regression with clustered standard errors at the group level in parentheses. The negative coefficient suggests that the agenda-setting measure captures strategic behavior, as participants that succeeded at setting the agenda displayed less attitude change regarding the topic of discussion than others.

5.3. *Power and Strategic Agendas: 2016 Presidential Debates*

Unlike deliberations, characterized by collaboration and thoughtful consideration of all perspectives prior to some decision-making task, debates are oppositional, strategic, and the goal is to identify a "winner" and "loser." To demonstrate the applicability of the model in both deliberation and debate contexts, I next assess the validity of the agenda-setting measure using the three 2016 U.S. presidential general election debates. I additionally demonstrate how the latent topics estimated by the model can be used to explore the different issue agendas promoted by candidates when setting the agenda during the debates.

The debates between Democratic nominee Hillary Clinton and Republican nominee Donald Trump took place on September 26, October 9, and October 19, 2016. With 84 million viewers, the first debate set the record as the most-watched debate in American history (Neilsen 2016). The literature on the influence of presidential debates, specifically the American general election presidential debates, suggests that these debates can increase issue knowledge, issue salience, and can even sway vote preferences of the viewers (Benoit, Hansen and Verser 2003). Recent research

Figure 6: Agenda-Setting of Debate Participants



Note: Agenda-setting measures and 99% credible intervals for debate moderators, candidates, and audience members that strictly asked questions during the town-hall style debate.

suggests these findings hold for the 2016 debates as well (Winneg and Jamieson 2017). However, for a candidate to garner these effects among viewers, candidates must make strategic choices during debates, specifically in regard to strategies they employ to set the debate's agenda (Boydstun, Glazier and Phillips 2013). SITS provides a means to measure the respective agenda-setting power of the presidential candidates as well as the issues they use their power during the debates to promote to viewers.

Figure 6 reports the estimated agenda-setting power for debate moderators, candidates, and audience members that strictly asked questions during the second town-hall style debate. I estimated SITS from the data with 30 topics, and set $\alpha = .1$, and $\beta = .01$ to induce sparsity in the topic-word distributions and document-topic distributions, respectively.[11] Points are the median draw from the Gibbs sampler after the burn-in period and bands are the 99% credible intervals (the .05 and 99.5 quantiles of the samples after burn-in). The model estimates Clinton was more successful at shifting the topic in a speaking turn than Trump, coming at little surprise as she has a reputation as a skilled debater and Trump's campaign team struggled to convince him to practice for the debates (Healy 2016).

Moreover, Figure 6 provides a source of construct validity for the agenda-setting measure when coupled with media accounts of the candidates' performances. That is, the latent variable π_m cap-

[11] Additional details pertaining to estimation and convergence are available in the appendix.

tures each candidate's propensity to change the topic, and media accounts of the debates describe this topic changing behavior as strategic agenda-setting. In regard to the first debate, panelists on a Fox News show, *Special Report with Bret Baier*, put Clinton's high agenda-setting measure and Trump's low agenda-setting measure into words (September 27, 2016).[12] Bill McGurn of the Wall Street Journal said, "Look, overall, I thought Mrs. Clinton did better than I expected...I think [Trump's] main problem was she put him on defense a lot on his business stuff. He spent a lot of time defensive and explaining himself." McGurn describes what we see in Figure 6—Trump spent valuable speaking time defending himself on the current topic rather than strategically steering the debate toward different, advantageous topics. The next commentator, Caitlin Huey-Burns of RealClearPolitics, expressed a similar sentiment, saying "He missed a lot of opportunities to change the course of the debate back to what he's comfortable talking about... he didn't seem prepared to take these attacks and move on." Huey-Burns laments that Trump failed to set his agenda and even detrimentally stayed *on* topic when Clinton shifted to topics that were disadvantageous to him. The third panelist, Monica Crowley of The Washington Times, arrived at a similar conclusion:

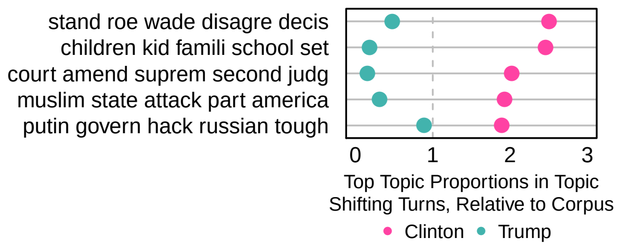
> "He has a tendency that doesn't work in his favor. It's not helpful when he extends the life of a story that is not helpful to him... he should not have fallen for her bait. Clearly at the end of the debate she had that talking point prepared about women. And since Lester Holt didn't bring it up... she felt she needed to interject it... And it was a problem because he felt that then he had to address that."

Crowley not only notes Trump's inability to strategically set an advantageous agenda, but she also notes Clinton's superior ability to do so.

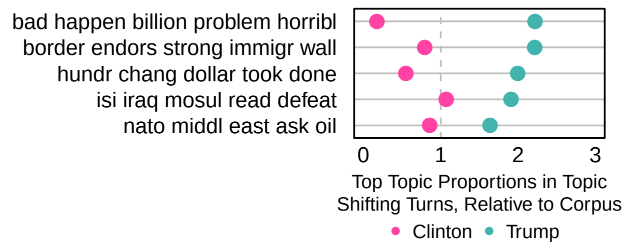
Overall, we see the sentiment of these Fox News contributors reflected in the candidates' agenda-setting measures. Lastly, it may seem counterintuitive that debate moderators would have such low agenda-setting measures as their role is to pose new, topic-changing questions to the candidates. However, the moderators' participation in the 2016 American presidential debates was namely in the form of enforcing time limits, allowing for responses, and re-asking questions when

[12] I present opinions from panelists on a Fox News program, because as a conservative network, the program should be the least critical of Trump. However, similar opinions of the debates were presented across media sources.

Figure 7: Power and Agendas in the 2016 Presidential Elections



(a) Clinton Shifted to Women's & Children's Issues, the Supreme Court, and Russian Hacking



(b) Trump Shifted to "Bad Problems," Immigration, and ISIS

Note: The x-axes show the topic proportions for turns in which a candidate changes the topic, relative to the topic proportions in the full corpus. The y-axes show top words selected using FREX weighting for the top five topics for each candidate.

they are diverted—all participation that does not change the substantive topic of discussion. An additional source of validity comes in the "Audience" participant in Figure 6 having a high agenda-setting measure as these participants' role was strictly to change the topic by posing questions to candidates in the second town-hall style debate.

As a topic model, SITS further allows the researcher to explore what topics candidates used their agenda-setting power to promote. Issue ownership theory argues that voters associate certain issues with certain parties and suggests that electoral candidates will seek to discuss topics that they "own" and find advantageous (Petrocik 1996). SITS provides a means to discover debate topics and how candidates use agenda-setting as a strategy to promote an advantageous agenda.

Figure 7 illustrates these agendas using the latent topics estimated from the model. Specifically, the x-axes show the topic proportions for turns in which a candidate changes the topic, relative to the topic proportions in the full corpus.[13] The vertical line at 1 demonstrates when the candidate is no more or less likely to discuss a topic when agenda-setting than it is discussed during the debates at large. The y-axes present top words for the five most shifted-to topics, relative to the corpus as a whole, for each candidate. Top words were determined using FREX weighting, thus taking into account both the frequency and exclusivity of a word in a topic rather than the words with the

[13]Specifically, I aggregated word topic assignments, $z_{d,t,n}$, in turns where a topic shift occurred, $l_{d,t} = 1$, for each candidate and calculated the topic proportions for such speaking turns. I also calculated topic proportions for the entire corpus. Thus the x-axes present the probability of discussing a topic relative to the probability it is discussed across the entire corpus.

highest probability of belonging to a topic (Bischof and Airoldi 2012; Roberts, Stewart and Airoldi 2016).[14]

Figure 7 shows that when setting the agenda during the debate, Clinton shifted to issues of women's and children's issues and Russian hacking, both issues that were advantageous to her and unfavorable for Trump. Compared to the extent to which these topics were discussed in the corpus at-large, Clinton was about twice as likely to discuss them when setting her agenda. On the other hand, Trump was twice as likely to discuss issues of foreign policy (e.g., issues of ISIS and the Middle East) and immigration following expectations of the issue ownership literature as republicans "own" these issues (Petrocik 1996).

6 CONCLUSION

Power is a fundamental theoretical concept in the study of politics but remained difficult to quantify beyond the formal political arena where votes, vetoes, and decision-making in general are observed. Yet, it is important to consider the exercise of power beyond these institutionalized contexts as the political lives of elites and citizens alike are filled with social interactions. Elite debate and deliberation is embedded in the framework of American government as a prerequisite to decision-making—presidential debates occur before each election, congressional committee hearings occur before bills are considered on the floor, and Supreme Court oral arguments occur before opinion writing, for example. Moreover, the everyday life of many citizens includes talking politics around the dinner table and watching politicians and pundits talk politics on TV.

These interactions are ubiquitous and often formalized in the political sphere because they are to serve as moderators for decision-making and behavior, yet we know little about the moderating role of political discussions on political outcomes. This is because the systematic study of interactions has proved a difficult endeavor as what we want to observe is usually a latent construct, such as persuasion, influence, and power. This paper proposed and validated a method to measure one important speaker behavior—agenda-setting power. Yet, future research should consider methodological approaches to additional quantities of interest pertaining to the content, structure,

[14]More details regarding the top words from all topics estimated by the model are available in the appendix.

and speaker behaviors in interactive communications.

As a prerequisite for decision-making and a part of the daily political lives of both citizens and elites, debate, deliberation, and discussion play a role in a wide variety of literatures across the discipline. While the interactive behavior of actors across these settings has remained a black box, this need not be the case. SITS provides a systematic approach to understanding the social dynamics of power, affording the opportunity for more theoretical development and principled analysis to explain how politicians interact and to what end.

6 References

Bachrach, Peter and Morton S Baratz. 1962. "Two Faces of Power." *American political science review* 56:947–952.

Bachrach, Peter and Morton S Baratz. 1963. "Decisions and nondecisions: An analytical framework." *American political science review* 57(3):632–642.

Bachrach, Peter and Morton S Baratz. 1970. *Power and poverty: Theory and practice*. Oxford University Press.

Baumgartner, Frank R and Bryan D Jones. 2010. *Agendas and instability in American politics*. University of Chicago Press.

Benoit, William L, Glenn J Hansen and Rebecca M Verser. 2003. "A meta-analysis of the effects of viewing US presidential debates." *Communication Monographs* 70(4):335–350.

Bischof, Jonathan and Edoardo M Airoldi. 2012. Summarizing topical content with word frequency and exclusivity. In *Proceedings of the 29th International Conference on Machine Learning (ICML-12)*. pp. 201–208.

Blei, David M, Andrew Y Ng and Michael I Jordan. 2003. "Latent dirichlet allocation." *Journal of machine Learning research* 3(Jan):993–1022.

Boydstun, Amber E, Rebecca A Glazier and Claire Phillips. 2013. "Agenda control in the 2008 presidential debates." *American Politics Research* 41(5):863–899.

Cox, Gary W and Mathew D McCubbins. 2005. *Setting the agenda: Responsible party government in the US House of Representatives*. Cambridge University Press.

Dahl, Robert A. 1957. "The concept of power." *Behavioral science* 2(3):201–215.

Dietrich, Bryce J, Ryan D Enos and Maya Sen. 2016. "Emotional arousal predicts voting on the us supreme court." *Political Analysis* .

Druckman, James N and Kjersten R Nelson. 2003. "Framing and deliberation: How citizens' conversations limit elite influence." *American Journal of Political Science* 47(4):729–745.

Druckman, James N, Matthew S Levendusky and Audrey McLain. 2017. "No Need to Watch: How the Effects of Partisan Media Can Spread via Interpersonal Discussions." *American Journal of*

Political Science .

Eggers, Andrew C and Arthur Spirling. 2016. "The shadow cabinet in Westminster systems: modeling opposition agenda setting in the House of Commons, 1832–1915." *British Journal of Political Science* pp. 1–25.

Gastil, John, Laura Black and Kara Moscovitz. 2008. "Ideology, attitude change, and deliberation in small face-to-face groups." *Political Communication* 25(1):23–46.

Griffiths, Thomas L and Mark Steyvers. 2004. "Finding scientific topics." *Proceedings of the National academy of Sciences* 101(suppl 1):5228–5235.

Grimmer, Justin and Brandon M Stewart. 2013. "Text as data: The promise and pitfalls of automatic content analysis methods for political texts." *Political analysis* 21(3):267–297.

Healy, Patrick. 2016. "New Debate Strategy for Donald Trump: Practice, Practice, Practice." *New York Times* .

URL: *https://www.nytimes.com/2016/09/29/us/politics/donald-trump-debate.html*

Hong, Liangjie and Brian D Davison. 2010. Empirical study of topic modeling in twitter. In *Proceedings of the first workshop on social media analytics*. ACM pp. 80–88.

Howell, William G. 2003. *Power without persuasion: The politics of direct presidential action*. Princeton University Press.

Huckfeldt, Robert, Paul E Johnson and John Sprague. 2004. *Political disagreement: The survival of diverse opinions within communication networks*. Cambridge University Press.

Johnson, Timothy R, Ryan C Black and Justin Wedeking. 2009. "Pardon the Interruption: An Empirical Analysis of Supreme Court Justices' Behavior During Oral Arguments." *Loy. L. Rev.* 55:331.

Karpowitz, Christopher F and Tali Mendelberg. 2014. *The silent sex: Gender, deliberation, and institutions*. Princeton University Press.

Karpowitz, Christopher F, Tali Mendelberg and Lee Shaker. 2012. "Gender inequality in deliberative participation." *American Political Science Review* 106(3):533–547.

Kathlene, Lyn. 1994. "Power and influence in state legislative policymaking: The interaction of gender and position in committee hearing debates." *American Political Science Review* 88(3):560–576.

King, Gary, Jennifer Pan and Margaret E Roberts. 2013. "How censorship in China allows government criticism but silences collective expression." *American Political Science Review* 107(2):326–343.

King, Gary, Jennifer Pan and Margaret E Roberts. 2017. "How the Chinese government fabricates social media posts for strategic distraction, not engaged argument." *American Political Science Review* 111(3):484–501.

Klar, Samara. 2014. "Partisanship in a social setting." *American Journal of Political Science* 58(3):687–704.

Krehbiel, Keith. 2010. *Pivotal politics: A theory of US lawmaking*. University of Chicago Press.

Levendusky, Matthew S, James N Druckman and Audrey McLain. 2016. "How group discussions create strong attitudes and strong partisans." *Research & Politics* 3(2):2053168016645137.

Lukes, Steven. 1974. "Power: A radical view." *London, New York* .

McCombs, Maxwell E and Donald L Shaw. 1972. "The agenda-setting function of mass media." *Public opinion quarterly* 36(2):176–187.

Mikhaylov, Slava, Michael Laver and Kenneth R Benoit. 2012. "Coder reliability and misclassification in the human coding of party manifestos." *Political Analysis* 20(1):78–91.

Neilsen. 2016. "FIRST PRESIDENTIAL DEBATE OF 2016 DRAWS 84 MILLION VIEWERS.".

URL: *http://www.nielsen.com/us/en/insights/news/2016/first-presidential-debate-of-2016-draws-84-million-viewers.html*

Nguyen, Viet-An. 2014. "Speaker Identity for Topic Segmentation (SITS)." `https://github.com/vietansegan/sits`.

Nguyen, Viet-An, Jordan Boyd-Graber and Philip Resnik. 2012. SITS: A hierarchical nonparametric model using speaker identity for topic segmentation in multiparty conversations. In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long*

Papers-Volume 1. Association for Computational Linguistics pp. 78–87.

Nguyen, Viet-An, Jordan Boyd-Graber, Philip Resnik, Deborah A Cai, Jennifer E Midberry and Yuanxin Wang. 2014. "Modeling topic control to detect influence in conversations using non-parametric topic models." *Machine Learning* 95(3):381–421.

Petrocik, John R. 1996. "Issue ownership in presidential elections, with a 1980 case study." *American journal of political science* pp. 825–850.

Polsby, Nelson W. 1964. "Community power and political theory.".

Prior, Markus. 2009. "The immensely inflated news audience: Assessing bias in self-reported news exposure." *Public Opinion Quarterly* 73(1):130–143.

Quinn, Kevin M, Burt L Monroe, Michael Colaresi, Michael H Crespin and Dragomir R Radev. 2010. "How to analyze political attention with minimal assumptions and costs." *American Journal of Political Science* 54(1):209–228.

Roberts, Margaret E, Brandon M Stewart, Dustin Tingley, Christopher Lucas, Jetson Leder-Luis, Shana Kushner Gadarian, Bethany Albertson and David G Rand. 2014. "Structural Topic Models for Open-Ended Survey Responses." *American Journal of Political Science* 58(4):1064–1082.

Roberts, Margaret E, Brandon M Stewart and Edoardo M Airoldi. 2016. "A model of text for experimentation in the social sciences." *Journal of the American Statistical Association* 111(515):988–1003.

Segal, Jeffrey A and Harold J Spaeth. 2002. *The Supreme Court and the attitudinal model revisited*. Cambridge University Press.

Special Report with Bret Baier. September 27, 2016. Fox News.

Wallach, Hanna Megan. 2008. Structured topic models for language PhD thesis University of Cambridge.

Winneg, Kenneth and Kathleen Hall Jamieson. 2017. "Learning From the 2016 US General Election Presidential Debates." *American Behavioral Scientist* p. 0002764217702770.