Measuring Agenda-Setting Power in Political Discourse*

Erin Rossiter

Department of Political Science

Washington University in St. Louis

April 22, 2019

ABSTRACT

How can we determine who holds the power in political discourse? In an interactive communication (i.e., a debate, deliberation, or discussion), I argue power is exercised by controlling the conversational agenda. Since in this framework 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 I show standard text methods fail at identifying agenda-setting behavior. I further validate the agenda-setting measure with 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 Please do not cite or distribute without permission.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. I posit that actors seek to control what is (and what is not) discussed as a way to exercise power in an interactive communication. In other words, *agenda-setting* is a form of power, and in this paper I introduce a text-based approach for measuring the agenda-setting power of actors.

Take, for example, a setting in which the fight over the agenda is particularly evidence—United States general election presidential debates. Candidates constantly seek the opportunity to shift the debate toward topics they "own" or to those that may harm their opponent (Petrocik 1996; Boydstun, Glazier and Phillips 2013). The following few lines from the first 2016 general election presidential debate between Donald Trump and Hillary Clinton demonstrate Clinton effectuating an advantageous change in the agenda.

> *Holt:* We are at—we are at the final question.
>
> *Clinton:* Well, one thing. One thing, Lester.
>
> *Holt:* Very quickly, because we're at the final question now.
>
> *Clinton:* You know, he tried to switch from looks to stamina. But this is a man who has called women pigs, slobs and dogs, and someone who has said pregnancy is an inconvenience to employers, who has said...

The moderator did not bring up Trump's history of insulting women; rather, Clinton successfully steered the next few memorable minutes of the debate toward this issue on *her* agenda.

As this example illustrates, 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 long-term or legislative agenda-setting are beyond the scope of this paper, because agenda-setting in *interactions* is uniquely a social game in which power must be negotiated in real time as the communication unfolds.

As an inherently social phenomenon, agenda-setting in political interactions requires a different approach to quantify. In this paper I propose utilizing the text of interactions as data to measure the latent agenda-setting power of actors. 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 extends Latent Dirichlet Allocation (LDA) (Blei, Ng and Jordan 2003), a topic model used widely in the discipline, to measure the agenda-setting power of actors. SITS does so by accounting for two distinguishing features of political interactions. First, it accounts for *temporal* dynamics in interactions—an actor likely responds to what was previous said when speaking. Second, it accounts for the *social* dynamics inherent in political interactions—multiple speakers must negotiate who has the floor at any point in time. In order to do so, this model supplements LDA with additional latent variables to simultaneously estimate (1) when agenda (i.e., topic) changes occur and (2) each actor's latent ability to initiate such changes in agenda, or, their agenda-setting power.

I proceed by first applying theories of political power to the context of political interactions to inform my measurement strategy of the agenda-setting power of political actors. I then outline my text as data approach to measuring agenda-setting power. To validate the agenda-setting measure, I present simulation results showing (1) the model performs well even with sparse texts which typify interactions, and (2) standard text methods in the literature do not perform well when tasked with identifying the topic changes within interactions. Then, I apply the model to laboratory-generated deliberation texts, and I show agenda-setters display less attitude change regarding the topic of discussion than other deliberators. I also apply the model to the more volatile setting of electoral debates to not only measure power dynamics 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

Robert Dahl's 1957 essay on power sought to formally define the phenomenon in such a way that it could be operationalized and political scientists could study the relative power of actors. His theory focuses on the behavior of actors in, and the outcome of, a decision-making situation (Dahl 1957). Dahl's operationalization of power was admittedly limited due to what researchers could and could not observe and measure at that time. In addressing his research on relative power of senators, Dahl writes, "Faced with this apparently insuperable obstacle, it was necessary to adopt a rather drastic alternative, namely to take the recorded roll-call vote of a Senator as an indication of his position and activities *prior to* the roll-call" (Dahl 1957, p. 210). He acknowledges that what precedes formal, observable decision-making stages of politics—for instance, *interactions* amongst actors—is important yet not taken into account in the empirical stages of his work on power. Political scientists since have adopted similar assumptions in order to study who has power and how is it used in congress (e.g., Krehbiel 2010), the executive branch (e.g., Howell 2003), and in the courts (e.g., Segal and Spaeth 2002).

Yet, the fight for and exercise of power extends beyond observable, concrete decisions. Actors do not make their decisions in a vacuum, but instead deliberate and discuss formally and informally before taking decisive action. Bachrach and Baratz introduce a second dimension or second "face" of power to account for power in these settings. They call this dimension "nondecision-making power," as this power precedes the formal decision-making stage and is thus "invisible" if one consults only the outcomes of a decision. They argue "power may be, and often is, exercised by confining the scope of decision-making to relatively 'safe' issues" (Bachrach and Baratz 1962, p. 948). In regard to political interactions, I argue actors seek to exercise nondecision-making power by controlling the scope of what is and what is not discussed to optimize the conversation in regard to their agenda.

In this way, political interactions are important moderators of the outcomes we typically observe. Debates, deliberations, and discussions are nondecision-making situations in which actors work to alter the scope of a given conflict (Schattschneider 1975). The means by which actors can do so is by gaining the floor and shaping the scope of the discussion to their preferred issues. Lukes calls this second face of power the "agenda-setting" dimension of power, as power over the decision-making stage can occur by shaping the agenda *before* any votes are cast (Lukes 1974). This interpersonal agenda-setting process is analogous to agenda-setting via formal institutions such as in a legislature (Cox and McCubbins 2005).

To be sure, a great deal of research has been done regarding how nondecision-making situations unfold and their consequences on the attitudes of participants and outcomes. For example, deliberative democracy theory advocates for the equal sharing and hearing of ideas among participants (Habermas 1989; Fishkin 1995; Thompson 2008), and scholars have investigated how deliberation affects policy opinions (Barabas 2004), and how the decision-making rule (Karpowitz, Mendelberg and Shaker 2012; Karpowitz and Mendelberg 2014) and gender diversity (Karpowitz and Mendelberg 2014; Kathlene 1994) of participants impacts participation. Similarly, scholars have studied informal political discussions, asking whether political discussion can lead to changes in attitudes and participation (e.g., Huckfeldt, Johnson and Sprague 2004; Mutz 2006). These studies seek to understand the effect of political interactions by studying outcomes of the interactions, but have yet to understand the power exercised within the interaction itself. I argue it remains an important task to address the moderating force of power within a political interaction on the outcomes we observe by investigating agenda-setting power, including who is able to gain such power, how they do so, and to what end.

3 PROPOSED APPROACH TO AGENDA-SETTING MEASUREMENT

While I argue that agenda-setting is a manifestation of power in an interactive political communication, the discipline lacks a framework for measuring this latent ability of actors, stalemating our ability to empirically investigate power dynamics in such settings. In this section, I outline an approach to measuring the power of actors in political interactions using text as data.

Since an interactive political communication is a verbal or written exchange, I propose using the text of interactions (i.e., transcripts) as data. I theorized that the agenda-setting dimension of power, as applied to political interactions, is evidence by successfully changing the course of a discussion to preferable topics. Therefore I propose using a topic model to not only estimate latent topics (Blei, Ng and Jordan 2003), but to also identify where in the changes in topic occur. Then, it follows to measure the latent agenda-setting abilities of actors by identifying who effectuated shifts in the agenda (i.e., shifts in topic) in a interaction. However, an actor's agenda-setting ability also influences where topic changes occur. A skilled agenda-setter is more likely to successfully exercise her power when speaking; therefore, it is pertinent to identify where shifts in the agenda occur using this information about actors. In order to do so, the approach I adopt incorporates two sets of additional latent variables in a familiar topic model to account for and simultaneously estimate these (1) where changes in topic occur and (2) each actor's latent agenda-setting power.

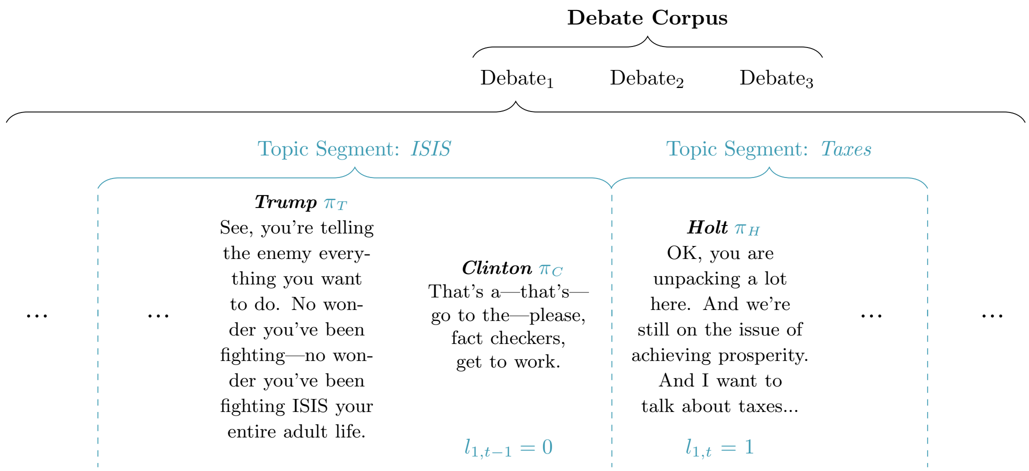
3.1. *Defining features of an interactive text*

While political scientists frequently use text as data methods for discovery and measurement (Grimmer and Stewart 2013), the discipline has yet to extend such methods to *interactions*. Such an extension is necessary because an interactive communication is fundamentally different than the texts usually studied in political science, namely because interactions are a social exercise in which speakers must negotiate who is speaking, when, and about what. Since interactive communications are a new class of texts to political science, in this section I outline the defining features—the temporal and social dynamics—of these texts.

Figure 1 illustrates the defining features of a interactive text using as an example the 2016 U.S. general election presidential debates. Just as a corpus of State of the Union addresses might contain eight speeches from the Obama presidency, this corpus contains three debates. Within each debate, however, there is additional structure by which the words can be organized. Notice the words are grouped by a natural temporal ordering in the form of speaking turns.

Furthermore, there is latent temporal structure in the text shown in Figure 1 in blue. Since topics in an interactive communication ebb and flow, it's natural to consider that each speaking turn could change the topic. For each turn $t \in [1, T_d]$ in each debate $d \in [1, 3]$, let the binary latent variable $l_{d,t}$ indicate if the turn changed the topic or not. Here we see that while Clinton simply stayed on the topic of ISIS ($l_{d,t-1} = 0$), Holt shifted the debate's topic to taxes ($l_{d,t} = 1$).

Figure 1: Visual representation of interactive communication structure and parameters of interest



Note: Figure displays text from the first 2016 general election presidential debate between Donald Trump and Hillary Clinton with moderator Lester Holt. Black font denotes structure inherent to a corpus of interactive communications. Blue font denotes the additional latent structure in an interactive communication of topic segments—a set of consecutive speaking turns on the same topic. Latent parameters to identify if a speaking turn t changed the topic in debate d ($l_{d,t}$) and each speaker m's ability to set the agenda (π_m) are also in blue. Figure shows Holt changed the topic (binary topic change indicator for this speaking turn is one, $l_{d,t} = 1$), initiating a new topic segment on taxes.

Using this latent speaking turn-level structure, a "topic segment" can be formed from a sequences of speaking turns that are all on the same topic. Figure 1 demonstrates two topic segments in which the candidates discuss ISIS followed by a shift in topic to taxes. Blue dashed lines denote these latent topical subsets of the debate.

In addition to the observable and latent temporal structure of interactive texts, a defining feature of these communications is that they are a social enterprise and thus speaker behavior influences how the text unfolds. In a political interaction, I argue we are particularly concerned about each speaker's agenda-setting behavior. Figure 1 denotes each speaker $m \in$ [Trump, Clinton, Holt] with a latent agenda-setting ability, π_m. When candidates fight over the agenda of the debate, their latent agenda-setting ability influences whether we observe a change in topic or not, thus incorporating speaker behavior into our understanding of such texts.

3.2. *Other approaches to agenda-setting measurement*

To be sure, text as data methods have been applied to understand the concept of agenda-setting, namely in the context of 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.

Furthermore, one could consider non-text as data methods for measuring agenda-setting abilities of actors. One could consider hand coding whether or not speaking turns change the topic in order to measure an actor's propensity to change the topic (e.g., Boydstun, Glazier and Phillips 2013). However, 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 one might consider is 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 certainly 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 assess any sort of *quality* of the participation of an actor. Relatedly, one might consider fielding survey items to get opinions on one's own and others' agenda-setting abilities, as is a common way to learn about other discursive habits (e.g., Huckfeldt, Johnson and Sprague 2004). Yet, 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.

Finally, 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), so one might consider this a useful methodology for learning agenda-setting abilities. However, 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.

4 A MODEL OF AGENDA-SETTING POWER

I use the Speaker Identity for Topic Segmentation (SITS) (Nguyen, Boyd-Graber and Resnik 2012; Nguyen et al. 2014) model to measure political actors' agenda-setting power in a political interaction. The model accounts for and measures the latent elements of an interactive text outlined in Figure 3.1. Specifically, SITS extends a widely used probabilistic topic model—Latent Dirichlet Allocation (LDA) (Blei, Ng and Jordan 2003)—to incorporate the defining temporal and social features of an interactive text. Since LDA poses limitations as applied to interactive texts, in this section I explain how SITS accounts for these limitations in order to measure agenda-setting behavior. For ease of exposition, I will refer to any single interaction 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*

Figure 2 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, I treat what is usually referred to as a "document" in LDA is defined in Figure 2 as a single speaking turn of one participant. Formally, for each discussion $d \in [1, D]$, I assume LDA treats each speaking turn $t \in [1, T_d]$ as a "document."[1]

[1] 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

Figure 2: 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).

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 $k \in [1, K]$ topics from a symmetric Dirichlet distribution with parameter β. 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 from a symmetric Dirichlet distribution with parameter α. Next, for each word index $n \in [1, N_{d,t}]$ in the speaking turn, a topic assignment ($z_{d,t,n}$) is drawn given the speaking turn's distribution over topics. Lastly, a word ($w_{d,t,n}$) is drawn conditional on the assigned topic.

LDA is not well-suited for discussion texts as it fails to capture the temporal and social dynamics of a discussion. Applying LDA to a corpus of texts assumes that each "document" is a *new* mixture over topics; however, in a discussion, the content of turn t is highly correlated with the content of $t-1$. What the current speaker says is likely to be in response to the previous speaker's comments. Further, LDA does not account for the social element of discussions. Some speakers will exert more power over the agenda of discussion than others. Therefore, topic changes are a function of the speakers' agenda-setting abilities.

4.2. *SITS*

SITS builds upon LDA to incorporate the temporal flow of discussion topics and agenda-setting power of speakers into the data-generating process outlined in Figure 3. Note the data generating process is similar to that of LDA presented in Figure 2 with extensions noted in blue. First, for

of discussions by obscuring all separate speaking turns into one instance of text.

Figure 3: 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).

each speaker $m \in [1, M]$, a topic shift probability (π_m) is drawn from a symmetric Beta distribution with parameter γ. As with LDA, K topics are drawn. Next, also similar to LDA, for each turn t in discussion d a topic distribution is drawn ($\theta_{d,t}$). If it is the first turn in a discussion, a topic change is considered to have occurred. This is noted by setting a turn-level topic shift binary variable equal to one ($l_{d,t} = 1$). 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 ($\pi_{a_{d,t}}$), where $a_{d,t}$ is the observed speaker of the speaking turn. That is, whether or not 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, otherwise topic distribution from the previous turn carries over to the current turn ($\theta_{d,t} \equiv \theta_{d,t-1}$). Then for each word index, topic assignments and words are drawn as they are with LDA. The data generating process of SITS captures both the *temporal* 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.

In the applications that follow, I estimate SITS using Markov chain Monte Carlo, specifically, a Gibbs sampler written by the original model authors (Nguyen 2014) with similarities to the collapsed Gibbs sampler for the LDA (Griffiths and Steyvers 2004). The latent topic distributions

($\theta_{d,t}$) and topics (ϕ_k) have been integrated out of the full conditional probabilities for $z_{d,t,n}$ and $l_{d,t}$, and these parameters are estimated using the posterior distributions of topic assignments. Similarly, speaker agenda-setting measures (π_m) are integrated out of the conditional probabilities and are estimated from the posterior distributions of topic changing indicators ($l_{d,t}$). Thus, an iteration of the sampler 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). [2]

4.3. *Simulations*

In this section I establish that SITS performs as expected and that model provides a valuable contribution to the suite of text as data methods political scientists have at their disposal via two simulation studies. The goal of the first simulation study is to validate that the model recovers the turn-level topic shift parameters and the speaker-level agenda-setting parameters 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 according to the data generating process outlined in Figure 3, containing ten discussions with five speakers and ten topics. Each discussion had 25 speaking turns, and each turn was randomly assigned a speaker.[3] Below I compare estimated topic shift indicators and agenda-setting measures to the true parameter values to assess model performance under different conditions.

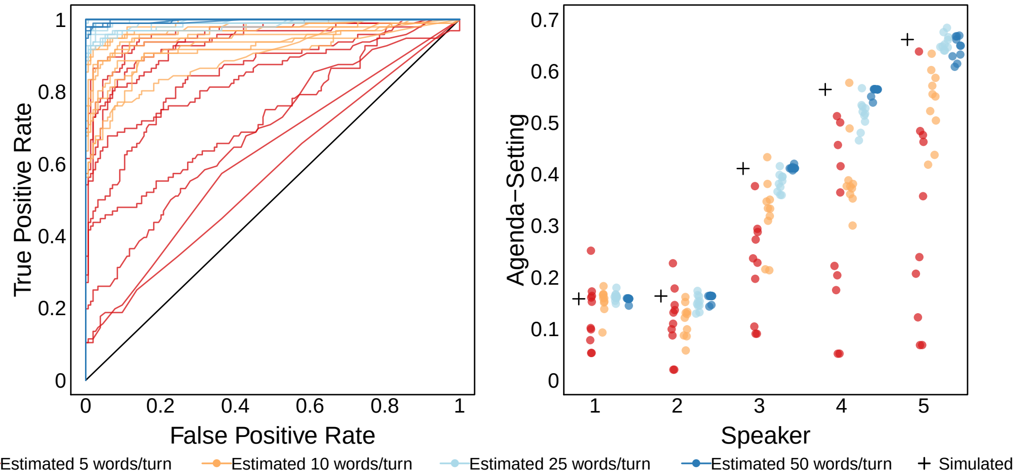
4.3.1. *Parameter estimation with sparse texts*

One crucial difference between discussion and non-discussion texts is that discussion texts are

[2]Note that $l_{d,t=1}$ is not sampled for turns that begin a discussion, but 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, topic assignments $z_{d,t,n}$ are sampled each iteration, regardless of turn length.

[3]The speaker agenda-setting measures was drawn from a Beta distribution with symmetric $\gamma = 1$. Each topic was drawn from a Dirichlet with symmetric $\beta = .01$ over a vocabulary of length 750. As per the data-generating process in Figure 3, 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 4: 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.

likely to feature few words per speaking turn. Existing topic models such as LDA do not perform well with short texts because topic models utilizes how words co-occur at the document-level to discover latent topics, thus the extremely sparse nature of short documents hinders coherent topic discovery (Hong and Davison 2010). Recall that SITS, however, estimates the latent topic segment structure within a discussion which should alleviate concerns about parameter estimation with short texts. However, given this known limitation of topic models, it is pertinent to evaluate the performance of SITS with short texts.

To do so, I simulated four datasets, all identical but for the number of words per speaking turn $N_{d,t}$.[4][5] The simulated datasets used $N_{d,t} = [5, 10, 25, 50]$ words per turn, respectively. I ran ten models for each simulated dataset. Each model had randomly drawn hyperparameters and a randomly drawn number of topics $K \in [5, 15]$.[6]

Figure 4 presents results from the simulation. The left figure plots receiver operating charac-

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

[5]I simulated the data using $\alpha = .1$, $\beta = .01$, and $\gamma = 1$.

[6]The hyperparameters were drawn according to $\alpha \sim \text{Uniform}(0, .5)$, $\beta \sim \text{Uniform}(0, .5)$, and $\gamma \sim \text{Uniform}(0, 5)$ to exaggerate the range of values researchers usually pick from for these hyperparameters in topic modeling. Each model ran for 45,000 iterations with 50,000 burn-in iterations.

teristic (ROC) curves for the turn-level topic shift variables. 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 one of 10 models estimated for each simulated dataset, differentiated by color. The x-axis is false positive rate and the y-axis is true positive rate. The model performs well at correctly identifying whether or not a topic change occurred, even with limited data of ten words per speaking turn (in orange). Even most of the models estimated using the five words per speaking turn data (in red) perform well; however, here the data is not able to overcome strong, unsuitable priors.[7] It comes at no surprise that the model improves as it is provided more data, with almost perfect classification when the simulated data had 50 words per speaking turn. Figure 4 also provides reassurance that the model is robust to choice of hyperparameter.

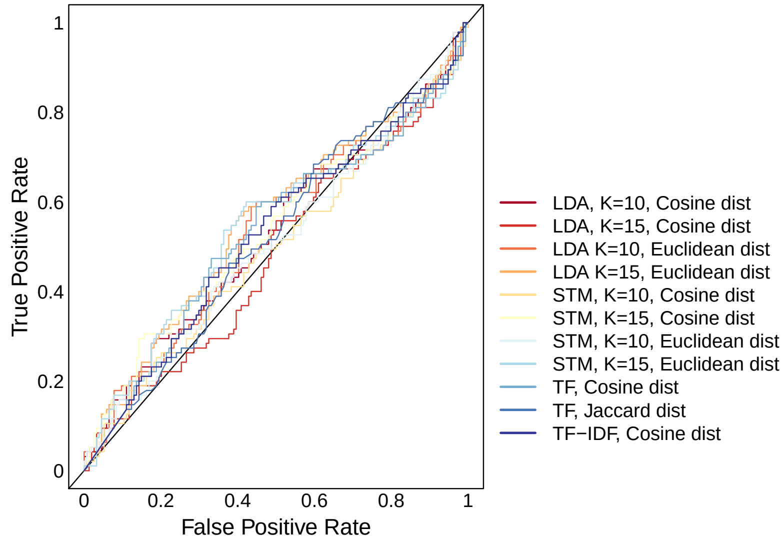
The right figure plots the true agenda-setting measure (in black) and the estimated measures for each of the ten models per dataset. Again it is apparent that more data allows for more accurate and precise estimation. Evident from both plots is that the model under-estimates topic shifts, and thus speaker agenda-setting, when the number of words per speaking turns is especially limited (i.e., five and ten words). However, as the number of words per turn increases, the true positive rate of topic shift detection and the accuracy of the agenda-setting estimation both increase.

4.3.2. *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 agenda-setting power of actors in a political interaction. One way to measure agenda-setting abilities could be the following "two-step" process. First, detect topic shifts by measuring dissimilarity of consecutive speaking turns. That is, if turn t is dissimilar to turn $t-1$ we might suspect the speaker shifted the topic. Second, calculate agenda-setting power as, for example, the proportion of a speaker's turns that were classified as changing the topic.

[7] The four worst performing models were estimated with hyperparameter $\beta > .3$ which is far from the true value of .01.

Figure 5: 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.

Detecting similarity of texts is an active area of research in political science as it is a difficult task due to the high-dimensional nature of text data (e.g., (Mozer et al. Forthcoming; Roberts, Stewart and Nielsen 2018)). To attempt to detect turns that change the topic, I first choose several ways to represent the text of consecutive speaking turns, including term frequency (TF) vectors, term frequency inverse document frequency (TF-IDF) weighted vectors, and with estimated latent topic proportions from the LDA and STM topic models.[8] I then assess the classification of topic shifts with several distance metrics including cosine distance, Jaccard distance, and euclidean distance.

Figure 5 plots the ROC curves for the classification of topics shifts using these methods. I use only the simulated 50 words per turn dataset, the largest simulated dataset, so to provide the methods as much data as possible to detect shifts in topic. Since there is no intuitive value of these metrics to consider as a threshold for determining if a topic shift occurred or not, I again use ROC plots which consider classification at any given threshold. We see none of the two-step methods do much better than random guessing as indicated by the diagonal black line. This

[8]The STM topic model included prevalence covariates indicating the speaker identity of the turn and which discussion the turn occurred in

simulation suggests that identifying documents that change the topic is not easily accomplished with commonly used text methods as applied to the short documents which typify discussions, demonstrating the usefulness of SITS for this task and thus the task of measuring agenda-setting behavior.

5 APPLICATIONS

5.1. *Agenda-setting in deliberations*

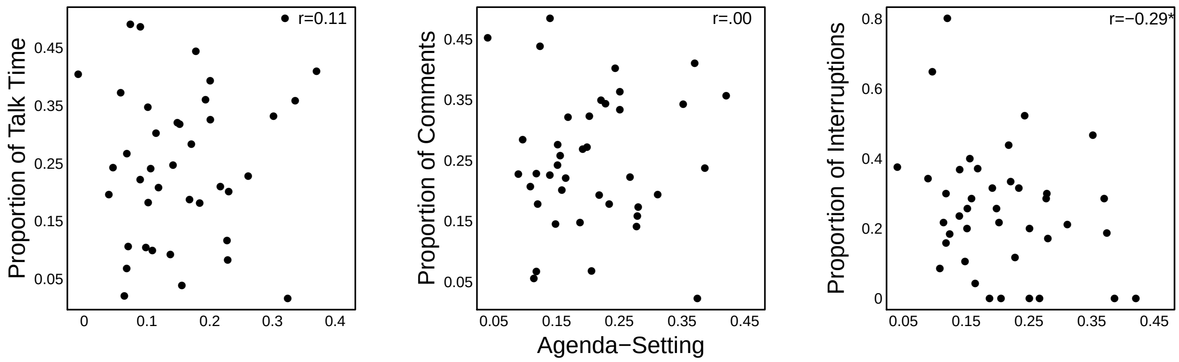
I next analyze discussion texts generated in a laboratory experiment to both demonstrate the wide applicability of the agenda-setting measure across research design settings as well as to illustrate the measure's contribution to the literature regarding deliberation's effects on attitudes and behavior.

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 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 ten discussion groups, each composed of four 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 topic of discussion, 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 ten topics, and set $\alpha = .125$, and $\beta = .01$ to induce sparsity in the topic-word distributions and document-topic distributions, respectively.

Without a statistical model of discussion text equipped to measure speaker behavior in the

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

Figure 6: 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.

form of agenda setting power, researchers have resorted to measuring more easily quantifiable discussion dynamics. Therefore, I first investigate how agenda-setting power relates to the status quo of quantifying participation in a discussion. Figure 6 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 spoke, the proportion of the group's comments made by a participant, 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 assesses a *quality* of participation in the form of how successful the participant was at effectuating change in the discussion. Second, we see a negative correlation between how often a participant interrupts others and their agenda-setting tendency. That is, participants that interrupt less are also more likely to successfully push their agendas. In all, we see agenda-setting does not correlate with typical participation measures as it moves beyond quantity of participation as it is equipped to discriminate effective 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 atti-

Table 1: Agenda-setters less likely to change attitude

	Dependent variable: Attitude Change			
	(1)	(2)	(3)	(4)
Agenda-setting	-0.763^{*}			
	(0.345)			
Proportion of comments		-0.167		
		(0.294)		
Proportion of talk time			-0.276	
			(0.246)	
Proportion of interruptions				0.245
				(0.175)
Constant	0.390^{*}	0.276^{*}	0.302^{*}	0.174^{*}
	(0.076)	(0.079)	(0.067)	(0.054)
Observations	39	39	39	39
R^2	0.120	0.009	0.034	0.052

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. Explanatory variables are those from Figure 6. One observation omitted as outlier due to high Cook's distance.

tude 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 one indicated the least critical stance and seven indicated most critical 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 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. Moreover, I find no evidence of an effect of the participation measures on attitude change.

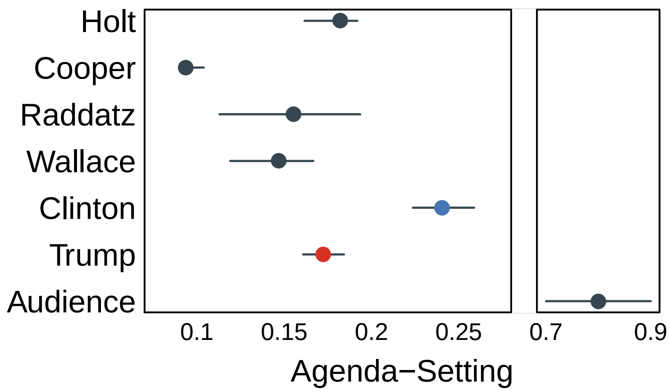
5.2. *Power and strategic agendas: 2016 presidential debates*

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 usefulness of the agenda-setting measure in 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 suggests that viewing presidential debates increases issue knowledge and salience (see Benoit, Hansen and Verser 2003), influences candidate evaluation (e.g., Houston et al. 2013; Miller and MacKuen 1979; Holbrook 1999), and yet has little influence on vote choice (e.g., Katz and Feldman 1962; Benoit, McKinney and Lance Holbert 2001; Benoit and Hansen 2004). Recent research suggests these findings hold for the 2016 debates as well (Winneg and Jamieson 2017). 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).

Figure 7 reports the estimated agenda-setting power for the debate moderators, the candidates, and the audience members that strictly asked questions during the second town-hall style debate. I estimated the model from the data with 30 topics, and set $\alpha = .1$, and $\beta = .01$ to induce sparsity

Figure 7: Agenda-setting of debate participants



Note: Posterior mean agenda-setting measures and 95% equal-tailed credible intervals for debate moderators, candidates, and audience members that strictly asked questions during the town-hall style debate.

in the topic-word distributions and document-topic distributions, respectively. Points are posterior means and bands are the 95% equal-tailed credible intervals. 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 7 provides a source of construct validity for the agenda-setting measure when coupled with media accounts of the candidates' performances. 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).[10] 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 7—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

[10]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.

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:

> "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.

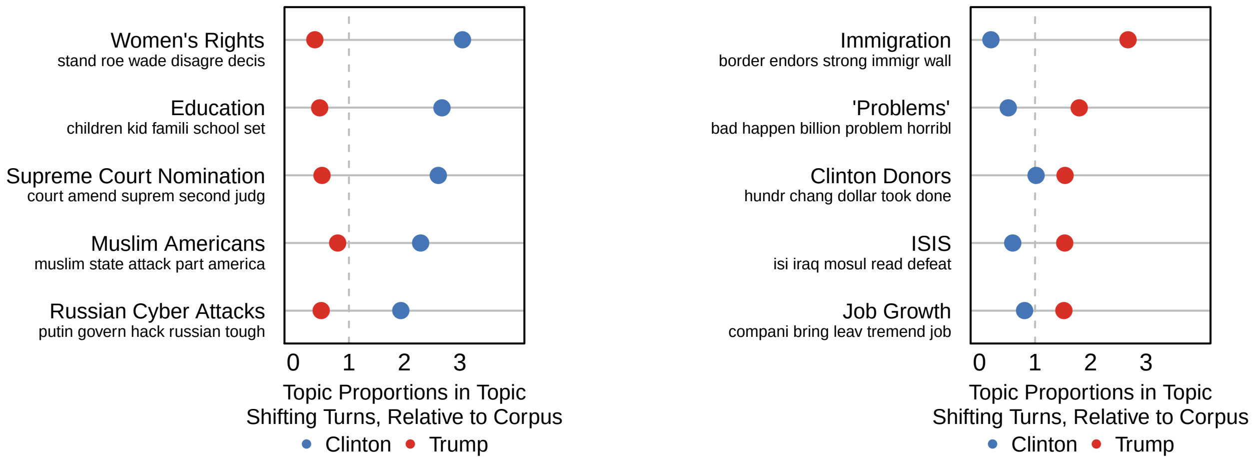
Overall, we see the sentiment of these Fox News contributors reflected in the candidates' agenda-setting measures. Lastly, it may seem counterintuitive that debate moderators would have such low agenda-setting measures as a moderator's role is to pose new, topic-changing questions to the candidates. 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 they are diverted—all participation that does not change the substantive topic of discussion, explaining their low agenda-setting measures. An additional source of validity comes in the "Audience" participant in Figure 7 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 8 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.[11] The vertical line at 1 demonstrates when the candidate is

[11] 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.

Figure 8: Power and agendas in the 2016 presidential election debates



(a) Clinton shifted to women's & children's issues, the Supreme Court, and Russian hacking

(b) Trump shifted to the country's "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.

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

Figure 8 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 interactive communications. 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 interactions 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, 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.

Barabas, Jason. 2004. "How deliberation affects policy opinions." *American Political Science Review* 98(4):687–701.

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

Benoit, William L and Glenn J Hansen. 2004. "Presidential debate watching, issue knowledge, character evaluation, and vote choice." *Human Communication Research* 30(1):121–144.

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.

Benoit, William L, Mitchell S McKinney and R Lance Holbert. 2001. "Beyond learning and persona: Extending the scope of presidential debate effects." *Communication Monographs* 68(3):259–273.

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* .

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.

Fishkin, James S. 1995. "The voice of the people." *Public opinion and democracy* pp. 363–378.

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.

Habermas, Jürgen. 1989. *Jürgen Habermas on society and politics: A reader*. Beacon Press.

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*

Holbrook, Thomas M. 1999. "Political learning from presidential debates." *Political Behavior* 21(1):67–89.

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.

Houston, J Brian, Joshua Hawthorne, Matthew L Spialek, Molly Greenwood and Mitchell S McKinney. 2013. "Tweeting during presidential debates: Effect on candidate evaluations and debate attitudes." *Argumentation and Advocacy* 49(4):301–311.

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.

Katz, Elihu and Jacob J Feldman. 1962. "The debates in the light of research: A survey of surveys." *The great debates* pp. 173–223.

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.

Miller, Arthur H and Michael MacKuen. 1979. "Learning about the candidates: The 1976 presidential debates." *Public Opinion Quarterly* 43(3):326–346.

Mozer, Reagan, Luke Miratrix, Aaron Russell Kaufman and L Jason Anastasopoulos. Forthcoming. "Matching with Text Data: An Experimental Evaluation of Methods for Matching Documents and of Measuring Match Quality." *Political Analysis* .

Mutz, Diana C. 2006. *Hearing the other side: Deliberative versus participatory democracy*. Cambridge University Press.

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 nonparametric 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.

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 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.

Roberts, Margaret E, Brandon M Stewart and Richard A Nielsen. 2018. "Adjusting for confounding with text matching.".

Schattschneider, Elmer E. 1975. "The Semi-Sovereign People: A Realist\'s View of Democracy in America.".

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.

Thompson, Dennis F. 2008. “Deliberative democratic theory and empirical political science.” *Annu. Rev. Polit. Sci.* 11:497–520.

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.