Testing the Etch-a-Sketch Hypothesis: Measuring Ideological Signaling via Candidates' Use of Key Phrases*

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August 2013

Abstract

Downsian theory predicts that presidential candidates should shift toward the general electorate's median voter after securing their parties' nominations. Motivated by this largely untested hypothesis, we test the theory using candidates' campaign speeches as data. We develop a model to identify ideological cues in political text. After performing validation and robustness checks, we fit the model using presidential candidates' speeches from 2008 and 2012. The results show that Barack Obama, John McCain and Mitt Romney did indeed make substantively significant shifts away from the ideological extremes after securing their parties' presidential nominations.

Well, I think you hit a reset button for the fall campaign. Everything changes. It's almost like an Etch-A-Sketch. You can kind of shake it up and restart all of over again.

-Eric Fehrnstrom, Spokesman for Presidential Candidate Mitt Romney

When a top advisor to presidential hopeful Mitt Romney compared the campaign to an Etch-A-Sketch, the classic toy that allows children to erase a previous image with the flick of a wrist and begin anew as if on virgin canvas, news of the comment spread like wildfire on television and across the blogosphere, with "#etchasketch" quickly trending on Twitter. Within hours, parodies referencing Mitt Romney and Etch-A-Sketch were appearing on YouTube. The statement became news and a source of derision not because the tendency for candidates to move to the ideological

*Prepared for *American Political Science Association* Annual Meeting, Chicago 2013

center once they have obtained their party's nomination had come as a surprise to anyone. What was striking was the candor with which Romney's advisor, Eric Fehrnstrom, actually admitted to it in such a memorable way in response to an interviewer's query about whether the prolonged nomination battle had forced his candidate too far too the right to be able to appeal to moderate voters in the general election.

Despite the criticism Romney faced after Fehrnstrom's moment of candor, the "Etch-a-Sketch" serves a perfect analogy for what political scientists expect to happen during presidential campaigns. Classic Downsian median voter theory predicts that candidates will appeal to median partisan voters during the primary, before converging to the point of the median voter in the national electorate for the general election.[1] Yet, despite the elegance and intuitiveness of the theory, empirically measuring the shift proves difficult. Typically, there is no opportunity for presidential candidates to demonstrate a shift in governing; sitting presidents who are running for reelection infrequently face a serious primary challenge, so they feel little pressure to make a special effort to appeal to primary voters. The main record of ideological positioning available during the nomination and general election phases consists of a candidate's own words (crafted with a team of speech-writers). It is easy to point to anecdotal evidence or slips of the tongue in accusing candidates of flip-flopping. But how might one go about determining whether a systematic rhetorical shift toward the center has taken place?

We model the manifestation of latent ideology through a speaker's key phrases. In so doing, we take a categorical (typological) approach to the representation of ideology, rather than treating it as continuously measured. We start from the perspective that there are a small number of prototypical ideologies in contemporary American politics, exemplified by well-known opinion leaders (e.g., talk radio hosts, columnists, prominent politicians of established adherence to particular per-

[1]This oversimplifies a bit. Strictly speaking, extending the logic of spatial modeling to multicandidate elections under the plurality rule does not lead to the same expectations (Cox 1985, Feddersen, Sened & Wright 1990). Primary elections are not, in fact operating under the plurality rule and, due to the complex multistage process by which candidates tend to pull out at different points in the nomination process, it is not obvious what should be anticipated under standard spatial models. Nonetheless, whatever the most strategic quantile pivot point may be, that of the Republican and Democratic primaries would naturally fall to the right and left, respectively, of the median during the general election.

spectives) associated with each. We may thus characterize prototypes in terms of the language that distinguishes these groups of communicators from one another and study the degree to which presidential candidates resemble these reference groups and consider whether the degree of resemblance changes in systematic ways across stages of an election season. In contrast to related work (Laver, Benoit & Garry 2003, Slapin & Proksch 2008, for example), our aim is not to infer *policy positions* from text. We do not presume that the words upon which we rely for data may be used to measure communicators' preferences in considering actual legislative proposals, though neither do we deny that such preferences may be successfully predicted from textual data.

Our aim is more modest. Within the flow of political speech, we can expect to find the traces of one's core political beliefs and values, or at least those one wishes to convey to a specific audience. We treat a politician giving a speech as switching among discrete states corresponding to different ideologies. The model is essentially a specialized hidden Markov model (HMM)[2], where the parameters governing the transition distribution are constrained in a convenient manner that imposes tree-like structure on the state-space, and an emission distribution that is carefully crafted to focus on ideologically indicative phrases. In this setup, we assume that speakers choose an ideological "state" and then select key phrases according to their chosen ideology. Communicators are presumed to change states according to a set of transition probabilities, and are deemed increasingly likely to have broken free of the chain's Markov dependence as time passes since the previous emission, converging on a stable proportion.

The HMM parameterization differs from bag-of-word (BOW) approaches in several ways, which we discuss later. Broadly speaking, the HMM better matches our intuition about how rhetoric is crafted and delivered. Political speech is not simply a jumble of words, and while such a simplifying assumption may be suitable for inferring broad topics of discussion, the utility of such an approach is less clear in distinguishing speakers discussing similar topics from distinct ideological perspectives. The efficacy of the BOW assumption from the point of view of machine learning may

[2]At each time point, the speaker is assumed to occupy one of a fixed number of latent states (ideologies) and is assumed to transition among these states with some unknown probabilities, but emits observable evidence of the current state at each time point (Scott 2002).

in fact be satisfactory, in the sense that the subtle differences in word-distributions across ideology are detectable by computer, but a political scientist's job of elucidation is hampered if there isn't at least some degree of face validity when one examines the results of such analysis in depth. As hypothetical examples, suppose it turns out that libertarians tend to use more words referring to time (e.g. clock, time, minutes, year) and that progressives frequently use first person plural pronouns (e.g., we, us, our). One might speculate on reasons for this or whether the apparent finding is simply a fluke, but to take advantage of this empirically discovered linguistic attribute would be atheoretical and will likely lead to a lack of trust in the results. One may surmise that certain words utterly unrelated to ideology may creep into likeminded peoples' vocabulary for purely social means—i.e., through years of communicating in semi-closed communities. It may be that certain regionalisms are good predictors of ideology in cases where the ideology is prominent in a given geographical location. Taking advantage of such correlations may make sense for pure prediction, but such serves as a poor mechanism for explanation. Thus, we seek to learn not simply from the individual words that speakers use but also, to a modest extent, the order in which the words are strung together. Our technique will not be immune to the concerns just raised, as we will still find ourselves relying on turns of phrase that are not always obvious in their connection to a political perspective, but we aim to take a large step in the direction of modeling the use of signals recognizable to astute observers of contemporary politics.

In Section 1, we look in greater depth at the motivation for the current work and where our modeling strategy sits relative to related work. We then go on in Section 2 to detail our two-stage method of vocabulary-building and measurement of ideological self-representation. In the following section, we use our modeling approach to provide evidence in support of the expectation that presidential candidates should moderate their message once their party's nomination has been secured. We finish with brief concluding remarks.

1 Motivation and Broader Research Context

American electoral politics comprise, in large part, the artful – though sometimes painfully inartful – use of language. Candidates for political office barnstorm for months at a time, making their cases and leveling criticisms of opponents' actions and points of view; legislators draft and debate bills; presidents issue statements; justices hand down legal opinions; information age rabble-rousers peddle conspiracy theories to anyone with a laptop; and journalists, columnists and bloggers dissect, reframe and disseminate it to the American public. For political scholars, the trove of data locked away in transcripts and manuscripts presents both a blessing and a curse. The answers to many fascinating questions lie within the written word; yet harnessing the data in ways both efficient and reliable poses considerable methodological challenges.

The complications inherent in mining usable data from text are not new to political science. As Krippendorff (2004) and Hopkins & King (2010) note, researchers have been "content analyzing" political text for at least six decades. For many years, content analysis required scholars and trained coders to wade through reams of documents, coding each by hand according to criteria established by the research project. Faster computing and more advanced technical capacity have permitted researchers to engineer tools for automated or semi-automated content analysis (Laver, Benoit & Garry 2003). Yet, as always, there must be tradeoffs. No algorithm or statistical model can perfectly process text for every scholarly application. More importantly, purely unsupervised approaches leave little room for theorists' particular questions and concerns to guide the empirical process. Within the constraints of our modeling strategy, we seek to provide a new perspective on text analysis, and present a class of questions which it is well calibrated to answer.

1.1 Assessing Ideology in Text

Many political science theories rely upon the concept of ideology, broadly defined, yet ideology is never directly observed (Converse 1964). Instead, researchers attempt to infer ideology based on other characteristics – policy preferences, partisanship, demographics, roll-call votes, and survey responses *inter alia*. Content analysis of text presents a natural data source for such evaluations.

Unlike survey responses or roll-call votes, texts such as speeches or manifestos allow for considerable nuance and richness which may aid scholars in accurately placing political actors in an ideological space (Slapin & Proksch 2008).

Despite the modeling challenges associated with processing and analyzing text, most approaches follow a simple intuition. Actors with different ideological predispositions will likely express themselves differently. In many situations, we would expect ideology to leave traces through the simple use of certain key terms (Laver, Benoit & Garry 2003). In but two of the more famous examples, a candidate who utters the term "death tax" rather than "estate tax," or "pro-abortion" instead of "pro-choice," is clearly signaling her ideological tendencies. Some instances of distinguishing word choice such as these are rooted in explicit partisan marketing strategies (Luntz 2007), but others may represent more subtle clues, including terms that may represent only the traces of more complex language that cannot as easily be detected. If an algorithm could be trained to identify the terms that divide liberals from conservatives, then it should in principle be able to classify according to more fine-grained distinctions and thus place new speeches or writings according to their resemblance to agreed-upon prototypes.

1.1.1 WORDSCORES

Within political science, Laver, Benoit & Garry (2003) present the most popular technique for accomplishing this end. By using reference texts to "anchor" the extremes of a one-dimensional ideological space, they use the WORDSCORES algorithm to place out-of-sample documents on a left-right scale. That is, the algorithm learns the distribution of words in the anchor texts, and then produces scores for new documents based on the average scores of words used in those documents. The probability of observing a given word, given a target document's class is estimated simply as the word's observed relative frequency within documents of that class *in the corpus of reference texts*. The document's ideology score is then calculated as the mean score of all its words. The posterior probabilities that we are reading a document of a given class are calculated via Bayes Rule, so that the probability of a class given the document's words is proportional to the estimated probability of the words given the document has this label, times the probability of a document having this label, where one assumes a flat prior on document probabilities. This yields a Naive Bayes classifier, as the words generated are assumed conditionally independent given the document class. This sort of conditional independence assumption is powerful and lies at the heart of most latent variable models, including latent trait (IRT), latent class, and factor analysis. See Lowe (2008) for a more complete exposition of WORDSCORES as revealed to be an approximation of another latent variable (descriptive) technique known as correspondence analysis.

In the years since its publication, scholars pointed to some drawbacks to the WORDSCORES formulation. Some, such as Martin & Vanberg (2008), argue that the raw scores are incomparable with the reference text scores, and suggest improved scaling methods for WORDSCORES which permit direct comparison. A few other researchers have sought to develop alternatives that address some shortcomings in the WORDSCORES methodology.

Slapin & Proksch (2008), for instance, point out that (as can be seen above) the WORDSCORES algorithm places equal weight on all terms. For reasons that we address in greater depth in our methods section, this poses multiple problems. Most seriously, the algorithm cannot allow different terms to vary in the degree to which they contribute to the inferential task. Many words bring little or no ideological content, and thus may only interfere with the ability of scholars to draw the intended inference from texts. And commonly used but non-ideological terms tend to shrink document scores toward the mean score of the reference documents. That is, frequent terms tend to be interpreted by the algorithm as evidence for centrism.

More recent content analytic tools adopt various techniques to avoid these pitfalls. Most common is the use of stemmers and stop words (Hopkins & King 2010, Slapin & Proksch 2008, Diermeier, Godbout, Yu & Kaufmann 2012). Stemming involves combining terms that share a common root (stem) so that tenses and plurals of terms are not counted separately. Removing stop words entails omitting common words ('and', 'the', 'a', 'in', and so forth) so that these terms will not be mistakenly interpreted as ideological (or other content-based) similarity. Yet even after removing stop words and combining terms with common stems, the WORDSCORES algorithm poses problems for many social science applications. First, the algorithm is not model-based, meaning that it does not reflect a theoretically-based story about how words or documents are generated (Lowe 2008). Without a probabilistic framework, the WORDSCORES algorithm cannot be parameterized to model uncertainty in the classes to which words are assigned, or assess uncertainty over words that are mentioned only a single time, perhaps by chance alone, in only one document class.

To address the first shortcoming, Monroe, Colaresi & Quinn (2008), Monroe & Schrodt (2008), Slapin & Proksch (2008) and Hopkins & King (2010) develop probabilistic models to reflect theoretic assumptions over text generation. Monroe, Colaresi & Quinn (2008) construct a model based largely on a popular computer science technique known as latent Dirichlet allocation (LDA) (Blei 2012), while Slapin & Proksch (2008) introduce WORDFISH to allow the estimation of party policy positions from word frequency.

Second, the intuition of the WORDSCORES approach assumes (a) a simple one-dimensional ideological space, at least in practice; and (b) the ability to understand each document as the average over its words (Laver, Benoit & Garry 2003, Hopkins & King 2010, Monroe, Colaresi & Quinn 2008, Lowe 2008). We will address this in greater depth in the next section, but to preview the argument: text provides ample room for nuanced ideological exposition – more than, say, roll-call votes do – and a single dimension collapses together many distinct and theoretically-relevant categories (religious right, libertarian, nationalist, environmentalist, progressive, socialist, and so on). Similarly, treating a document (i.e., a single speech) as the average over its words may produce biased and inconsistent estimates of the aggregate (document-level) classification (Hopkins & King 2010). It also assumes that an average can serve as a sufficient measure of ideology. That is, it assumes that a speaker who uses only centrist terms is the same, in all theoretically interesting ways, as a candidate who speaks half from the far right and half from the far left. Neither of these assumptions seems appropriate for our own research purposes.

1.1.2 The Modeling Goal

Many previous models perform well in certain applied contexts. The topic model employed by Monroe, Colaresi & Quinn (2008), for instance, may work in research on Congressional speech-giving, where the authors' assumption that each speech comprises a single "topic" (or a small set of topics) may approach the truth. And the time series content-analytic model developed by Slapin & Proksch (2008) may provide insights on placing parties in a single-dimensional ideological space.

For our own research, however, we begin to develop a more general framework for understanding political ideology by an application of a generative model. In an ideal world, researchers would have sufficient time to fully and accurately code text documents; yet as many of the aforementioned scholars have argued, this approach is not feasible. We agree with this assessment, and appreciate the need for techniques such as WORDSCORES, WORDFISH, and LDA—itself generative but insufficiently focused on the factors of interest to us, but wish to consider alternate techniques that take better advantage of human judgment, while utilizing computational tools to scale up to large data sets without sacrificing the ability to incorporate that which has been learned through smaller-scale qualitative coding.

In contest to standard techniques such as WORDSCORES, we seek to tell a generative story about political rhetoric by specifying a model of *individual* political behavior. This stands in contrast to many approaches which attempt to model the aggregated ideological expressions of political parties or voting blocs. In the current project, we also make no attempt to predict policy preferences or positions. That is to say, our model seeks to expose the ideological worldview espoused by a given speaker *at a given time*, as opposed to predicting any specific legislative behavior.

To put this more explicitly, our model shall speak to the relationship between a speaker's ideology—at least as publicly presented—and the words and phrases she chooses to use to frame specific topics of political debate. We wish to ask questions about speakers' preoccupations and the objects of their attention, as well as how they frame the issues that they choose to discuss, and how these vary according to their ideological outlook. Ideology, attention budgeting (or agenda-setting), and framing choices all are latent constructs, with language operating as the manifest variables in all cases.[3]

1.1.3 A Two-Stage Approach

We begin with the simple yet liberating assumption that ideology need not be measured on a single left-right dimension or through Euclidean scaling at all. Though methods such as DW-NOMINATE [CITE? –NAS] scores find that a single left-right scale provides a sufficiently powerful explanation for roll-call voting in Congress, textual data allows for much greater ideological nuance, and we believe our model should reflect this. Though a libertarian and a religious conservative may both find themselves on the right of a unidimensional scale, it is not necessarily helpful to ask which is located *further* to the right. There are qualitative differences between their prototypical worldviews and the preoccupations of each are distinct. We should also expect these two hypothetical actors would draw on different vocabularies; the religious conservative would draw heavily on Biblical themes and traditional moral arguments, whilst the libertarian would speak more frequently on individual liberty, free markets, and limited government. Of course, individuals in their complexity may—and often do—combine aspects of each ideal type, as well as others. Certain libertarian perspectives (and language) have become popular with conservatives of all stripes, and religious conservatives find scriptural justification for economic arguments espoused in libertarian circles. Qualitative heterogeneity may not be adequately captured by a Euclidean representation. A natural way to represent individuals' ideological diversity without being derailed by the curse of dimensionality resulting from an abundance of interval-level dimensions is by comparison to recognizable types, or how much of their discourse tends to fall in each of several "bins."

Defining the discrete ideological "bins" leaves considerable discretion to the researcher. This is a strength of our approach, not a weakness, for it requires thoughtful specification of both ideological categories and prevents pure data-driven induction that may not comport with our theoretical understandings of the political world. Explicit description of ideological categories also renders the process more flexible and transparent, allowing us to check the robustness of our findings to

[3] We are currently exploring additional manifest variables to be employed in an auxiliary fashion; for example, Amazon ratings of books in the corpus, and expert opinion on these authors' ideologies.

such decisions, and encouraging scholars to review our decision making process. This stands at the center of the semi-supervised approach to modeling text (Hillard, Purpura & Wilkerson 2007).

With user-specified ideological bins, we can begin constructing a vocabulary intended to capture ideological differences in rhetoric. Unlike the Laver, Benoit & Garry (2003) approach, we do not assume that the ideological space can adequately be anchored by its extremes; instead, we seek to build vocabularies representative of each ideology. These sets of terms are not mutually exclusive—a term can be associated with more than a single ideology, but the assessment of whether an individual token is evidence of one ideology rather than another will be probabilistic and based in part on nearby terms. Furthermore, we take as atomic terms bigrams, trigrams and higher-order n-grams instead of individual words, and stem the terms so that, for instance, different tenses of the same word (i.e., "threaten", "threatens", "threatening") are not read as separate terms. We will be highly selective about what terms are used to infer speaker ideology rather than attempting to assess every token for ideological content. Specifically, we shall begin with an initial stage in which we select the vocabulary to be used for all subsequent analysis. For this task, we employ a **S**parse **A**dditive **Ge**nerative (SAGE) model for text, which allows us to induce sparsity in the terms comprising the ideological vocabularies (Eisenstein, Ahmed & Xing 2011). The model allows us to select only terms that adequately differentiate between the ideological categories. This leaves us with a large and growing vocabulary of ideologically-charged terms, as well as an empirically induced prior distribution over the relative frequency with which they should be generated from a particular ideological state.

From this point, we begin to build a theoretical model to reflect our generative theory of political text. Much previous work implicitly or explicitly seeks to model document generation through a "bag-of-words" approach. Theoretically, various ideologies bring unique vocabulary distributions that researchers might observe. The inferential task, then, is to figure out from which bag a speaker is drawing the terms we observe. No speaker will draw exclusively from a single bag, but one's tendency to draw heavily from certain "bags" should provide insights into how one wishes to be perceived. A Republican whose sentences look as if they could have taken from books by Sean

Hannity and Glenn Back (far right radio talk show hosts) is signaling something different from one whose language sounds a lot more like David Frum and Meghan McCain (writers associated with more moderate strains of conservatism). Similarly, a Democrat whose speeches look as if they could have been written by Arianna Huffington or Paul Krugman (progressives often critical of President Obama from the left) can expect to be perceived differently from one who sounds more like former Senator Bill Bradley.

We extend this framework by dropping the assumption that documents are simply a bag of words, instead recognizing (to some extent) that they are sequences of words. For simple mixture models, the order of words does not matter; the "data" could be scrambled into random order and inference would remain virtually unaltered. Our model, building on the intuition of hidden Markov models (HMMs), seeks to explicitly specify not just an aggregate sense of which bag a speaker draws from, but how the speaker transitions between ideologies. In this sense, we can treat ideologies as hidden "states" – latent characteristics which we must impute.

Given a document (an article, speech, letter, bill, *et cetera*), our modeling approach will consider the order in which terms appear, and infers not just from which ideology (state) the observed datum was drawn, but also the tendency of a speaker to transition frequently or infrequently among ideologies. Put another way, how likely is a speaker to transition from populist conservatism to speaking like a prototypical libertarian? Using our model specification, we can describe the balance of time a speaker spends in various ideologies, and how he or she transitions amongst them. Moreover, by relying upon bigrams, trigrams, and larger n-grams as the atoms, we are able to capture the higher-order interaction between words without sacrificing the simplicity of bags-of-words. That is, conditional on one's presumed state (operating ideology), one draws from the bag-of-phrases associated with that state; as long as one remains in the current state, the phrases are selected at random according to their distribution, so that ordering is modeled only in the latent state space and within the n-grams themselves.

This approach offers unique contributions heretofore absent from the relevant scholarly literature. First, we need not summarize the speaker's ideology as a simple average over the ideologies of each word he employs. As Hopkins & King (2010) argue, such measures can often produce poor estimates of the latent variable of interest. Instead, we express the ideology of a speaker as a mixture of various discrete ideologies, which comports more cleanly with our understanding of how candidates should choose the vocabularies to use. Second, we can observe nuanced changes in a speaker's ideology at various points in time. Many important theories hinge on the incentives of candidates to alter their behavior depending on external conditions (audience, campaign stage, major events) but much of this movement will be washed out in a simple univariate scaling.

In fact, our modeling strategy allows us to offer a somewhat non-standard conceptualization of ideology, what may be thought of as *salience-weighted ideology*. The phrase distributions characterizing a particular book or sub-corpus may reflect not only beliefs, values, ideals, and attitudes, but also preoccupations or priorities. Thus, two left-leaning ideologues may both consider themselves "progressives," may even identically fill out a survey in which they must agree or disagree with various statements using a Likert scale. And yet one tends to focus primarily on identity politics and multicultural perspectives while the other emphasizes economic class as the primary object of attention.

Such distinctions can be learned from their writings and speech, but would be difficult to intelligibly scale in Euclidean space. By employing a typological approach, we allow for various exciting possibilities depending on research question. (For instance, sub-types characterized by affect/tone in order to distinguish those inclined to use more emotionally charged rhetoric or a tendency to make ad hominem attacks; one could add sub-corpora of non-ideological books, say books on business leadership, in order to infer the extent to which different candidates use lingo learned from their experience in private enterprise.) The possibilities are limited only by the researcher's imagination and access to suitable reference texts.

2 The CLIP Model: Cue-Lag Ideological Proportions

We now can begin specifying the model itself. To understand the assumptions built into our generative model, imagine that you are listening to a speech delivered by a particular candidate. Depending on all sorts of factors (the location, the audience, the stage of the campaign, the current perceived strengths and weaknesses of the candidate, and so on), there is much that the candidate and his or her team may attempt to communicate.[4] Often, we can expect that a speech is intended to convey various different sorts of signals. The tone of the speech may be crafted to humanize a seemingly wooden candidate, references to childhood struggles may counter perceptions of the candidate as a wealthy elite, style of speech may be intentionally folksy, and various other strategic and personal choices may all be mixed into a speech. Just as, from the point of view of the geneticist, strands of DNA are composed of strings of signal surrounded by lots of noise—and which is which depends on what aspects of the animal are being studied—it is incumbent upon us to focus on ideological fingerprints, while ignoring the many terms which carry less relevant messages and idiosyncratic flourishes. In our case, there is no "right" set of clues that we must find in order to correctly characterize the speaker's ideological profile. We might try to use all of the candidate's words—but this may bury the signal amidst the noise—or simply identify the single best cue in a speech—but this approach would likely lack robustness to the choice of cue and result in high variance in measurement. In seeking balance between these extremes, by identifying a vocabulary of likely cues that help distinguish recognized sets of ideological opinion leaders from one another (stage I), and then reasoning about these within target candidates' speeches (stage II), we imagine that there are an enormous number of potential subsets of terms that would point us to similar results.

We represent the candidates' speeches as a sequence of ideological cue terms interspersed with strings of "filler" terms. The model assumes that speakers can adopt and transition between many different ideological states, even within a single speech. Accordingly, the model attempts to leverage all available relevant information in a speech, including the ideologically-important cue terms *and* the number of filler terms between each cue. The inferential goal is to learn the ideological state for every cue emitted by a speaker, and then to use the number of lag terms to roughly

[4]For convenience, we will refer to the candidate, speechwriters and team of advisors simply as *candidate*. More generally, we refer to the speaker who wishes to convey ideological signals through speech or written communication as *ideologue*.

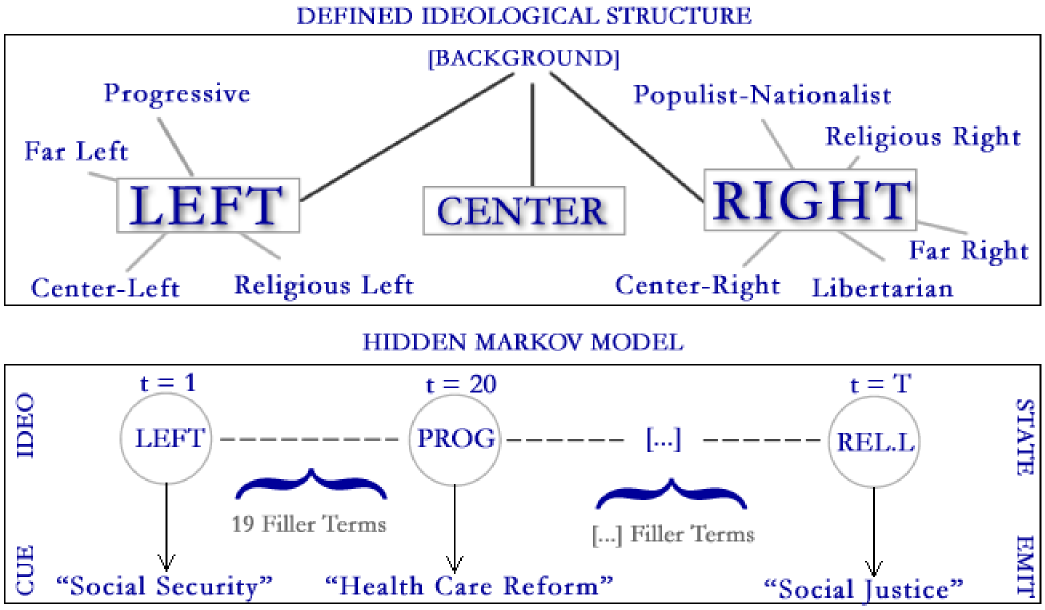

Figure 1: We structure ideology as"bins within bins". We employ three broad ideologies (Left, Right, Center) and subideologies nested within the left and right. The CLIP model treats speeches as sequences of terms as draws from ideological bins interspersed with non-ideological filler words.

approximate "how long" the speaker spent in that ideological state.

To provide a simplified example, we imagine a speaker just before she delivers her speech. Other than assuming that the speaker is making a political speech, we make no assumption about her specific ideological state, rather assuming that she begins in a "background" mode. As she begins speaking, we assume she adopts her first ideological state and, accordingly, samples an ideological cue term from that ideology's bag of terms. At some point, we assume she might transition to a new ideological state, at which point she will begin sampling from that bag of terms. To impose some structure, we assume her transition to follow the tree diagram in Figure 1 **[1 –jg]**, and that a transition between any two ideologies follows the shortest, non-repeating path along the edges of the graph. As a result, transitions from far-right to far-left subideologies become longer and thus less likely, though by no means impossible.

Of course, we cannot observe the ideological states directly; all information we have comes in the form of the speech. Within that speech, we look for instances of the ideological cues that fill our dictionary, and we count the filler terms that occur between cues. The inferential objective, then, is to use the information in the sequence of terms to attach an ideological label to each cue.

We do that by considering the ideological profile of each cue, the inferred tendency of a speaker to adopt each ideological state, and the tendency of a speaker to transition from her last "observed" state to each of her possible current states. Put another way, for a current cue term, we construct a probability profile for each ideology, and sample an ideology according to those probabilities.

Let us look more closely detail at two stages of inference. First, we examine the method of vocabulary section and then we describe the model of ideological cue transmission and estimation of time spent communicating from each perspective.

2.1 Initial Vocabulary Selection: Characterizing Ideological Types by Distributions of Key Phrases in Reference Texts

We begin by selecting a number of books by authors of well-known ideological leanings. This current ideological corpus includes 170 books and magazines, mostly written over the period from 2008–2012 so as to reduce variability in temporal context and to best exploit the authors' qualitative knowledge of contemporary political commentators.[5] We choose to rely exclusively on books and magazines, due to the freedom authors have to express key aspects of their political beliefs, values, ideals and attitudes in such a forum. Contrast books with titles such as *Saving Freedom*, *Keeping the Republic*, the charmingly titled *After America: Get Ready for Armegeddon*, or Mitt Romney's own *No Apology: The Case for American Greatness* with the typical scope of an op-ed column, editorial or transcript from one day's talk radio or cable TV program. From experience with a number of formats, we are inclined to believe that books and ideologically-defined magazines come the closest to personal political manifestos, offering authors the greatest opportunity to communicate their broad vision, referencing particular events as illustrative of chosen themes rather than being required to report on particular events that may be less conformable to favorite narratives.

On a given day, a commentator or politician may feel compelled to react to the dominant news story or rumor, but a book is typically the product of a year or two of work. The author can be expected to choose specific events or news items from over this longer period in order to illustrate

[5] Eventually, we intend to extend the corpus backward in time; we will need to rely upon archives of political periodicals and speeches, due to the sparsity of digitally available books comparable to those in the current corpus.

the primary narrative of the book rather than the other way around. Put simply, it is our (untested and perhaps untestable) theoretical claim that these books most often represent a set of claims about what is wrong and right in the United States, with specifics offered as supporting details. Daily blog posts, speech, columns, and editorials are instead based to a greater degree, on the demands of the day (ideologically-driven choices perhaps but within tight constraints). In the case of the former, the ideologue chooses stories to make broader points, while in the latter, he searches for ways to frame current events in terms of his favored narratives.

We use the sparse additive generative (SAGE) model (Eisenstein, Ahmed & Xing, 2011) to characterize the reference texts by ideologically informative n-grams. Like other probabilistic language models, SAGE assigns probability to a text as if it were a bag of terms. It differs from most language models in parameterizing the distribution using a generalized linear model, so that different effects on the log-odds of terms are additive. In SAGE, the deviation of each term in log frequencies from a background lexical distribution can be seen as an additive sum of these effects. For our purposes, the deviation is modeled as an additive function of corpus, main ideological type, subclass, and book specific effects. Furthermore, a Laplace prior is employed to encourage sparsity (most log frequency effects shrink to zero). This is especially convenient for our purposes, as we may limit our ideological vocabularies to those terms whose effects are not shrunk to zero by the procedure.

Moreover, SAGE provides us with a framework for learning cue terms that fit in elegantly with our hierarchical ideology structure. For simplicity, let $\mathcal{A}(d)$ denote the set of attributes of a document (book or magazine) d and $\mathcal{A} = \cup_d \mathcal{A}(d)$. The parametric form of the distribution is given, for term w in document d, by

$$p(w \mid \mathcal{A}(d); \boldsymbol{\eta}) = \frac{\exp\left(\mu_w + \sum_{a \in \mathcal{A}(d)} \eta_w^a\right)}{\sum_{w' \in W} \left(\mu_{w'} + \sum_{a \in \mathcal{A}(d)} \eta_{w'}^a\right)} \tag{1}$$

where W is the set of terms – in this context, bi-, tri-, and four-grams – that may possibly overlap multiple ideological classes.

Each of the μ_w and η_w^a weights can be a positive or negative value influencing the probability of the word, conditioned on various properties of the document. When we stack an attribute a's weights into a vector across all words, we get an $\boldsymbol{\eta}^a$ vector, understood as an effect on the term distribution due to attribute a. (We use $\boldsymbol{\eta}$ to refer to the collection of all of these vectors, including μ_w.) The effects in our model, described in terms of attributes, are:

- $\boldsymbol{\mu}$, the background (log) frequencies of words, which we fix to a term's log relative frequencies in the overall corpus:

$$\mu_w = \log \frac{\mathrm{freq}(w; \mathcal{D})}{\sum_{w' \in W} \mathrm{freq}(w'; \mathcal{D})} \tag{2}$$

  where $\mathcal{D}$ is the set of documents in our corpus. Hence the other effects can be understood as *deviations* from this background distribution.

- $\boldsymbol{\eta}^{i_c}$, the coarse ideology effect, which takes different values for our three broad ideologies: Left, Right and Center.

- $\boldsymbol{\eta}^{i_f}$, the fine ideology effect, which takes different values for the fine-grained ideologies corresponding to the leaves in Figure 1.

- $\boldsymbol{\eta}^{t}$, the topic effect, taking different values for each of the 61 manually assigned topics. We further include one effect for each magazine series (of which there are 10) to account for each magazine's idiosyncrasies (topical or otherwise).

- $\boldsymbol{\eta}^{d}$, a document-specific effect, which captures idiosyncratic usage within a single document.

The ideological effects $\boldsymbol{\eta}$ are estimated by solving the unconstrained convex problem:

$$\max_{\boldsymbol{\eta}} \sum_{d \in \mathcal{D}} \sum_{i=1}^{N_d} \log p(w_{d,i} \mid \mathcal{A}(d); \boldsymbol{\eta}) - \sum_{a \in \mathcal{A}} \lambda_a \sum_{w \in \mathcal{W}} |\eta_{a,w}| \tag{3}$$

The hyperparameter λ_a controls the sparsity of each effect vector η^a, and is a form of sparsity inducing ℓ_1 prior that forces many of its weights to zero. Equivalently, the weights η^a can be seen as being generated from a zero-centered Laplace distribution, with λ_a^{-1} variance (Tibshirani 1996).

To encourage similar levels of sparsity across the different effect vectors, we let, for each ideology attribute a,

$$\lambda_a = \frac{\lambda \cdot \mathcal{V}(a)}{\max_{a' \in \mathcal{A}} |\mathcal{V}(a')|} \tag{4}$$

where $\mathcal{V}(a)$ is the set of unique terms appearing in the data with attribute a (i.e., its vocabulary) , and λ is a single hyperparameter we can adjust to control the overall sparsity in the each of the effect vectors. For the non-ideology effects ($\boldsymbol{\eta}^t$ and $\boldsymbol{\eta}^d$), we let $\lambda_a = 10$ (not tuned).

The MAP estimates of the parameters give the added log-odds that each term appears in an ideological category. Because the original corpus was thinned considerably, the resulting matrix is fairly sparse. This matrix serves as the foundation for classifying speakers from transcripts of their speeches, as introduced in the next section.

Cue lexicon Of the effects vectors $\boldsymbol{\eta}$ we estimate in stage 1, we are only interested in the ideological effects ($\boldsymbol{\eta}^i$ and $\boldsymbol{\eta}^c$). For each of these ideological attributes, $i \in \mathcal{I}$, we take the terms with positive elements of this vector to be the cues for ideology i; call this set $\mathcal{L}(i)$ and let $\mathcal{L} = \cup_{i \in \mathcal{I}} \mathcal{L}(i)$. We call $\mathcal{L}$ our cue lexicon.

2.2 Inference about Candidates via Speeches

Learning (statistical inference) proceeds through estimation of parameters for each speaker. We explain the process here, with formal description in the appendices.**[Decide what to include –jg]**

2.2.1 Details of the CLIP model

Consider a candidate's speech, where terms not in the cue lexicon have been filtered out and treated as "fillers". We start at the beginning of a speech, where we assume the originating ideological state

x_0 can be treated as some generic background political state v_0. Let us assume that we are in the middle of a speech, at w_3, and suppose that w_3 =“personal liberty.” Now, before w_3 is produced, the candidate has had to decide which ideological bag/hat he wants to draw w_3 from.

Emission distribution For each possible ideology type i, our model has an emission distribution $\boldsymbol{\psi}_i$ over $\mathcal{L}$. $\boldsymbol{\psi}_i$ is assumed to be drawn from a Dirichlet distribution, but instead of a uniform prior, we seed the prior for each emission distribution differently. For an ideology i and cue term t, the prior

$$\beta_{i,t} = \begin{cases} \beta_{cue} & \text{if } t \in \mathcal{L}(i) \\ \beta_{def} & \text{if } t \notin \mathcal{L}(i) \end{cases} \tag{5}$$

and β_{cue}, β_{def} are hyperparameters such that $\beta_{cue} > \beta_{def} > 0$. This has an effect of favoring cue terms that are found in the ideology’s lexicon and hence push the candidate towards choosing a hat where “personal liberty” is in the cue lexicon. (More precisely, this pushes our model’s belief about the state x_3 toward an ideology with which “personal liberty” is associated.)

Transition distribution However, the choice of which hat to use is not determined only by the cue lexicon. Suppose that in the previous cue term, we estimated that the candidate drew from x_2^* = “Religious Right”, we must ask ourselves how likely it is that the speaker would then jump to, say, the “Progressive Left” state. While such a jump is not impossible – and our model does not assume it so! – surely such a jump would be less likely than a transition to the same or a nearby state.

This is really where the HMM-style framework begins to make a difference. We think of “ideology” as a multilevel structure of related but discrete ideologies. We can thus model transitions between ideological states as a function of how “far” the speaker will have to travel to his next possible state. Given that our current best guess of the previous state x_2^* is “Religious Right,” we can consider the edges (i.e., bridges between ideological “nodes”) that the speaker must travel to get to any next possible ideology. For instance, to get to “Far Right,” the speaker would have to traverse the path "Religious Right" $\rightarrow$ "Right" $\rightarrow$ "Far Right."

The probability of traversing from ideological state x_2^* to x_3 consists of a few steps.

1) First, we consider the probabilities of traversing each edge in the most direct path from x_2^* to x_3. Labeling $x_3 =$ "Progressive Left" would require the speaker to cross four edges, going from "Far Right" $\rightarrow$ "**Right**" $\rightarrow$ "$\boldsymbol{v}_0$" $\rightarrow$ "**Left**" $\rightarrow$ "Progressive Left", whereas switching to other conservative ideologies would only require traversing two edges.

2) The "speaking" or stopping probability is roughly analogous to mixing proportions in the strict bag-of-words tradition. At each node it lands on during it traversal, the speaker has a choice of stopping and draw a term from the respective hat or continuing on to an adjacent node. The stopping probability at ideological state x_3, is denoted by ζ_{x_3}, which is a hyperparameter in our model, and estimated from the data in an empirical Bayes framework. Also, we note that the background state v_0, which every speech starts from, has a stop probability of 0, meaning that with the exception of the initial state x_0, the speaker at no point in time will land on v_0 and emit a cue term. He will simply move on to an adjacent coarse ideological state.

3) The emission probability distribution, $\boldsymbol{\psi}_{x_3}$, as discussed earlier, denotes the probability that eac possible value of w_3 was selected from x_3's ideological bag of phrases.

Putting these pieces together mathematically, we can imagine a direct computation of each conditional probability, for example:

$$p(x_3 = X_3 \mid x_2^* = \text{Religious Right}) = \left(\prod_{\langle u,v \rangle \in \text{Path}(\text{Religious Right}, X_3)} (1 - \zeta_u)\theta_{u,v} \right) \zeta_{X_3} \tag{6}$$

We would explicitly consider all possible states to which our speaker could travel to and then specify the paths necessary to get there.[6] For the simple case where a speaker remains in his current state, the path is empty and the probability is simply $\zeta_{\text{Religious Right}}$.

[6]Note: we make the assumption that potential paths are unique, minimal and non-repeating. This means that there is only one path between any two ideologies, and that all paths are direct. We do not allow for wandering between states or for backtracking (i.e., FR $\rightarrow$ R $\rightarrow$ FR $\rightarrow$ Libertarian.)

This formulation models our intution that speakers are unlikely to transition frequently between "distant" states. This is accounted for by two elements of the joint probability: long paths have lower traversal probabilities, and the more nodes that exist along the path increases the chance that the speaker "stops" to speak before arriving at the end of the path.

This may appear to be an assumption-saturated modeling decision, but we urge the reader to bear three points in mind. First, a speaker is unlikely to bounce with reckless abandon from far left to far right and back again. If a speaker has decided to sample from a conservative bag of words, she will most likely intend to keep drawing from those bags, at least for a time. Second, the model does not preclude a speaker from bouncing if indeed the data supports this trajectory. Indeed, if we observe the speaker transitioning frequently between ideologies, this will be factored into the joint transition probability. All things equal, the model merely makes such trajectories less likely. Third, as we explore in the next section, we allow for the model to hit a reset button and begin over at the background (v_0) position.

2.2.2 Hitting Reset

Our primary inferential task is to ascertain how long an ideologue spends in each ideological state. To do so, we tally the "lag" periods between ideologically interesting cue terms – that is, we count the filler words between cues. For shorter lag periods, where cues come fairly frequently, this makes good sense. It makes less sense, however, when a speaker uses cue terms infrequently, since it becomes increasingly harder to assume that the speaker has not changed ideological states with long lag periods. To account for this possibility, we introduce the reset probability.

In essence, the reset represents growing uncertainty in the model as the lag between cues increases. When, say, ten filler words – a lag of 10 – comes between cues, it seems reasonable to say that the speaker spent 10 periods in one ideology before potentially moving to another state to sample the next term. If the lag were 100 or 1,000 periods, we cannot be confident that the speaker "stayed put" in the previously inferred ideological state. As the lag period increases, the probability that the model resets the speaker to the "root" node of the ideological tree – that is, restarts him at the node without an ideological label. Once reset, inference continues as it did for the very first cue term, meaning that traversal and emission probabilities are computed beginning from the root node, and not from his previously observed state.

2.2.3 The whole generative story

The basic generative story goes like this: The candidate/ideologue is assumed to be, at any given moment during a speech, occupying a latent ideological state (among the categories defined by the researcher). One may think of this speaker switching among proverbial hats. The structure of the typology is also defined by the researcher; we have found it reasonable to assume that ideologies in the United States are arranged hierarchically, with fairly clear distinctions at the top level between the Left and Right (and to a degree, the anti-polarization Center), with subtypes on the Left and Right subjective, but operationalized clearly in terms of specific prominent commentators or publications taken to exemplify them. Wearing one's Left-hat, one is assumed to sporadically draw a cue-term from the overall left-vocabulary. Furthermore, according to one's hidden predispositions, one may trade in one's general Left (or Right) hat for a specialized sub-ideological hat (in our current specification these include far left, progressive/populist left, religious left, moderate liberal on one side and far right, populist/cultural conservative, religious right, libertarian, and moderate conservative on the other). Conditional on which hat one is wearing (i.e., which latent state one currently occupies) one is assumed to randomly choose a phrase from that type's probability distribution over its vocabulary, with individual cues taken to be independent of one another, given the state. Unconditionally, one's set of ideological cue phrases does not consist of independent draws, but rather is governed by a tendency to stay in certain states and transition probabilities among the states, which are the parameters we learn through a combination of data (speeches) and informed priors (based on the tendency for certain phrases to be heavily used by different ideological groups in the training corpus).

More precisely, the generative model can be communicated in the follow way, as represented in the accompanying algorithmic representation.

2.3 Generative story

Algorithm 1 Generative story for a single candidate. The algorithm describes the randomized procedure by which a candidate's speeches are assumed to be generated by the model.

for each ideological state $u \in \mathcal{V}$ **do**
  Draw a distribution over vocabulary, $\boldsymbol{\psi}_u \sim \text{Dirichlet}(\boldsymbol{\beta}_u)$
end for
for each epoch in an election $e \in \Omega$ **do**
  for each ideological state $u \in \mathcal{V}$ **do**
    Draw a distribution over transitions from u, $\boldsymbol{\theta}_{e,u} \sim \text{Dirichlet}(\boldsymbol{\alpha})$
  end for

  for each speech document $d \in \Omega_e$ **do**
    for $i = 1 \to N_d$ **do**
      Draw the number of filler terms before $w_{d,i}$, $t_{d,i} \sim \text{Poisson}(\lambda)$
      Draw the reset variable $r_{d,i} \sim \text{Bernoulli}(\mathcal{R}_{t_{d,i}})$
      if $r_{d,i} =$"reset" **then**
        Draw latent ideological state, $x_{d,i} \sim \boldsymbol{\pi}(v_0 \mid \boldsymbol{\zeta}, \boldsymbol{\theta})$
      else
        Draw latent ideological state, $x_{d,i} \sim \boldsymbol{\pi}(x_{d,i-1} \mid \boldsymbol{\zeta}, \boldsymbol{\theta})$
      end if
      Draw observed cue term, $w_{d,i} \sim \text{Multinomial}(\boldsymbol{\psi}_{x_{d,i}})$
    end for
  end for
end for

3 Results and Discussion: Testing the Etch-A-Sketch Hypothesis

As Anthony Downs wrote in 1957, we can imagine a density of voters over a single-dimensional left-right ideological space. In a two party system, political parties should rationally seek to position themselves in the area of the space that is most densely populated (Downs 1957) Accordingly, Downs concludes, in a two-party political system, each party faces an incentive to converge toward the median voter. Put another way, parties wish to maximize the votes they receive, and will thus position themselves in the ideological 'neighborhood' where the most voters exist. This expectation, called the Median Voter Theorem, serves as the foundation for most spatial voting models in modern political science scholarship.

Modern presidential campaigns, however, do not unfold in a single stage. A candidate must secure a party nomination through the primary and caucus process; and only then may he proceed to the general election. This implies that the spatial model can be brought to bear in two stages. First, a candidate should seek to appeal to the median *party* voter in the primaries, and then to the median *general election* voter for the general election. This theory finds considerable traction in most popular presidential campaign narratives: each party's candidate runs to the ideological-left or -right before tacking back to the ideological-center in the general election.

To capture candidate movement from primary to general election rhetoric, we propose using text from the 2012 and 2008 elections. We separate speeches by Mitt Romney, John McCain and Barack Obama into election-year epochs.[7] Speeches falling between a candidate's *official* announcement and the night on which he secures enough delegates to secure his party's nomination are labeled "primary" speeches. Speeches falling between the latter time and Election Day are labeled as "general election" speeches. We examine the degree to which Romney's, Obama's and McCain's behavior changed as each transitioned from his primaries to the general election.

For further validation, we collected speeches from presidential candidates in 2008 and 2012 in both major party primaries. To provide a fair test of the model, we constructed a set of hypotheses about candidate ideology, based on area expertise and candidate reputation, and recorded these hypotheses before fitting the model. The results from the model, and how it performed on our preregistered hypotheses, is discussed in the following section.

3.1 Analysis

On the most basic hypotheses, which concern basic left-right distinctions between Democrats and Republicans, CLIP results match our intuition nicely. All Republicans were placed as mostly drawing terms from conservative ideological bins, while Democrats sampled mostly from liberal bins. Of particular interest was the model's output for Jon Huntsman, a former Utah governor and U.S. Ambassador to China under President Obama, who was known as the centrist voice of the Republican party during the 2012 election: Huntsman was considered evenly balanced between Left and

[7] Speeches collected from the University of California, Santa Barbara presidency project.

Right in his rhetoric, which matches our intuition about Huntsman's centrist ideology.

The model output also adheres to our expectation that Republican candidates would hardly sample from leftist subideologies, and that Democrats would rarely sample from rightist subideologies. Referring to Figures 6 and 7, it is apparent that Republican candidates in 2008 and 2012 almost never (with 95% credible intervals crossing zero) speak as progressive or radical leftists[8], while Democrats rarely speak as libertarians, populist or radical conservatives. Using posterior means as point estimates, candidates also largely project into a left-right space in ways that match our intuition, with candidates like Bachmann, Gingrich Paul occupying the more extreme right, and candidates like Biden and Clinton occupying the liberal left.

Perhaps unexpectedly, however, the model also finds relatively little evidence for subideological speech amongst any candidates. Few candidates seem to draw more than 10% of their speech from any particular subideology. This is surprising, especially for candidates like Ron Paul who clearly identifies and is identified as a libertarian. Viewed another way, however, this is not entirely surprising. Reading through Paul's speeches, one notes some clear libertarian cues, but we also notice language dominated by mainstream Republican ideas, culturally conservative principles, issues of the day and campaign-centric rhetoric. With additional vocabulary – and, for many candidates, if we had more speeches – the model may be better able to pinpoint subideological language, but even then we might not expect candidates, who are running in competitive elections, to ever look like an ideal ideological type.

Turning to the Etch-a-Sketch hypothesis, we find clear movement toward the center by McCain, Obama and Romney. A visualization of CLIP's proportions for the three general candidates is shown in Figure 2, with their speeches grouped together by epoch. For 2008, the model finds that Obama significantly increased his conservative and centrist language as he transitioned from the Democratic primary to the general election. McCain, too, increased his use of leftist language, and drastically increased his use of centrist rhetoric, after securing the Republican nomination.

The 2012 election tells a similar story for Romney, as he speaks less as a conservative, and

[8]Fred Thomson's few available speeches account for the large credible interval; Romney in the 2008 general election comes the closest

moderately more as a liberal, as he transitioned from the Republican primary to the general election. Romney appears to have actually receded in his use of centrist language as he moved to the general election, but the change is small and difficult to confirm statistically. For point estimates and credible intervals on all three candidates, see Figure 5.

4 Conclusion

Much of politics occurs via written and spoken word, yet scholars have had relatively few options for processing and modeling large amounts of textual data. Motivated by a substantive question central to, but heretofore untested in, the elections literature, we have sought to develop a model capable of detecting ideological language in campaign speeches by presidential candidates. To that end, we present the Cue Lag Ideological Proportions (CLIP) model.

Underlying CLIP is a large and growing corpus of ideological texts by political figures and commentators, from which we have developed an ideological "vocabulary" of words and phrases associated with various American political ideologies. Using this information, we deploy CLIP to measure the ideological content of presidential candidates' campaign speeches and, for Obama, McCain and Romney, measure the extent to which candidates "collapse toward the median voter" when transitioning from the primary campaign to the general election.

We believe our contribution to the literature is three-fold. First, we present and are maintaining an expanding ideological vocabulary and, perhaps more importantly, the tools for other scholars to test other formulations where they may disagree with our ideological labels. For example, the model can be reduced to a simple left-right dichotomy, or expanded to account for any number of sub-ideologies and any number of book and/or author partitions.

Second, the CLIP model provides a sound, efficient way for scholars to estimate ideological content of any number of political documents. We use campaign speeches from presidential candidates, but scholars could easily adjust the framework to examine speeches by members of Congress or by sitting executives, any number of advertisements, newsletters or web content, or newspapers, blogs or other social media. Further, the model can be adjusted to detect other important aspects of text, like sentiment or hostility. The room for expansion with the model is effectively unbounded.

Finally, the CLIP model provides a way of processing speeches in ways that match our intuition about how speakers select their ideological words. Unlike most previous modeling strategies, we do not simply lump all key words and phrases together in a mixture model. Instead, we leverage all information in the speech by maintaining the order in which cues are taken. We thus better inform ourselves about the likely ideological label of a given cue by examining the proximity and inferred label attached to temporally adjacent terms.

Using pre-registered hypotheses and expert evaluation, we find that the model is capable of identifying key ideological phrases, and places candidates largely in line with where experts expect. We thus find credible the model's results, which show that Barack Obama, John McCain and Mitt Romney did indeed make substantively significant shifts away from the ideological extremes after securing their parties' presidential nominations. We believe this to provide perhaps the best test to date of Downs' median voter theory, and marks a significant step forward for leveraging the written and spoken word to evaluating theoretically-important scholarly questions.

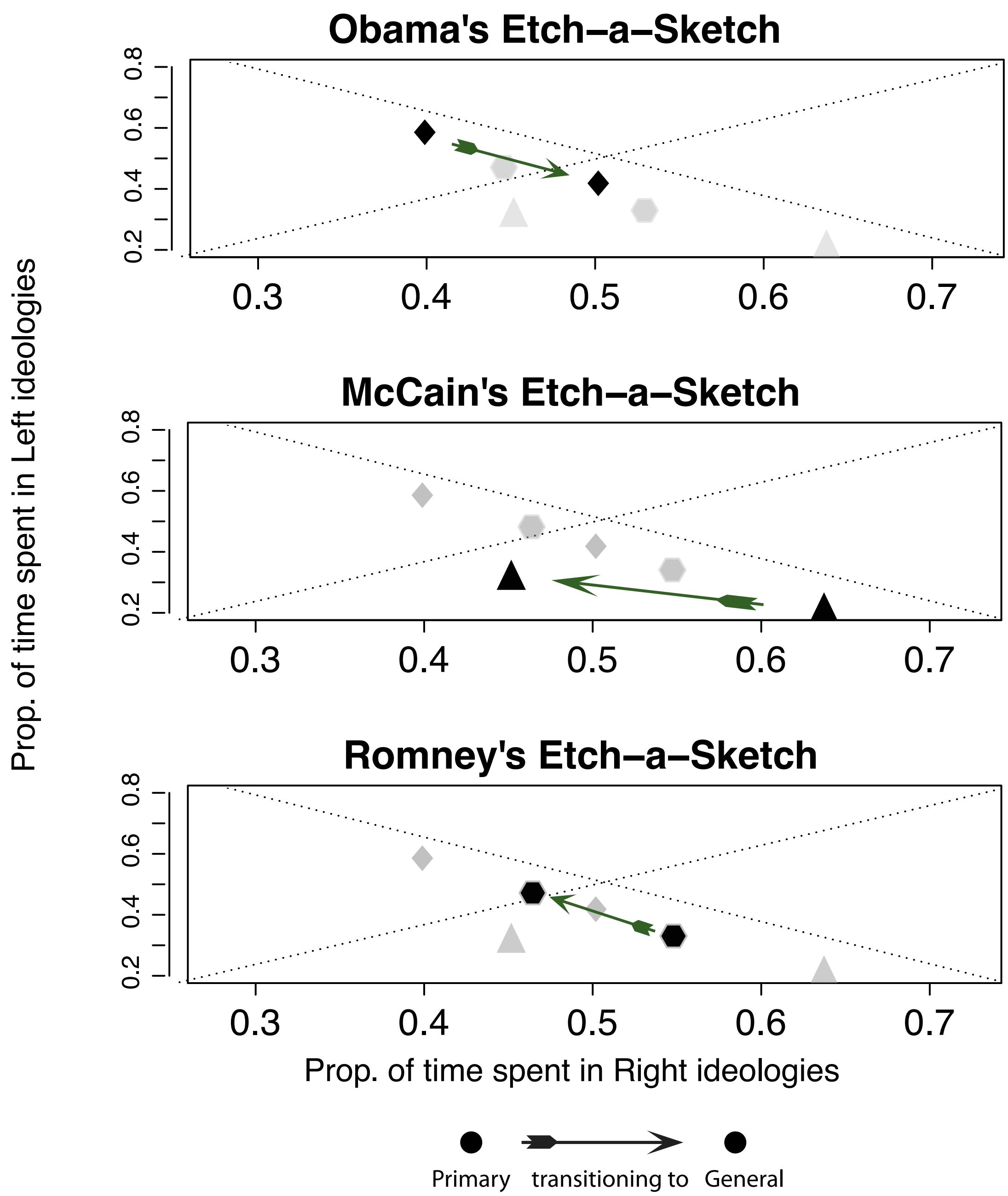

Figure 2: Each panel shows the change in Left/Right balance from the primary to the general election for Barack Obama in 2008, John McCain in 2008 and Mitt Romney in 2012. Obama in 2012 is not featured because he did not face a primary challenge in that cycle. Points show the posterior mean estimate of time spent in the Right (horizontal axis) and Left (vertical axis) ideologies. The figures need not sum to one, as time spent in the Center category is estimated as well, but not pictured in the figure. The intersection of the dotted lines represents perfect balance between Left and Right. Each candidate shows substantial movement toward the center transitioning from the primary to the general election

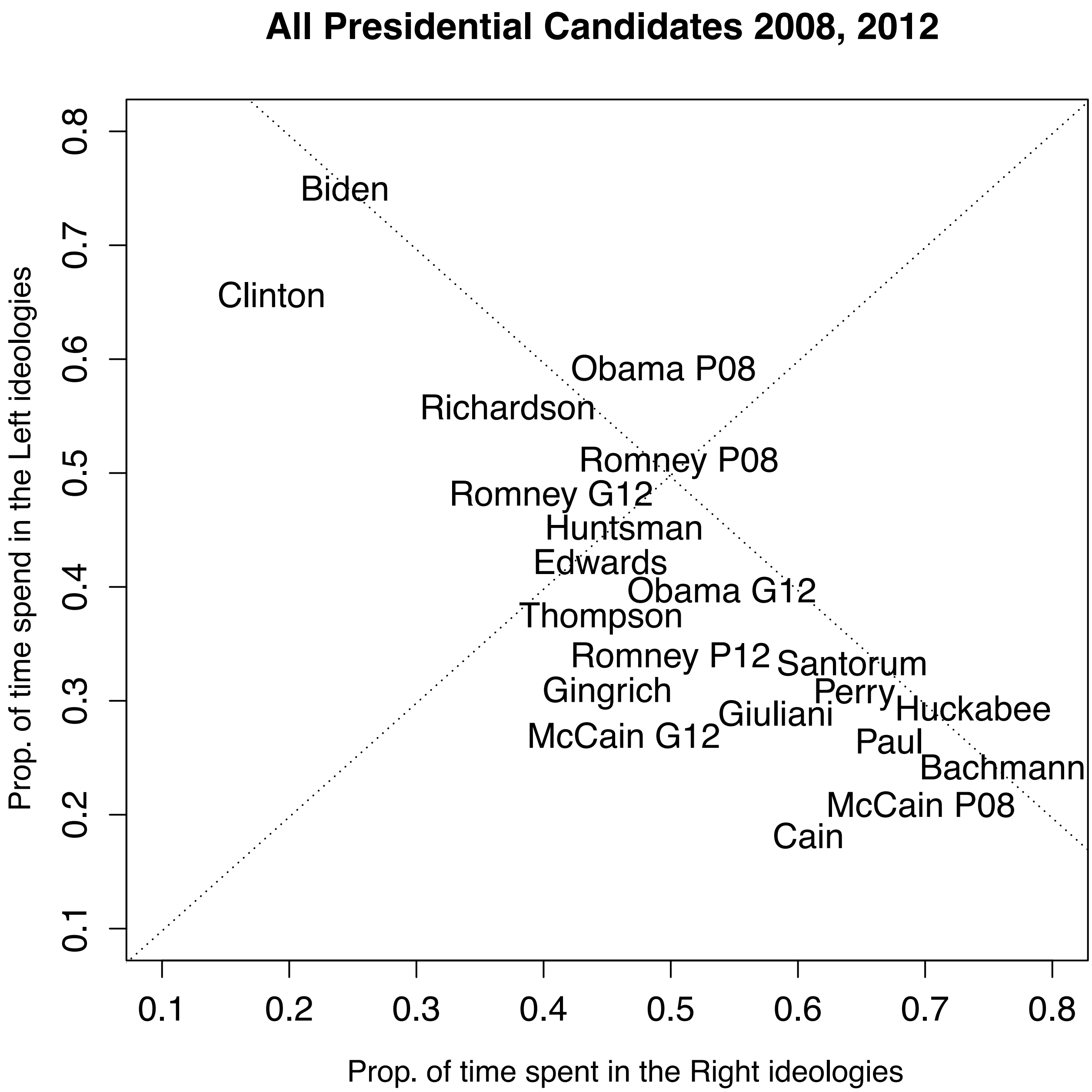

Figure 3: 2008/2012 Candidates' estimated proportions of aggregated time spent in the Left (vertical) and Right (horizontal) ideologies. The figures need not sum to one, as time spent in the Center category is estimated as well, but not pictured in the figure. The point estimates lie at the center of each name.

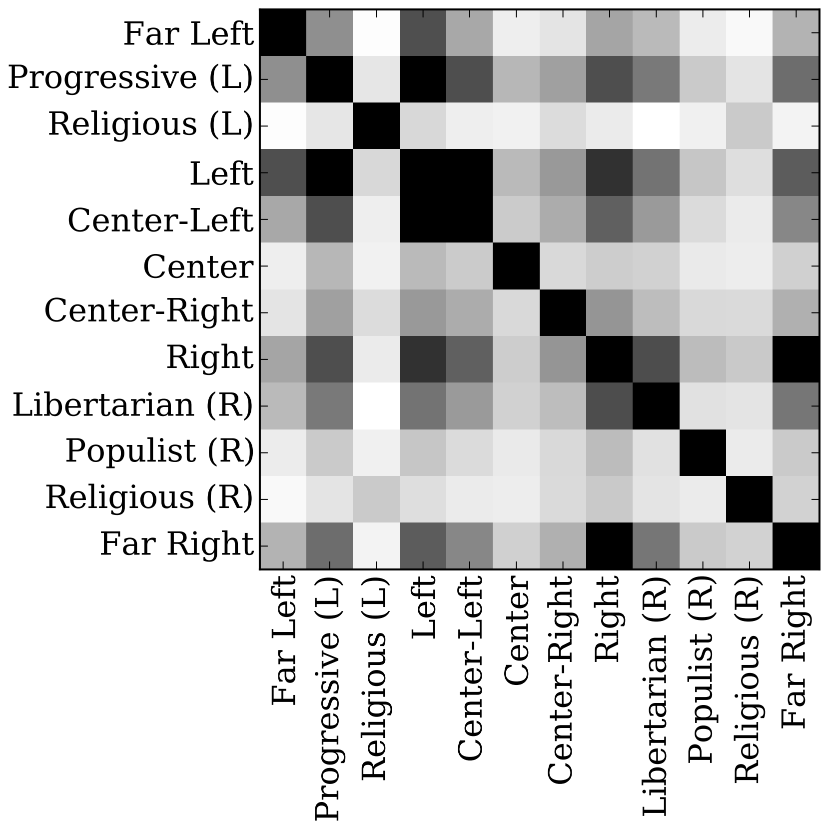

Figure 4: Heat map of Jaccard Similarities between ideology effect vectors from Stage I, where darker implies greater overlap in language patterns between ideologies. The overall Left shares the most in common with the Center-Left (typified by the Democratic Leadership Council and *The New Republic* magazine. The overall Right is dominated by what we have called the Far Right, typified by hard right radio (e.g., Michael Savage, Glenn Beck, Sean Hannity)

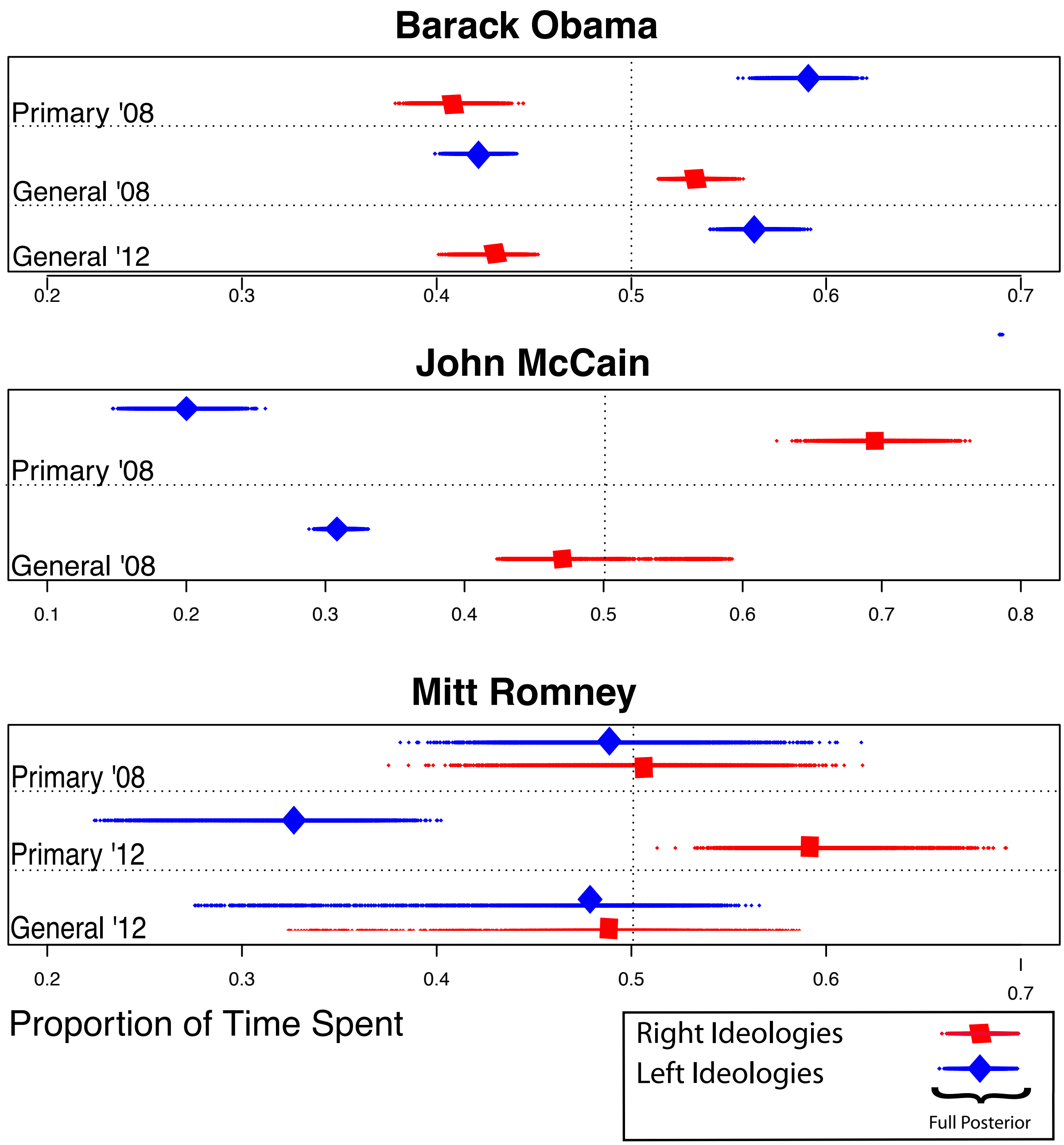

Figure 5: For each candidate in each epoch (primary/general), the points represent posterior means of time spent in all left and right ideological states, surrounded by full posterior sample bars. The top panel shows Barack Obama, the middle John McCain and the botom shows Mitt Romney. In all three cases, the candidate appeals to the "base" in the primary before converging toward the center in the general election. McCain is a particuarly interesting case. The sum of the posterior means for Left + Right is less than 1; this is because McCain, more than Romney or Obama, considerably increased his use of Centrist terms in the general election 2008.

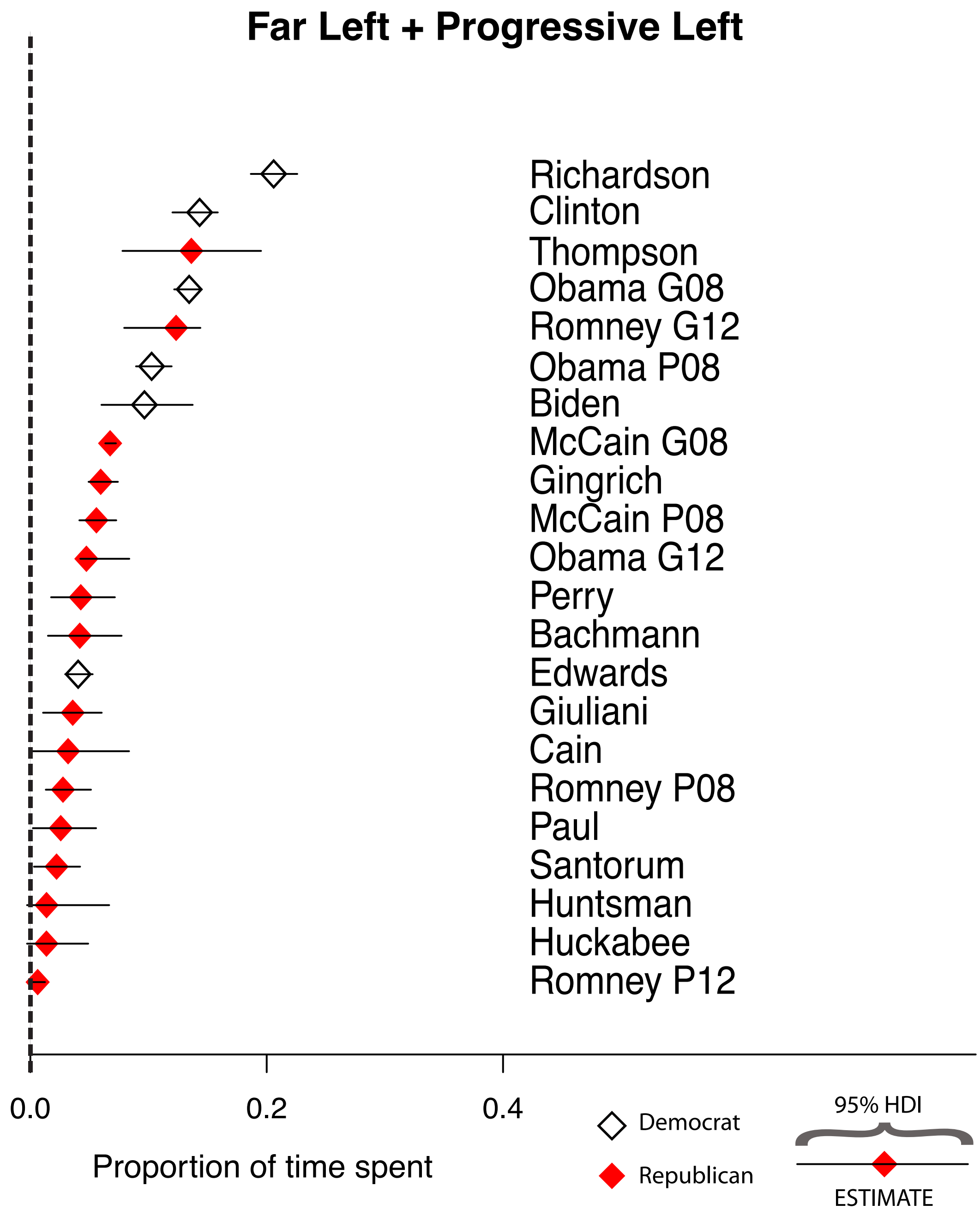

Figure 6: For each primary and general election candidate in both major parties, 2008-12, we show the posterior mean of time spent in the Far Left + Progressive subideologies, with 95% high density interval (HDI) bars. Fred Thompson's point estimate (MAP) is misleading; his credible interval is quite wide, likely owning to his few speeches available for training. On the other hand, Romney (General 2012) appears to be at the higher end of Republican candidates, which accords with the Etch-a-Sketch hypothesis, as well as the results for President Obama and John McCain.

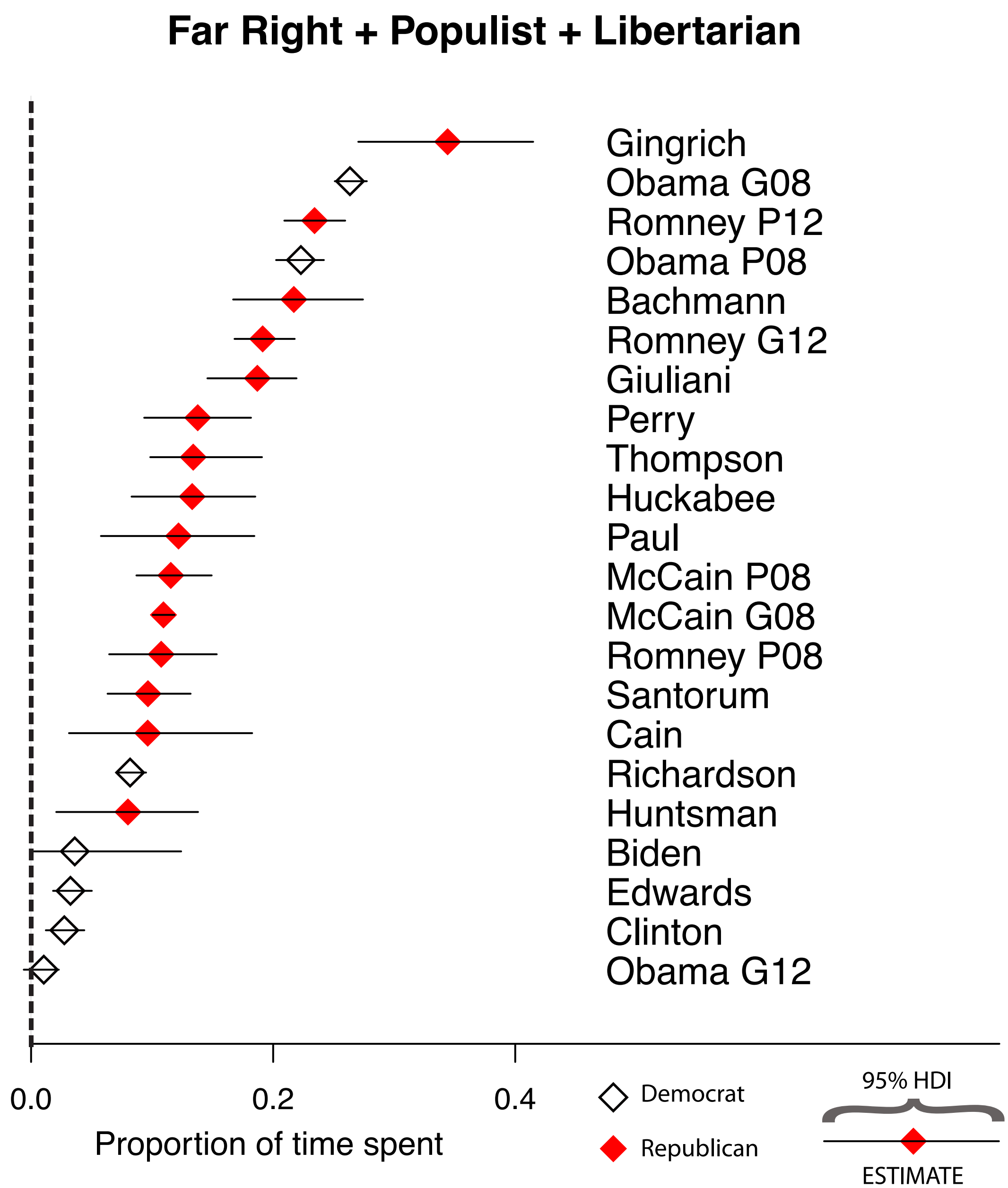

Figure 7: For each primary and general election candidate in both major parties, 2008-12, we show the posterior mean of time spent in the Far Right + Populist Right + Libertarian subideologies, with 95% high density interval (HDI) bars. One notices the unexpectedly high level for Obama in the 2008 primary elections, perhaps pointing to a weakness in our model. A challenge left for future work is to consider whether we might be able to distinguish between extreme language said sincerely and such language cited by an opponent to claim that they are radical. One suspects that may be the issue here.

FAR LEFT (2,802)	monopoly capital, class struggle, capitalist economy, social movements, occupy movement, political economy, capitalist system, trade union, labor movement, ruling class, developing countryy, world bank, working people, labor power, economic crisis, communist party, latin american, world economies, latin america, social justice, fossil fuel, natural resources, nineteenth century, south africa, working class, human development, multinational corporation, capitalist society,
PROGRESSIVE LEFT (2,319)	# [of] people, recent year, abu ghraib, # [of] states, executive director, public info, state department, public policy, vice president, # centuri, mental illness, John Kerry, make sense, political party, presidential election, Unitied Nations, web site, interest rate, New York City
RELIGIOUS LEFT (941)	biological family, progressive religion, nuclear family, Mother Teresa, bad theology, religious issue, early church, tax collector, God's love, religious community, American creed, early Christian, Luke [chapter] #, church leader, Matthew [chapter] #, great recession, moral issue, base initiative, evangelical Christian, religious leader, religious tradition, Sunday school, strict father, ordinary radical, God bless, overcome poverty, created equal, political leader, christian nation, economic crisis, social gospel
LEFT (2,580)	North Carolina, econom policy, executive director, public opinion, cell phone, mental illness, # [of] states, Abu Ghraib, early #, decade ago, West Bank, presidential election, good job, air force, homeland security, political system, vast majority, John Kerry, Clinton administration, Al Gore
CENTER-LEFT (3,050)	young woman, eighteenth century, Al Jazeera, nineteenth century, good deal, young man, twentieth century, long ago, Mitt Romney, great deal, presidential campaign, twenty years, Al Qaeda, young men, John McCain, Hillary Clinton, law school, make sense, long time, recent years, World War II, nuclear weapon, thirty years, same thing, War II, decades ago, prime minister, presidential candidate, gay marriage, economic growth
CENTER (1,230)	Long Beach, debt limit, stock option, country music, average American, corporate America, original intent, Georg Washington, cousin John, tax increase, loan office, Alexander Hamilton, debt ceiling, parking lot, proof text, House Republicans, # visas, hundred years, James Madison

Table 1: Top cue terms associated with each coarse/fine-grained ideology, with the total number of terms in parentheses. Words in [brackets] are included to aid the reader's comprehension. The terms are ordered by log-deviation weights in the $\boldsymbol{\eta}^i$ vectors. # denotes any numeral.

CENTER-RIGHT (1,450)	Governor Bush, class voter, health care, Republican president, George Bush, state police, move forward, Miss America, Middle Eastern, water buffalo, fellow citizen, Sam's Club, political career, american life, working class, election night, general election, culture war, status quo, human dignity, same-sex marriage, limit government, moderate Republican
RIGHT (2,415)	McManus source, foreign aid, North Korea, National Review, North American, George Washington, Communist party, armed forces, emphasis added, European Union, limited government, Constitutal Convention, President George Bush, presidential candidate, # [of] minutes, labor union
LIBERTARIAN (2,268)	medical marijuana, reality taught, intuititive temptation, raw milk, Rand Paul, economic freedom, health care, govern intervention, market economy, commerce clause, military spending, govern agency, due process, drug war, government policy, minimum wage, federal law, # percent coalition, government official, economic activity, Ron Paul, private property
POPULIST RIGHT (1,155)	corporate America, working men, border security, national interest, big business, national media, birth rate, hundred years, special interest, million people, American citizen, immigration law, open border, mass immigration, border patrol, trade deficit, latin america, culture war, great nation, elected official, forty year, twentieth century, immigration reform, white America, public service, working people, American jobs, American companies
RELIGIOUS RIGHT (960)	daily saint, Holy Spirit, Matthew [chapter] #, John [chapter]#, Jim Wallis, modern liberals, individual liberty, positive law, God's word, Jesus Christ, elementary school, natural law, limited government, emerging church, private property, Planned Parenthood, Christian nation, Christian faith, Romans [chapter] #, foot soldier, Joseph Smith, political correctness, hundred years, school district, Psalm [chapter] #, culture war
FAR RIGHT (2,410)	McManus source, Ron Paul, North American, emphasis added, American citizen, foreign aid, European Union, world government, Communist party, North Korea, Constitutional Convention, government spending, # century, # Amendment, police officer, central bank, executive branch, limited government, government official

Table 2: Top cue terms associated with each coarse/fine-grained ideology, with the total number of terms in parentheses. Words in [brackets] are included to aid the reader's comprehension. The terms are ordered by log-deviation weights in the $\boldsymbol{\eta}^i$ vectors. # denotes any numeral.

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