Competitive Primaries and Polarization in the US Senate

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Introduction

Literature on legislative polarization has identified a puzzle: While voters have remained relatively moderate, their representatives in Congress have become increasingly polarized in their voting patterns (Fiorina et al. (2008), Ansolabehere et al. (2006)). Primaries are theorized to be a major cause of this polarization because they force candidates to take more extreme positions in order to advance to the general election (Burden (2001); Fiorina et al. (2008); Fiorina and Levendusky (2006); King (2003)). However, direct evidence of the link between competitive primaries and polarization has been hard to find. In a study of US Senators, Hirano et al. (2010) find no evidence that primary competition contributes substantially to polarization in Senate roll call voting. Additionally, Hirano et al. (2010) find that while Senators gain votes in their primaries from taking relatively extreme positions, they lose support in the general election when they adopt such a strategy. Looking at the relationship between types of primaries and candidate platforms, Rogowski (2012) concludes that there is no evidence that different types of primary systems are associated with more ideologically extreme candidates and McCarty et al. (2009) find little evidence of the theory.
that partisan gerrymandering in House districts spills over into the Senate in the form of polarization.

So the puzzle remains—Why are we seeing increasing polarization in Congress? In this paper I propose a research project which attempts to shed light on this question through two new observations: First, I call attention to the fact that voting behavior is not the only thing a congresswoman can manipulate to try and capture both primary voters and general election voters. Previous studies have ignored the fact that congresswomen can manipulate their projected partisanship (through press releases, Twitter, Facebook etc...) separately from their roll call voting and that they can do this strategically. Strategically manipulating one’s projected partisanship can allow Senators to vote in the more polarized way while still trying to capture a more moderate electorate or visa versa. The existence of this strategic manipulation may help account for the lack of relationship between primary competition and roll call voting polarization. In this paper I will present some preliminary evidence that this strategic manipulation is occurring using a new dataset of Senator Tweets.

Second, I argue that while voting polarization may be driven by many factors, there may still be a relationship between primaries and polarization which has been missed by previous scholarship. This relationship has not be found previously because it depends not just on the competitiveness of primaries, but on the interaction between competitive primaries, competitiveness of the general election, the type of competitiveness of the general election and the latent ideology of the Senator. In this paper I will argue that competitive primaries lead to polarization when moderate Senators are exposed to competitive primaries in states that will not punish them for voting in a more polarized way and when moderate Senators must compete in competitive primaries and competitive general elections in states where the general election voters have two-peaked preferences (and therefore running towards the party is the best strategy to mobilize the base and win in the general election).
The evidence in this proposal shows that Senators strategically manipulate their partisan images using Twitter. While this on its own is not surprisingly, the overarching goal of this research is to reconcile two different theories of Senator behavior and show that this can explain the lack of evidence for the relationship between primary competition and roll call polarization. On the one hand, the theory developed by [Aldrich (1995)] is a candidate-centered one that theorizes that elected representatives manipulate parties when it is convenient for them (i.e. the dog wags the tail). On the other hand, the theory developed by [Cohen et al. (2008)] argues that parties are “intense policy demanders” who choose candidates for their policy properties and can choose extremism (i.e. the tail wags the dog). I argue that both theories may be correct depending on the circumstances and that it is because both are occurring that sometimes competitive primaries do not lead to voting polarization (because the dog wags the tail) and other times competitive primaries do lead to voting polarization (because the tail wags the dog).

This proposal proceeds in three parts. First, I will lay out my theory of strategic manipulation and the relationship between primaries and polarization. Second, I will show the results from my research using Senator Tweets which supports part of this theory. Third, I will elaborate on how I would test this theory given unlimited time and resources.

Theory

Senator Behavior

My theory of senator behavior draws on observations from many major works in American politics. First, following [Mayhew (2004)], I start with the assumption that Senators are ratio-
nal actors who are motivated by re-election\(^\text{1}\). Second, following [Downs (1957)](1957), I assume that to win an election, be it a primary or a general election, the Senator must capture the median voter. Third, I extend [Poole and Rosenthal's (2007)](2007) concept of “ideal points” to include not just ideology as it pertains to voting behavior, but ideology more generally and stipulate that Senators have a “latent ideological type” which is defined as the voting behavior and projected partisanship the Senator would exhibit in the absence of any constraints.

Finally, I consider two different theories regarding the role of political parties. The role of parties in American politics is a matter of much debate. First, I consider the theory developed in [Cohen et al. (2008)](2008) that parties manipulate the candidates through “intense policy demanders” (p.30) who not only pressure candidate to be extreme but who “choose them to be extreme” (p.145). A different theory of political parties can be found in [Aldrich (1995)](1995) in which it is argued that politicians manipulate the party by running to the party and giving up their personal autonomy when they are facing an “imminent threat of defeat” (p.26).

I think it is possible that both forces are at work—Senators will run to the party, acting in a codified partisan manner in both their speech and their votes when they feel they are under pressure, but sometimes this will not be enough and the “intense policy demanders” will oust them in favor of a more extreme candidate. While replacing representatives with more extreme representatives is one way we might see polarization, I am more curious about how the fear of [Cohen et al. (2008)](2008) “intense policy demanders” leads Senators to manipulate their votes and their images as theorized by [Aldrich (1995)](1995) or perhaps just manipulate their projected partisanship (as [Cohen et al. (2008)](2008) might theorize). I argue that in some cases a Senator may simply manipulate her image, while in other cases a Senator will manipulate both her image and her voting behavior. The strategy a Senator chooses is determined by

\(^{1}\)At this point I am not considering senators who are retiring or leaving office because they will experience different pressures because they are not motivated by the desire to remain in office.
whether she thinks she will be called to task by the “intense policy demanders” or whether she can appease them by cheap talk. In this paper I will theorize that a Senator makes this decision based upon the competitiveness of her primary election and the competitiveness of her general election.

The model then consists of Senators, motivated by re-election, trying to capture the median voter of both the primary and general electorates by manipulating their voting, their speech or both to avoid being brought to task by “intense policy demanders.” Within this framework there could be many factors which influence Senator behavior and could lead to polarized voting behavior, but in this paper, I will focus on two factors which are the competitiveness of the primary and the competitiveness of the general election. In the absence of these two constraints there are likely other constraints that lead to more polarized voting behavior (e.g. Party enforcement of roll call voting once in office), but if we take Mayhew’s (2004) point that Senators are motived by re-election, the key two barriers to re-election are the primary and the general election so I will begin by focusing on those (other factors I would like to consider will be discussed in the final section).

The story of my theory goes as follows: In an attempt to get re-elected, a Senator chooses a two-part strategy to try and capture both primary voters (when applicable) and general election voters. The two-party strategy includes a “Voting Strategy” (how the Senator will manipulate her roll call votes) and a “Image Strategy” (how the Senator will manipulate her projected partisanship). While projected partisanship can be easily manipulated, voting behavior is more costly to manipulate and may take more time to change. Given this, I assume that during a re-election year a Senator can manipulate her projected partisanship between the primary and general election, but that she can only choose one voting strategy during that time. Now I will describe my independent and dependent variables and the predictions my theory generates.
Independent Variables

• **Competitiveness of the primary election**—For the purposes of this paper I will simply classify primary elections as either competitive or not competitive. How to best measure this variable is a matter of some debate in the literature. Hirano et al. (2010) measure it using the average level of primary competition in previous primary elections for non-Senate statewide offices and measure this value in two ways, first, the average number of incumbents contested in previously primary elections and second, the average number of incumbents who win less than 60% of the vote in previous primary elections. In this paper, I will consider Senators to have foresight and consider any primary in which a challenger receives about 20% or more of the vote to be a “competitive primary,” but clearly this definition will have to be refined in future work. Primaries are characterized by partisan voters (Burden (2001); Fiorina et al. (2008); Fiorina and Levendusky (2006); King (2003)) who may fit the mold of Cohen et al.’s (2008) “intense policy demanders.” I will assume that, in the case of a competitive primary, the voters will be very aware of not only a Senator’s image strategy but also the Senator’s voting record. While primaries are sometimes thought of as merely a formality, Mayhew (2004) notes that during the 1964-1972 ten House committee chairmen lost their primaries (fn 51, p.26).

• **Competitiveness of the general election**—For the purposes of this paper I will classify the competitiveness of general elections into three categories: Not competitive, Competitive with single-peaked preferences or competitive with two-peaked preferences. Following Downs (1957) I note that there could be two different types of general election electorates which generate image and vote strategies. First, if the preferences of the general election voters are single peaked and the general election is competitive then to capture the most voters the ideal strategy is to be moderate and less partisan.
However, if the election is competitive and the preferences of general election voters are two-peaked then being more partisan may be a plausible strategy to capture the most voters. The competitiveness of the general election will be measured using the vote returns and assuming that Senators have good foresight—If an election is within a 10% margin I will consider it competitive, but clearly this is another variable which will need to be refined in future work. I will also look at the data from Senator Tweets to see whether senators perceive themselves to be in a single-peaked or two-peaked competitive race, though again this could be improved in the future.

- **Latent ideology of Senator**—This variable is the vote strategy and projected partisanship a Senator would show in the absence of political constraints. It is currently unobserved, but could potentially be measured by studying Senator ideology before joining the Senate. This variable is important because the polarization of an individual Senator occurs when a Senator adopts a vote strategy that is “against type.” For example, conservative states which have already elected conservative congressmen will not be affected by more competitive primaries because the Senator is already voting in an extreme way and would do so with or without having to appeal to a primary electorate.

**Dependent Variables**

- **Vote Strategy**—Because changing voting behavior is potentially costly and also time-intensive, I allow Senators to choose one of two voting strategies: A moderate strategy which is less polarized or an extreme strategy which is more polarized. This will eventually be measured using DW-Nominate Scores, but in this paper I focus on testing my predictions for image strategy.
• **Image Strategy**—Because changing projected partisanship is much less costly and much less time intensive, I allow Senators to choose a two-part image strategy in which they choose a projected image for the primary period and the general election period separately. During each period a Senator can choose from one of two positions: Less Partisan or Highly Partisan (LP or HP). Currently this is measured using data from Twitter but I would like to expand this in future projects to use press releases, Facebook posts and other image-related media generated by Senators.

**When Do Competitive Primaries Cause Polarization vs. Cheap Talk?**

I agree with Hirano et al. (2010) that, in general, the relationship between competitive primaries and polarization is diluted by the fact that general election voters punish Senators for taking extreme positions despite the power of “intense policy demanders.” When Senators fear the retribution of general election voters, I argue that they will choose a strategy that includes manipulating their partisanship between the primary and the general election while not adopting an extreme vote strategy. However, when Senators do not fear the retribution of general election voters (when the general election is not competitive or when the general election is competitive but general election voter preferences are two-peaked) a moderate Senator is more likely to change both her voting strategy and her image strategy to be more polarized. Table 1 shows when I predict that competitive primaries will lead to more polarized voting (in yellow) and when they will lead to cheap talk (in gray). Additionally, I argue that the previous null results are caused by variable cases (no color) or when more competitive general elections lead to more polarized voting in the absence of more competitive primaries (in pink). I also predict that in one case competitive general elections lead will to less polarized voting when the primary is not competitive and the preferences of the general
electorate voters are single peaked (in green).

<table>
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<tr>
<th>Latent Type</th>
<th>Competitive Primary</th>
<th>Competitive General Election</th>
<th>(SP?)</th>
<th>(DP?)</th>
<th>Vote Strategy</th>
<th>Image Strategy</th>
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<td>X</td>
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<td>✓</td>
<td>Extreme</td>
<td>HP-HP</td>
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Table 1: Predictions

Strategic Image Manipulation Using Twitter

Before testing all the implications of my theory, it is first important to check whether Senators do in fact strategically manipulate their partisanship. Using a new dataset of Senator Tweets I examine the relative partisanship of a Senator’s Twitter feed over time.

Gathering tweets

All but seven US Senators use Twitter regularly\(^5\). To collect their tweets, I went to their Twitter homepagae and scrolled down as far as I could then saved the HTML to my hard drive. Unfortunately, one of the limitations of Twitter data is that I cannot disclose my

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\(^2\)If the general election is competitive is it because the preferences are moderate and single peaked?

\(^3\)If the general election is competitive is it because the preferences are more extreme and double peaked?

\(^4\)HP-LP indicates highly partisan during the first primary period and less partisan during the general election period, HP-HP indicates highly partisan during both periods and LP-LP indicates less partisan during both periods

\(^5\)At the time of writing, Herb Kohl (D-WI), Jim Risch (R-ID), Jeff Bingaman (D-NM), Kent Conrad (R-ND) and Jim Webb (D-VA) did not have Twitter accounts and John Kyl (R-AZ) had an account that had not been used since 2011 and Mark Kirk only tweeted 9 times during 2012 so is excluded from my dataset.
collected tweets as a dataset, but I can provide instructions as to which tweets were used such that those who want to replicate my work can generate their own dataset.

**HTML to Dataset**

I wrote a Python script to turn the raw HTML into a .csv file with a row for each tweet. The current version of the script is available at [http://people.fas.harvard.edu/~wise/Code/Senator_Tweet_Cleaning.py](http://people.fas.harvard.edu/~wise/Code/Senator_Tweet_Cleaning.py). In addition to the text of the tweet, I saved the day, month and year of publication and linked it to a senator’s Twitter handle. Figure 1 shows what the final .csv file looks like for Barbara Boxer’s tweets.

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<th>B</th>
<th>C</th>
<th>D</th>
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</thead>
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<td>2012</td>
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<td>2</td>
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</tbody>
</table>

![Figure 1: An example of the CSV dataset](https://via.placeholder.com/150)

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6See: [https://dev.twitter.com/discussions/8232](https://dev.twitter.com/discussions/8232) for a description of this policy.

7The BeautifulSoup package is particularly useful for this task, see [http://www.crummy.com/software/BeautifulSoup/](http://www.crummy.com/software/BeautifulSoup/).
Dataset to Document Term Matrix

The .csv files were read into R and then turned into a matrix which contained all the tweets in my dataset. Because the availability to tweets varies, I consider only tweets from 2012 in this paper, leaving me with a total sample of 42,229 tweets from 93 Senators. Using the TM library in R, I turn the tweet dataset into a Document Term Matrix by calculating the term frequencies for each word in a tweet. The term frequency is simply the number of times each possible word appears in a tweet—for each tweet there is a “fingerprint” of numbers (mostly 0s) that show the words which appear in that tweet as a function of all the words in the dataset.

Descriptive Statistics

From January 2012—October 2012 the 93 Senators in my dataset generated a total of 42,229 tweets. The average number of tweets per senator during this period was 454 but the number of tweets varies quite a bit across senators and Republicans tend to tweet less than Democrats (Republicans average 402 tweets over the January–October period while Democrats average 500 tweets over the same time). The distributions of average tweets for each party is shown in Figure.

Do Democrats and Republicans tweet about different things?

Before attempting to classify tweets by party it is interesting just to look at word frequencies to see which words Democrats and Republicans use the most frequently. While there is significant overlap in the language used, this cursory examination leads us to think that

\footnote{Before calculating the term frequencies I remove convert the tweet to lower case, remove punctuation, remove numbers and remove stopwords (the, and, it etc..)}
there may be some words which divide parties (for example, Obamacare, women, budget, families).

Figure 3: Word Clouds For Democrats and Republicans
Classification: Support Vector Machine Classifier

A support vector machine is a classifier which attempts to maximize the margin between the two classes of data in the training set and then use this information to make predictions about the test set. The classifier is coded following (Hastie et al., 2009, 372–375) and Hsu et al. (2003).

In the general case, the training data consists of $M$ data-class pairs. Each vector of data has a feature space of $N$ features (in my case each tweet (data) has certain words (features) which we will use to predict the party of the Senator (class)). If the two classes are completely separable (i.e. no word occurs in both Republican and Democratic tweets) we could simply draw an $N-1$-dimensional hyperplane through the data. We define the “margin” as $C = \frac{1}{||\beta||}$.

The goal is to find the hyperplane that creates the biggest margin.

This basic support vector machine will not be sufficient in my case because features (words) can belong to both Democrat and Republican tweets, that is to say, the classes overlap in feature space. The basic intuition behind the support vector machine can still apply, but we will need to allow for some points to be on the wrong side of the margin. We do this by introducing slack into the system through a series of slack variables for each feature, $\xi = \{\xi_1, \xi_2, \ldots, \xi_N\}$ which are the distance between the feature and the margin (when the feature is on the “wrong side” of the margin). This idea is illustrated in Figure is reproduced from (Hastie et al., 2009, Figure 12.1, 372).

These slack variables allow for a “soft margin” – an idea first introduced by Cortes and Vapnik (1995). Once we have introduced these slack variables, we want to perform the following optimization to maximize $C$ (or minimize $||\beta||$):

\[
\min ||\beta||
\]

subject to the constraint that $y_i(a_i^T\beta + \beta_0) \geq 1 - \xi_i$, $i = 1, \ldots, N$. 

13
Where $x_i$ is a vector of features belonging to the class $y_i$ where $y_i$ can have the values $-1$ or $1$. If the error penalty function is linear the optimization problem becomes\footnote{I investigate using a radial function in the analysis section, but the linear function seems to work just as well. According to Hsu et al. (2003) this is to be expected given that I have a very large number of features (words). Hsu et al. (2003) note that: “If the number of features is large, one may not need to map data to a higher dimensional space. That is, nonlinear mapping does not improve the performance. Using the linear kernel is good enough” (p.12).}

$$
\min_{\beta, \beta_0} \frac{1}{2} ||\beta||^2 + C \sum_{i=1}^{N} \xi_i
$$

The Lagrange primal function is:

$$
L_p = \frac{1}{2} ||\beta||^2 + C \sum_{i=1}^{N} \xi_i - \sum_{i}^{N} \alpha_i [y_i (x_i^T \beta + \beta_0) - (1 - \xi_i)] - \sum_{i}^{N} \mu_i \xi_i
$$

We minimize this with respect to $\beta, \beta_0$, and $\xi_i$. Setting the respective derivatives to 0...
gives:

\[ \beta = \sum_{i=1}^{N} \alpha_i y_i x_i \]

\[ 0 = \sum_{i=1}^{N} \alpha_i y_i \]

\[ \alpha_i = C - \mu_i \]

By substituting these into the primal function we obtain the Lagrangian dual objective function:

\[ L_D = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{i=1}^{N} \alpha_i \alpha_i' y_i y_i' x_i^\top x_i' \]

We maximize \( L_D \) subject to \( 0 \geq \alpha_i \leq C \) and \( \sum_{i=1}^{N} \alpha_i y_i = 0 \). According to Hastie et al. (2009) we must also include the Karush-Kuhn-Tucker constraints which require that:

\[ \alpha_i [y_i (x_i^\top \beta + \beta_0) - (1 - \xi_i)] = 0 \]

\[ \mu_\xi_i = 0 \]

\[ y_i (x_i^\top \beta + \beta_0) - (1 - \xi_i) \geq 0 \]

Given these constraints, the solution for \( \beta \) has the form:

\[ \hat{\beta} = \sum_{i=1}^{N} \hat{\alpha}_i y_i x_i \]

where \( \hat{\alpha}_i \) are only nonzero for those observations for which \( y_i (x_i^\top \beta + \beta_0) - (1 - \xi_i) \geq 0 \). These
\( \alpha_i \) are the support vectors which lie near the margin (or on the margin if \( \xi_i = 0 \)). These margin points \( (\xi_i = 0) \) can be used to solve for \( \beta_0 \).

For classification purposes a SVM computes a decision function which is simply \( \hat{G}(x) = \text{sign}[x^\top \hat{\beta} + \hat{\beta}_0] \). But we can also compute a posterior probability of the class given the data.

We find the posterior probability by fitting a logistic regression model to the estimated decision values, \( f \), as follows:

\[
P(y = 1|f) = \frac{1}{1 + \exp(Af + B)}
\]

Where \( A \) and \( B \) are estimated by minimizing the negative log-likelihood function\(^{10}\)

**Results: Classifying Tweets According to Party**

To run the SVM classifier, I randomly drew a sample of 5,000 tweets from my total dataset of 42,229 to be the training set leaving me with a test set of 37,229 tweets. Using the set-up above and the \texttt{svm} library in R, I generated the posterior probability that a given tweet belonged to a Democratic senator. In order to test dependence on the training set, I repeated this procedure 160 times for each tweet\(^{11}\). Over all repetitions, my SVM classifier classified 76.8% of the tweets correctly. This may sound like a good statistic, but considering that a 50% classification rate could be found from chance, this is not incredibly high. Instead of

\(^{10}\)Practically this is done by setting \texttt{probability=T} inside of the \texttt{svm} function in the R package \texttt{e1071} which, according to the documentation “fits a logistic distribution using maximum likelihood to the decision values of all binary classifiers, and computes the a-posteriori class probabilities for the multi-class problem using quadratic optimization. The probabilistic regression model assumes (zero-mean) laplace-distributed errors for the predictions, and estimates the scale parameter using maximum likelihood” (Dimitriadou et al. (2009), 51)

\(^{11}\)Ideally I would have done more repetitions, however, the cost of computing a Term Document Matrix for a dataset of 37,229 tweets is very high and unfortunately caused some simulations to crash.
focussing on the best possible classification, I am actually more interested in what cases are hard to classify and which senators show more variation in their posterior probabilities. I will now turn to a discussion of the posterior probabilities which are calculated using the \texttt{svm} function as described above.

**Results: Posterior Probabilities as Projected Partisanship**

I argue that the posterior probability of being a Democrat condition on a tweet is a signal of projected partisanship. In order to assess whether or not I am picking up projected partisanship or model dependence I run a variety of diagnostics to assess how dependent the posterior probabilities are on the training set.

Using the distribution of posterior probabilities (scores) I can assess how much dependence there is on the training data by repeating the analysis for 160 datasets. This gives me the added benefit of being able to use the mean posterior probabilities across these 160 trials as a cleaner data source in my applications. Figure 5 shows the distribution of scores for a random draw of 250 tweets from the tweets for each party (Democrats and Republicans).

I also ran a test on one month, September, using a training set of 500 (1/10 th of the original amount) and looked at the distribution of posterior probabilities for each tweet across the 160 different training sets. A random sample of 100 tweets is shown in the Appendix in Figure 11.

We might wonder what these tweets look like. The most predictably Republican tweet in this sample is from Senator Mitch McConnell (R-KY). It reads: “Sen. McConnell welcomes Daw

---

\footnote{I call the value shown a bootstrapped confidence interval, but it is not a non-parametric bootstrapped confidence interval because the tweets were not sampled with replacement. The goal of this exercise was to assess dependence on the training data, not necessarily generate the most precise estimate.}
Figure 5: Distribution of posterior probability for a random sample of 100 tweets from each party

Aung San Suu Kyi to the University of Louisville today. #Burma #ASSK [pic.twitter.com/g8G8myRH](https://twitter.com/aung_suu_kyi/status/1341748272561923840) The most predictably Democratic tweet in this sample is from Senator Chris Coons (D-DE). It reads: “Fun! RT @SenCoonsOffice: Photo: Sen. Coons reads to children at @Nemours in Milford as part of @reachoutandread #netDE [pic.twitter.com/nhXncv0](https://twitter.com/ChrisCoons/status/1341747697689554689).” Another way of getting at what kinds of tweets are typical is to look at tweets which were easily classified. Figure 6 shows 6 different tweets from September which had 95% intervals that placed them clearly in one party. For each tweet I give the Twitter handle of the senator who tweeted it and the text of the tweet.
Figure 6: 6 highly partisan tweets from September

Distribution of Pr(Dem) for amyklobuchar −− Just met w/ American #Milk Producers Inc. in Rochester... It's time 4 the House 2 separate the curds from the whey and pass the #farmbill

Mean Pr(Dem) = 0.814
95% CI = [0.541, 0.955]

Distribution of Pr(Dem) for DavidVitter −− Thank you to @NFIB for naming me as one of its Guardians of Small Business. http://bit.ly/RITfQX #tcot #smallbiz

Mean Pr(Dem) = 0.168
95% CI = [0.023, 0.363]

Distribution of Pr(Dem) for GrahamBlog −− Always enjoy speaking with Brian Kilmeade on Fox News Radio. http://flic.kr/p/deRt7g

Mean Pr(Dem) = 0.117
95% CI = [0.022, 0.346]

Distribution of Pr(Dem) for SenRandPaul −− #Teaparty #tcot @SenRandPaul coming up on @ThisWeek in #Philly area #patcot

Mean Pr(Dem) = 0.07
95% CI = [0.01, 0.176]

Distribution of Pr(Dem) for SenJohnMcCain −− Watch Lindsey @GrahamBlog on @FoxNews now, talking Obama failed foreign policy

Mean Pr(Dem) = 0.071
95% CI = [0.004, 0.375]

Distribution of Pr(Dem) for ChuckSchumer −− Farm Bill expires today and if House members dont act fast, the price of milk could double for middle−class farmers http://ow.ly/e6kfV

Mean Pr(Dem) = 0.826
95% CI = [0.535, 0.972]

Distribution of Pr(Dem) for kaybaileyhutch −− Way to pull it off tonight Rangers!

Mean Pr(Dem) = 0.165
95% CI = [0.106, 0.244]

Distribution of Pr(Dem) for @senatorshaheen −− Wishing Hawaii's @Daniel_Inouye, the most senior member of the U.S. Senate, a happy birthday.

Mean Pr(Dem) = 0.797
95% CI = [0.634, 0.963]
While individual tweets are not too hard to classify, senators tend to have a wide distribution of tweets which, while they often exhibit a clear partisan pattern seem to retain a lot of flexibility. To see the distribution of posterior probabilities for each Senator in my dataset see Figure 12 in the Appendix.

**Strategic Manipulation of Partisanship, Primary Competition, General Election Competition**

While Latent Ideological Type is a hidden variable in my analysis, we can took at variation in primary competition and general election competition for Senators who ran for re-election in 2012. No highlighting indicates the case in which neither the primary nor the general election is competitive. Gray highlighting indicates a competitive general election and a competitive primary. Pink indicates a competitive general election without a competitive primary. Yellow indicates a competitive primary without a competitive general election.
<table>
<thead>
<tr>
<th></th>
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</tr>
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<tbody>
<tr>
<td>CA</td>
<td>Dianne Feinstein</td>
<td>D</td>
<td>No</td>
<td>No</td>
<td>Variable/M</td>
<td>Variable</td>
</tr>
<tr>
<td>DE</td>
<td>Tom Carper</td>
<td>D</td>
<td>No</td>
<td>No</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>FL</td>
<td>Bill Nelson</td>
<td>D</td>
<td>Nelson (78.7%), Burkett (21.3%)</td>
<td>Nelson (55.1%), Mack (42.3%)</td>
<td>Variable/M</td>
<td>HP-LP (if SP) or HP-HP if (DP)</td>
</tr>
<tr>
<td>IN</td>
<td>Richard Lugar</td>
<td>R</td>
<td>Yes – Lugar (39.5%), Moneracle (60.5%)</td>
<td>Yes (in expectation for Lugar)</td>
<td>Variable/M</td>
<td>HP-LP (if SP) or HP-HP if (DP)</td>
</tr>
<tr>
<td>MD</td>
<td>Ben Cardin</td>
<td>D</td>
<td>Cardin (74.2%), Musas (15.7%)</td>
<td>Cardin (55.4%), Bongino (26.7%), Sobhani (16.6%)</td>
<td>Variable/M</td>
<td>HP-LP (if SP) or HP-HP if (DP)</td>
</tr>
<tr>
<td>MA</td>
<td>Scott Brown</td>
<td>R</td>
<td>No</td>
<td>Yes Brown (46.2%), Warren (51.2%)</td>
<td>M if SP, E if DP</td>
<td>LP-LP (if SP) or HP-HP (if DP)</td>
</tr>
<tr>
<td>MI</td>
<td>Debbie Stabenow</td>
<td>D</td>
<td>No (unopposed)</td>
<td>Stabenow (58.8%), Holchstra (38.6%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>MN</td>
<td>Amy Klobuchar</td>
<td>D</td>
<td>No</td>
<td>No Klobuchar (65.2%), Bills (30.6%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>MS</td>
<td>Roger Wicker</td>
<td>R</td>
<td>No</td>
<td>Wicker (57.4%), Goos (40.3%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>MO</td>
<td>Claire McCaskill</td>
<td>D</td>
<td>No</td>
<td>No McCaskill (74.7%), Akin (39.2%), Dine (6.1%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>MT</td>
<td>Jon Tester</td>
<td>D</td>
<td>No</td>
<td>Yes Tester (48.7%), Feihberg (44.8%)</td>
<td>M if SP, E if DP</td>
<td>LP-LP (if SP) or HP-HP (if DP)</td>
</tr>
<tr>
<td>NV</td>
<td>Dean Heller</td>
<td>R</td>
<td>No Heller (86.3%)</td>
<td>Yes Heller (45.9%), Berkley (44.7%)</td>
<td>M if SP, E if DP</td>
<td>LP-LP (if SP) or HP-HP (if DP)</td>
</tr>
<tr>
<td>NJ</td>
<td>Bob Menendez</td>
<td>D</td>
<td>No (unopposed)</td>
<td>Menendez (58.6%), Kyrillos (39.9%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>NY</td>
<td>Kirsten Gillibrand</td>
<td>D</td>
<td>No (unopposed)</td>
<td>No Gillibrand (71.9%), Long (36.7%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>OH</td>
<td>Sherrod Brown</td>
<td>D</td>
<td>No (unopposed)</td>
<td>Yes Brown (50.3%), Mandel (45.1%)</td>
<td>M if SP, E if DP</td>
<td>LP-LP (if SP) or HP-HP (if DP)</td>
</tr>
<tr>
<td>PA</td>
<td>Bob Casey, Jr.</td>
<td>D</td>
<td>Casey (80.9%), Verdura (19.1%)</td>
<td>Yes Casey (53.5%), Smith (44.8%)</td>
<td>Variable/M</td>
<td>HP-LP (if SP) or HP-HP if (DP)</td>
</tr>
<tr>
<td>RI</td>
<td>Sheldon Whitehouse</td>
<td>D</td>
<td>No</td>
<td>No Whitehouse (65.0%), Hinckley (35.6%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>TN</td>
<td>Bob Corker</td>
<td>R</td>
<td>Corker (85.1%)</td>
<td>No Corker (64.9%), Clayton (30.4%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>UT</td>
<td>Orrin Hatch</td>
<td>R</td>
<td>Yes Hatch (57.25%), Liljenquist (28.28%)</td>
<td>No Hatch (65.2%), Howell (30.2%)</td>
<td>Extreme</td>
<td>HP-HP</td>
</tr>
<tr>
<td>VT</td>
<td>Bernie Sanders</td>
<td>I</td>
<td>No</td>
<td>No</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>WA</td>
<td>Maria Cantwell</td>
<td>D</td>
<td>No (55.4% in blanket primary)</td>
<td>Cantwell (60.1%), Baumgartner (39.8%)</td>
<td>Variable</td>
<td>Variable</td>
</tr>
<tr>
<td>WV</td>
<td>Joe Manchin</td>
<td>D</td>
<td>Manchin (79.5%), Fletcher (20.1%)</td>
<td>Manchin (60.5%), Rouse (36.5%)</td>
<td>Extreme</td>
<td>HP-HP</td>
</tr>
<tr>
<td>WY</td>
<td>John Barrasso</td>
<td>R</td>
<td>No</td>
<td>No</td>
<td>Variable</td>
<td>Variable</td>
</tr>
</tbody>
</table>

To explore these predictions I show the projected partisanship for Senators in each of these groups. In the following graphs the variable on the Y-axis is the average probability that a Senator’s tweets are from a Democrat. Each line represents the trend for one US Senator (Republicans are shown in red while Democrats are shown in blue) from January 2012—October 2012. Republicans are much harder to classify than Democrats (probably due to differences in tweets between mainstream Republicans and more extreme Tea Party representatives). The green line indicates the date of the primary election (when applicable).
Figure 7: Senators who had a competitive general election and a competitive primary—HP-LP (if SP) or HP-HP if (DP)—Generally we see senators manipulating the image if they had a competitive primary in a single-peaked state.
Figure 8: Senators who had a competitive general election without a competitive primary—LP-LP (if SP) or HP-HP (if DP)—Generally we see senators sticking with a more consistent projected partisanship with Scott Brown and Jon Tester being quite true to the predictions.
Figure 9: Senators who had a competitive primary without a competitive general election—HP-HP—Orrin Hatch in particular seems to follow this pattern.
Some of my predictions pan out in the Twitter data. The ones that I got correct are in bold:

- **Bill Nelson (D-FL)**—I predict that he should go stay highly partisan before and after given that he and Marco Rubio (R-FL) seem to be speaking to different constituencies (double peaked preferences). Despite running to the party right around his election he does not seem to exhibit quite the HP-HP I predicted.

- **Richard Lugar (R-IN)**—I predict that Lugar should either go from HP to LP (if preferences are single peaked) or from HP-HP (if preferences are double peaked). Given that Lugar lost in the primary it is hard to judge the second part of the graph, but perhaps Lugar lost because he did not go HP enough during the primary period.

- **Ben Cardin (D-MD)**—If preferences in the general election are double peaked in Maryland, Cardin exhibits the HP-HP strategy my model predicts.

- **Bob Casey (D-PA)**—Though he is not highly partisan on an absolute scale, Bob Casey remains consistently partisan in a way that seems characteristic of double peaked preferences (he is certainly more partisan than his Republican counterpart Pat Toomey)

- **Scott Brown (R-MA)**—Scott Brown exhibits the LP-LP strategy of someone who has a competitive election without a competitive primary in a state where preferences are single peaked

- **Jon Tester (D-MT)**—Jon Tester exhibits the HP-HP strategy of someone who has a competitive election without a competitive primary in a state where preferences are double peaked

- **Dean Heller (R-NV)**—Heller is less partisan than we would expect in a state where
preferences seem to be double peaked.

- **Sherrod Brown (D-OH)**—It is not clear whether preferences in Ohio are single peaked or double peaked.

- **Orrin Hatch (R-UT)**—Orrin Hatch exhibits the HP-HP of a senator in a state where there is a competitive primary without a competitive general election

- **Joe Manchin (D-WV)**—Manchin is probably not the best example because it is not clear that the primary in WV was really competitive (this is why I would want to improve on this definition given more time). In any case, he does seem to go slightly more partisan for his primary and remain that way.

These results suggest that there is 1) Evidence that Senators manipulate their projected partisanship and 2) That in some cases Senators manipulate their projected partisanship in a strategic way. These results are also very tentative and should not be taken as causal evidence. However, while this is a very rough first cut, I think it highlights the potential insight we can gain from using new forms of image-related data.

These results suggest that both Aldrich (1995) and Cohen et al. (2008) may be correct about the role of policy demanders and parties—Sometimes the dog wags the tail and sometimes the tail wags the dog. The insight from this paper is that Senators can manipulate not only their votes, but their images and that this explains why primaries do not necessarily lead to polarization (as they would if “intense policy demanders” always got their way), but that they may lead to polarization when a Senator is truly under pressure and will not be penalized for adopting an extreme voting strategy. This paper has focused on the image manipulation of Senators, future research is needed to test whether the voting strategies of Senators also align with my theory.
With unlimited time and resources...

With unlimited time and resources I would test the theory more carefully by refining the definitions and measurements of my variables as follows:

- **Primary Competition:** I would test the operationalizations used by Hirano et al. (2010) which uses the average level of primary competition in previous primary elections for non-Senate statewide offices and measure this value in two ways, first, the average number of incumbents contested in previously primary elections and second, the average number of incumbents who win less than 60% of the vote in previous primary elections.

- **Competitiveness of General Election:** Ideally I would like to get a measure of how competitive a specific election is thought to be and how generally competitive a state’s senatorial elections are.

- **Image Strategy:** While I think Twitter is a good proxy for a general image strategy, I would like to eventually include press releases, Facebook posts, interviews and other image-manipulating data generated by Senators in this data.

- **Latent Ideology:** I would study the positions taken by Senators before they became Senators to try and get a sense for Senator type. For Senators who have been in the Senate for many years, I will study their positions during times of less constraint.

A longer project would also leverage a longer time frame and consider a wider variety of actors and factors which might affect polarization and projected partisanship. For example, instead of simply looking at primary competition, it would be good to consider factors such as open or closed primary systems which may lead to more primary competition. States such as Washington and California which changed primary systems could be used as natural experiments to test the primary system effect in conjunction with other factors using syn-
thetic controls. The role of donors could also be expanded as they may be another reason to manipulate projected partisanship (either to appease donors or conceal donor-endorsed activities from voters). A fully fleshed out model might look something like the one shown in Figure 10.
Figure 11: Random sample of 100 Tweets from September with 95% intervals
Figure 12: Distribution of Average Projected Partisanship by Senator

Distribution of Pr(Dem) for JimDeMint
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500 2000
Mean Pr(Dem) = 0.682
95% CI = [0.042, 0.874]

Distribution of Pr(Dem) for clairecmc
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 1000 2000 3000 4000 5000
Mean Pr(Dem) = 0.602
95% CI = [0.142, 0.94]

Distribution of Pr(Dem) for ChrisCoons
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 5000 10000 15000 20000
Mean Pr(Dem) = 0.769
95% CI = [0.221, 0.993]

Distribution of Pr(Dem) for GrahamBlog
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 2000 4000 6000 8000
Mean Pr(Dem) = 0.357
95% CI = [0.022, 0.866]

Distribution of Pr(Dem) for Daniel_Inouye
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 5000 10000 15000
Mean Pr(Dem) = 0.763
95% CI = [0.306, 0.985]

Distribution of Pr(Dem) for alfranken
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500 2000 2500
Mean Pr(Dem) = 0.693
95% CI = [0.237, 0.97]

Distribution of Pr(Dem) for @senatorshaheen
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500 2000 2500
Mean Pr(Dem) = 0.484
95% CI = [0.055, 0.919]

Distribution of Pr(Dem) for FrankLautenberg
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500 2000 2500
Mean Pr(Dem) = 0.402
95% CI = [0.036, 0.896]

Distribution of Pr(Dem) for ChuckSchumer
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 2000 4000 6000 8000
Mean Pr(Dem) = 0.682
95% CI = [0.166, 0.979]

Distribution of Pr(Dem) for amyklobuchar
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 2000 4000 6000 8000
Mean Pr(Dem) = 0.674
95% CI = [0.193, 0.973]

Distribution of Pr(Dem) for GrahamBlog
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 2000 4000 6000 8000
Mean Pr(Dem) = 0.357
95% CI = [0.022, 0.866]

Distribution of Pr(Dem) for ChuckGrassley
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500 2000 2500
Mean Pr(Dem) = 0.457
95% CI = [0.036, 0.896]

Distribution of Pr(Dem) for JohnBoozman
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500 2000 2500
Mean Pr(Dem) = 0.484
95% CI = [0.055, 0.919]

Distribution of Pr(Dem) for JoeLieberman
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500 2000 2500
Mean Pr(Dem) = 0.484
95% CI = [0.055, 0.919]
Mean Pr(Dem) = 0.64
95% CI = [0.308, 0.995]

Mean Pr(Dem) = 0.627
95% CI = [0.144, 0.962]

Mean Pr(Dem) = 0.359
95% CI = [0.012, 0.905]

Mean Pr(Dem) = 0.853
95% CI = [0.355, 0.996]

Mean Pr(Dem) = 0.817
95% CI = [0.286, 0.995]

Mean Pr(Dem) = 0.767
95% CI = [0.239, 0.992]

Mean Pr(Dem) = 0.433
95% CI = [0.037, 0.889]
Distribution of Pr(Dem) for Sen Gillibrand

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.777
95% CI = [0.271, 0.99]

Distribution of Pr(Dem) for Sen Dan Coats

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.385
95% CI = [0.025, 0.875]

Distribution of Pr(Dem) for Sen John Hoeven

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.544
95% CI = [0.119, 0.917]

Distribution of Pr(Dem) for Sen Jack Reed

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.71
95% CI = [0.178, 0.985]

Distribution of Pr(Dem) for Sen Dean Heller

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.448
95% CI = [0.038, 0.92]

Distribution of Pr(Dem) for Sen Bob Corker

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.238
95% CI = [0.013, 0.764]

Distribution of Pr(Dem) for Sen Bill Nelson

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.568
95% CI = [0.096, 0.941]

Distribution of Pr(Dem) for Sen John Barrasso

Probability of being a Democrat

Frequency

Distribution of Pr(Dem) for Sen John McCain

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.367
95% CI = [0.03, 0.864]

Distribution of Pr(Dem) for Sen Jeff Merkley

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.709
95% CI = [0.201, 0.983]

Distribution of Pr(Dem) for Sen Blumenthal

Probability of being a Democrat

Frequency

Distribution of Pr(Dem) for Sen Carl Levin

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.784
95% CI = [0.279, 0.991]

Distribution of Pr(Dem) for Sen Feinstein

Probability of being a Democrat

Frequency

Mean Pr(Dem) = 0.702
95% CI = [0.177, 0.985]
Distribution of Pr(Dem) for SenThadCochran
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 100 200 300 400 500 600 700
Mean Pr(Dem) = 0.501
95% CI = [0.06, 0.935]

Distribution of Pr(Dem) for SenMarkPryor
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 1000 2000 3000 4000
Mean Pr(Dem) = 0.635
95% CI = [0.143, 0.971]

Distribution of Pr(Dem) for SenJohnsonSD
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 1000 2000 3000 4000 5000 6000
Mean Pr(Dem) = 0.691
95% CI = [0.202, 0.973]

Distribution of Pr(Dem) for TomCoburn
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500
Mean Pr(Dem) = 0.429
95% CI = [0.032, 0.883]

Distribution of Pr(Dem) for SenToomey
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 1000 2000 3000 4000 5000 6000
Mean Pr(Dem) = 0.405
95% CI = [0.033, 0.895]

Distribution of Pr(Dem) for SenShelbyPress
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 50 100 150 200 250
Mean Pr(Dem) = 0.474
95% CI = [0.049, 0.924]

Distribution of Pr(Dem) for SenRockefeller
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 2000 4000 6000 8000 10000 12000
Mean Pr(Dem) = 0.686
95% CI = [0.196, 0.975]

Distribution of Pr(Dem) for SenJohnThune
Probability of being a Democrat
Frequency
0.0 0.2 0.4 0.6 0.8 1.0
0 500 1000 1500 2000 2500 3000
Mean Pr(Dem) = 0.405
95% CI = [0.02, 0.913]
References


Hastie, T., R. Tibshirani, and J. Friedman (2009). *The Elements of Statistical Learning:*


