Etch A Sketch Ideology: Post-Primary Moderation in Congressional Elections

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Abstract

Theories of elections assume that candidates adopt static ideological positions at the outset of campaigns and maintain that position throughout their respective primary and general elections. Yet evidence remains mixed whether this static position-taking behavior results in moderate or extremist candidate ideologies. A potential cause of these ambiguous results is that candidates' ideologies evolve dynamically over the course of a campaign to differentially appeal to primary and general voters. In effect, the existence of primaries motivates candidate to be both moderate and extreme at different stages of their two-part electoral contest. By analyzing the social media messages of congressional candidates in the 2016 election I estimate the daily expressed ideological position of those candidates and evaluate the degree to which the extremity of their positions shifts after the success of their primary contest. In contrast to static theories of candidate position-taking, I find that candidates dynamically moderate their expressed ideology after winning a primary election.

Popular accounts of elections characterize candidates as espousing extreme beliefs during primary contests in order to deter or defeat challengers who appeal to the party's base. Upon successful completion of their primary contest, these candidates then moderate their expressed positions in order to appeal to swing voters who are critical for capturing a majority of the general electorate. Eric Fehrnstrom, senior campaign advisor to Mitt Romney's 2012 presidential bid, notoriously compared his candidate's position-taking strategy to that of an Etch A Sketch. Responding to criticism that his candidate had been forced to adopt more extreme conservative positions during the 2012 Republican presidential primary, Fehrnstrom remarked, "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 we start all over again" (Cohen, 2012-03-22).

Fehrnstrom's statement received ridicule from Romney's primary opponents, who questioned the candidate's conservative credentials due to his apparent wavering ideological commitment. Nonetheless, whatever costs Romney's primary campaign faced from appearing ideologically inconsistent, the candidate went on to secure the nomination from his party for the 2012 presidential election. Following recent theories that predict this dynamic candidate position-taking (Agranov, 2016; Hummel, 2010), I investigate whether U.S. congressional candidates in the 2016 election implement dynamic messaging strategies during the campaign to express different ideological positions before and after winning their primary contests. Using a novel dataset of 27,325 Facebook posts authored by U.S. congressional candidates in the year preceding the 2016 general election, I construct a daily measure of candidates' instantaneous, expressed ideology and use it to test for post-primary moderation. The analysis implements emerging methods in time-series causal inference (Imai & Kim, 2019, n.d.; Xu, 2017), and finds evidence that a successful primary election causes candidates to moderate the ideological tenor of their social media messages. These results offer new insight into the ongoing debate regarding

candidate behavior and the purported polarizing effects of primary elections. The findings suggest that the relationship between partisan primaries and partisan polarization may be more complicated than previously theorized.

Primary Elections & Candidate Ideology

Spatial models of elections draw varying conclusions about the optimal ideological positioning of candidates. In the context of single elections, spatial models predict that candidates' expressed ideology will converge to the preferences of the median voter when politicians are electorally motivated (Downs, 1957). These predictions holds even when candidates are motivated by policy and / or possess incomplete information about voter preferences (Calvert, 1985). However this convergence result fails in two-stage models of elections, which predict that candidates will adopt the ideological position of the median primary voter (Coleman, 1971; Owen & Grofman, 2006). Consequently, candidates will possess divergent ideological positions in the general election (to the extent that parties are ideologically distinct), which has implications for the quality of general election candidates (Adams & Merrill III, 2008; Snyder & Ting, 2011), the difficulty of winning the general election (Agranov, 2016; Hall, 2015; Snyder & Ting, 2011), and the ideological extremity of officeholders (Snyder & Ting, 2011).

A critical assumption underlying these models maintains that candidates make binding commitments to their espoused platforms or ideologies (Aaronson & Ordeshook, 1972; Coleman, 1971; Downs, 1957; Owen & Grofman, 2006). Thus these models necessarily avoid the possibility of dynamic position-taking or ideological moderation in concluding that candidates adopt static ideological positions in anticipation of the ideological landscape of their constituents. More recent spatial models (Agranov, 2016; Hummel, 2010) explicitly permit candidates to modify their ideological position over the course of a campaign. These models assume the existence of an audience cost imposed for lying about their true beliefs (Agranov, 2016) or "flip-flopping" on their policy position (Hum-

mel, 2010), but which is meager enough to allow candidates to strategically incur the cost of modifying their position in exchange for the offsetting benefit of appealing to voters' preferences. In traditional voting models, these audience costs are substantial enough to prevent candidates from modifying their ideological position, and require adoption of a static, optimal position throughout the campaign. Relaxing the strict assumption that candidates commit to a single ideological position results in models that predict candidates engaging in dynamic ideological position-taking depending on their current electoral context. In equilibrium, candidates pander to both primary and general election voters by modifying their expressed position after winning the primary contest.

Empirical research suggests that this latter set of assumptions regarding the low cost of flip-flopping are justified in light of voters' behavior. Experimental evidence reveals that citizens do engage in proximity voting (Tomz & Van Houweling, 2008) and accordingly prefer candidates who adjust policy positions closer to their own beliefs despite any penalty incurred for having "waffled" (Doherty, Dowling, & Miller, 2016). Other research finds no evidence of a flip-flop penalty, but instead shows that voters evaluate candidates on their current policy position without regard for their past pronouncements on the issue (Croco, 2016; Croco & Gartner, 2014). In total, these results indicate that candidates may adjust their expressed ideological position during a campaign given that the costs of adjusting are not evidently prohibitive.

Nonetheless, direct empirical tests of candidate position-taking behavior have offered mixed results. Some conclude that primaries have little effect on candidate polarization (Hirano, Snyder Jr., Ansolabehere, & Hansen, 2010; McGhee, Masket, Shor, Rogers, & McCarty, 2014; Rogowski & Langella, 2015). While others find evidence of candidates adopting ideological positions closer to their primary constituency (Brady, Han, & Pope, 2007; Bullock & Clinton, 2011; Butler, 2009). A potential cause of the mixed evidence for the ideological position-taking in campaigns is that ideological position-taking is treated

as a static procedure. Rather than merely selecting an optimal ideological location at the outset of their two-stage electoral contest, however, candidates may dynamically adapt their ideological position over the course of the campaign. Ample evidence suggests that candidates implement dynamic strategies over the course of a campaign in a variety of contexts, including television advertising (Carsey, Jackson, Stewart, & Nelson, 2011; Granato & Wong, 2004), campaign expenditures (Box-Steffensmeier, Darmofal, & Farrell, 2009), campaign themes (Carsey, 2000), and issue ownership (Damore, 2004). Therefore it stands to reason that candidates' expressed ideological position might also vary over the course of a campaign in order to optimize their immediate electoral prospects. Despite the plausibility of this process, little research has attempted to empirically investigate this dynamic process. Notably, Burden (2001) attempts to investigate post-primary moderation directly, and finds suggestive evidence in favor of its existence. However the analysis relies on candidates' NOMINATE scores, generating separate scores for each candidate based on votes recorded in the primary period versus those recorded in the general election stage.

The attempt by Burden (2001) to find evidence of post-primary moderation underscores an additional limitation to past research on the question of dynamic ideological repositioning. Ideal point estimates generated from roll call votes (Poole & Rosenthal, 1991, 1997) or campaign contributions (Bonica, 2014) fail to measure how candidates might subtly change their *expressed* ideology over the course of an election. Nonetheless numerous studies rely on these measurement techniques to draw conclusions about the static nature of candidates' ideological positioning (Bullock & Clinton, 2011; Butler, 2009; Gerber & Morton, 1998; Hirano, Snyder Jr., Ansolabehere, & Hansen, 2010; Rogowski & Langella, 2015).

Rather than inferring candidates' ideology from *ex ante* campaign contributions or *ex post* voting behavior, a superior measure of candidate ideology can be estimated from

candidates' campaign communications, which directly demonstrate policy positions, and how those evolve over time. Whereas candidates are constrained in their ability to alter their voting and campaign donation records, they are relatively unconstrained in how they communicate with voters. For example, Mayhew (1974) posits that the primacy of electoral concerns among politicians' competing considerations impels them to engage in advertising, credit claiming, and position taking — each of which *communicates* their fitness for office, apart from actual policymaking. Moreover, there is substantial evidence that legislators condition their communicative styles on both the preferences of their constituents and their voting record in Congress (Fenno, 1978; Grimmer, 2013; Grimmer, Westwood, & Messing, 2014). This ability to fine-tune communications to suit citizen preferences implies that evidence of dynamic ideological re-positioning may exist in candidate communications opposed to candidate's voting records or campaign funding.

Though candidates may modify the content of their campaign communications over time, many forms of communication are not suitable for measuring a candidate's instantaneous ideology. For example, campaign advertisements can, in principle, dynamically shift over time, but the cost of producing polished advertisements inhibits continual updating alongside candidates' changing positions, and microtargetting will differentially expose subsets of voters to a candidate's expressed position within a single time period and geographic unit (Hillygus & Shields, 2014). Generally, candidates' campaign messaging strategies are subtly tailored to the perceived preferences of the target audience. Research finds that during campaigns, politicians strategically manipulate which messages are sent to specific news media organizations (Flowers, Haynes, & Crespin, 2003), what issue areas are addressed in certain campaign advertisements (Damore, 2004), and the locations in which advertisements are run (Panagopoulos, 2009). Therefore a better measure of a candidate's instantaneous ideological position can be gleaned from the candidates public communications, which continually provide more information to *all*

voters about the candidate's current position over the course of the campaign and are not designed to appeal only to specific demographic or policy-oriented constituencies.

Social media posts are one form of public communication that candidates produce during a campaign. Social media posts, unlike other campaign communications cannot be manipulated to appeal differentially to specific viewers and are open to scrutiny from voters in both a candidate's primary and general election constituencies, as well as voters, journalists, and electoral opponents. For example, communications authored on the popular platforms of Facebook and Twitter are publicly visible to anyone with a valid user account on the respective website. Moreover extant research suggests that candidates use social media messages to complement other campaign communications (Graham, Jackson, & Broersma, 2016; Jungherr, 2016; Larsson, 2016) [1]. Therefore candidates' campaign communication strategies should observably affect social media posts as systematically as they affect town halls, stump speeches, TV spots, press releases, mailers, and other official campaign messages.

If social media posts are reflective of candidates' campaign communications, and discrete communications contain information about the expressed ideology of a candidate at the time of authorship, then social media posts can offer insight into the ideological dynamics in which candidates engage during the course of their elections. Dynamic models of candidate ideology thus imply the following hypothesis:

> Candidates moderate their expressed ideology after successfully winning a contested primary election.

ESTIMATING THE EFFECT OF PRIMARY ELECTIONS ON IDEOLOGY

Testing the previous hypothesis requires assessing whether candidates for public office modify the ideological tenor of their campaign messages after successfully winning a primary contest. Such an analysis precludes examining the difference in ideological

[1] Notably, the role of social media in U.S. elections remain under-evaluated.

messaging between primary victors and losers, as losers have little incentive to appeal to general election voters with any ideological consistency. Instead I propose to analyze the difference in ideological messaging by the winners of contested primary elections versus general election candidates who won "uncontested" primaries, wherein they face no competitors other than their general election opponents. These two types of primary candidate can thus be separated into observational treatment and control groups, respectively, wherein treated candidates win a contested primary, and control candidates face no primary competition.

Despite the occurrence of natural treatment and control groups, estimating the effect of treatment in this context is non-trivial. First, estimation is complicated by a variety of confounders — observed and unobserved — that differentially condition the effect of treatment on candidates' expressed ideology. Second, treatment is administered to various candidates at different time periods during an election year due to state-specific primary election dates. The current standard in causal inference for panel data of this nature relies on fixed effects to control for observed and unobserved confounding affecting individual units and time periods, an approach that has been used to model the effects of primary elections on candidates' ideology in the past (McGhee, Masket, Shor, Rogers, & McCarty, 2014; Rogowski & Langella, 2015). Therefore I estimate a series of models that compare changes in expressed ideological extremity both within and across candidates in order to robustly estimate the effect of treatment under various functional specifications.

First, I employ the non-parametric, unit fixed effect estimator proposed by Imai and Kim (2019), which consistently estimates the average treatment effect (ATE) by controlling for time-invariant confounding. This within-unit matching estimator compares each of a unit's treated outcomes to a matched set of that unit's control observations, weighting each by its inverse propensity score. The overall ATE is then recovered by averaging across units. This approach improves upon a linear fixed effects estimator, which pro-

vides a consistent estimate of the ATE only when "the within-unit ATE or the within-unit proportion of treated observations is constant across units" (Imai & Kim, 2019). Thus relaxing the linearity assumption with this method improves the robustness of inference, yet inference still requires three key assumptions: (1.a) past treatments do not affect current outcomes, (1.b) past outcomes do not affect current treatment, and (1.c) no unobserved time-invariant confounding. Assumption 1.a is satisfied as a feature of this analysis's data generating process, which only permits a single treatment within the period of analysis. Assumption 1.b can be relaxed by including a lagged dependent variable in the regression equation to control for the effects of past outcomes. Assumption 1.c is a firm requirement for inference, which cannot be relaxed via the inclusion of controls, and can only be proven by assertion. Therefore to guarantee that inference is robust to potential violations of Assumption 1.c, I estimate a second model that applies fixed effects to both units and time periods.

Imai and Kim (n.d.) proposes an extension to the previous non-parametric estimator which utilizes two-way fixed effects to control for both unit-specific and time-specific confounding. This approach is equivalent to a multi-period difference-in-difference (DID) estimator whereby matched sets are constructed for both treated and controlled units in each period and the differences between groups are evaluated. The resulting estimate from this approach is for the average treatment effect among the treated (ATT) for candidates who win their primary contest. As with the previous inference method, the non-parametric nature of the matching estimator relaxes the linearity assumption of standard linear two-way fixed effects models. However it requires the following assumptions for unbiased inference: (2.a) units' outcomes are unaffected by past treatment and the treatment statuses of other units, (2.b) no unobserved time-invariant and unit-invariant confounding, (2.c) all units have a positive probability of treatment in any period, and (2.d) the average potential outcomes for treatment and control groups have parallel time

trends. As before, the data generating process for this analysis precludes units' outcomes from being affected by past treatments, as treatment occurs only once when a candidate wins their respective primary contest. The spillover component of assumption 2.a cannot be verified empirically, and must be assumed by assertion. In the context of this study, asserting that no spillover effects exist may not be plausible if candidates modify the expressed ideology of their messages in response to the electoral fortunes of candidates in states with primary election that occur before their own. Imai and Kim (n.d.) note that this assumption is often not credible in a variety of two-way fixed effects contexts, but existing methods fail to compensate for the violations of this assumption. As such I maintain the assumption of no spillover applies to this analysis since it is required for inference, but permit that violations of this assumption may introduce bias into the treatment effect estimates, though no more so than other applications of two-way fixed effects to panel data. As with Assumption 1.c, Assumption 2.c cannot be verified and is assumed by assertion. Assumption 2.d cannot be verified empirically, but visual inspection of the outcomes for treatment and control groups over time offers insight into the the plausibility of this assumption.[2]

Finally, I estimate the ATT using the generalized synthetic control (GSC) method proposed by Xu (2017). GSC performs a DID estimation where, first, each unit's past outcomes are used to predict post-treatment outcomes, and predicted outcomes are compared to actual post-treatment outcomes. Counterfactuals are estimated with a combination of linear interactive fixed effects regression and factor analysis, where the number of optimal factors is evaluated through leave-one-out-cross-validation. This technique relaxes the parallel trends assumption required for identification in standard DID models. However the method assumes that (3.a) outcomes are a function of a linear factor model,

[2] I perform a visual diagnostic of parallel trends in Figure 4, but reserve discussion of the figure until after describing the data.

(3.b) errors are independent of treatment assignment, observed covariates, and unobserved cross-sectional and longitudinal confounders, (3.c) weak serial dependence of errors, (3.d) regularity conditions, and (3.e) cross-sectionally independent and homoscedastic errors. The key assumptions that distinguish each model are summarized in Table 1.

Table 1: Key Modeling Assumptions

	Unit FE	Two-way FE	GSC
Functional Form			
Linearity			✓
Parallel trends		✓	
Observables			
$\text{Treatment}_{i,t} \perp\!\!\!\perp \text{Outcome}_{i,t-1}$	✓		
$\text{Outcome}_{i,t} \perp\!\!\!\perp \text{Treatment}_{i,t-1}$	✓	✓	✓
$\text{Outcome}_{i,t} \perp\!\!\!\perp \text{Treatment}_{i',t}$		✓	✓
$\text{Outcome}_{i,t} \perp\!\!\!\perp \text{Treatment}_{i',t-1}$		✓	✓
$\text{Outcome}_{i,t} \perp\!\!\!\perp \text{Outcome}_{i,t-1}$		✓	✓
Unobservables			
No unit-invariant confounding	✓	✓	
No time-invariant confounding	✓		
No time-variant confounding		✓	✓

Key assumptions required for unit fixed-effect matching estimator (Imai & Kim, 2019), two-way fixed-effect matching estimator (Imai & Kim, n.d.), and generalized synthetic control estimator (Xu, 2017). Checkmarks indicate the presence of an assumption for the corresponding model.

DATA

To conduct this analysis, I study the Facebook posts authored by congressional candidates in the 2016 election who were subsequently elected to the 115th U.S. Congress. Posts were only collected from the official Facebook pages of congressional candidates, which are denoted on Facebook by a blue verification badge on the candidate's page. Each post used for analysis received at least 100 likes from Facebook users as of July 2017, when the data was collected. The data consists of 27,325 Facebook posts authored by 357

congressional candidates (325 House; 32 Senate)[3] from November 9, 2015 to November 8, 2016[4].

This data is part of a novel dataset of Facebook posts collected through Facebook's Graph API in July of 2017 encompassing all posts published on the official, public Facebook pages of legislators elected to the 115th U.S. Congress. Table 2 enumerates the amount of Facebook posts available for the relevant partisan and cameral cross-sections. In general candidates authored an average of 76.5 Facebook posts in the year preceding the 2016 general election. This corresponds to 0.210 posts per day, or approximately 1 post every 5 days. In this period, more Republicans posted to Facebook than Democrats in total, on average, and on average per day. In total, House candidates produced nearly five times the amount of Facebook posts than Senate candidates, however on average Senate candidates produced more than double the amount of Facebook posts, both in aggregate and per day. House candidates produced approximately 1 post every 5 days, whereas Senate candidates produced nearly 2 posts every 5 days.

Table 2: Descriptive Statistics of Congressional Facebook Posts

	All	Democrats	Republicans	House	Senate
Posts	27,325	11,724	15,601	22,645	4,680
Avg. Posts per Candidate	76.5	74.2	78.4	69.7	146.0
Avg. Daily Posts	0.210	0.203	0.215	0.191	0.401

Descriptive statistics for Facebook posts produced by elected officials in the 115th Congress which received more than 100 likes. Observations range from November 8, 2015 to November 8, 2016, and contain posts authored by 32 Senators and 324 House members.

From the Facebook post data I construct a daily time-series by averaging each candidate's post ideology per day (ideal point estimation is described in detail below). For

[3]This number excludes 66 incumbent senators not up for re-election in 2016 and 2 senators who create official Facebook pages after assuming office in 2017. It also excludes 2 House members who do not post to Facebook in the year before the 2016 general election, 52 members who only post after the 2016 general election, 1 member who produces only a single post in the year preceding the 2016 general election, 35 members who do not create a post with more than 100 likes after treatment, 10 members representing D.C. and unincorporated territories, and 10 members who did not have active Facebook pages in July 2017.

[4]November 8, 2016 is the day of the general election

days in which candidates do not author a post, I carry forward the previous day's ideology estimate as the most current representation of their expressed ideology. Observations in the time series range from March 1, 2016 (the day when the first set of congressional primary elections is held in Alabama, Arkansas, and Texas) to November 8, 2016.[5] Candidates who do not post on March 1, 2016 begin the time-series with the ideology of their most recent prior post, going as far back as November 9, 2015.

The treatment group consists of 286 candidates (261 House; 25 Senate) who ran in competitive primaries, while the control group contains 71 candidates (64 House; 7 Senate) who ran unopposed in their respective primaries. Candidates are scored as unopposed if the 2016 Federal Election Commission results (Federal Election Commission, 2017) indicate that the candidate (a) ran unopposed, (b) was nominated by party convention without a primary runoff[6] , or (c) ran in a state which does not have a primary election[7]. Treatment is administered to candidates in the treatment group on the day after their state's primary election is held. However observations are not coded as post-treatment until a candidate produces a new Facebook post from which ideology can be measured. This prevents improperly deflating the treatment effect estimates for candidates who do not author a new post receiving more than 100 likes on the day after their primary victory, and who have their previous day's ideology carried forward. Table 3 details the primary election dates for all 50 states, and indicates the number of candidates in treatment and control conditions at each phase. To ensure that the treatment and control groups do not systematically vary apart from the competitiveness of their primary elections, I conduct a balance test of the difference in means between groups. Table 4 uses

[5]Though Facebook posts are available for candidates in a wider range, the estimation method drops observations in which all candidates are in the control condition. Hence all observations prior to the first primary are dropped in analysis.

[6]In the 2016 congressional election, this only applies to candidates from Connecticut, Utah, and Virginia.

[7]Louisiana is the only state without a congressional primary election in 2016. Under Louisiana's voting rules, if no congressional candidate receives a majority vote in the general election, then a runoff election is held among the top two candidates.

OLS and logistic regressions to test the balance of candidate-specific confounders across treatment and control groups for potentially problematic moderators of post-primary ideology. Neither model finds a single moderator which exhibits a statistically distinguishable difference based on treatment assignment. As a result, no evidence exists to suggest that imbalances in treatment assignment will introduce bias in the estimated effects of treatment.

Table 3: 2016 Primary Elections and Cumulative Treatment Administration

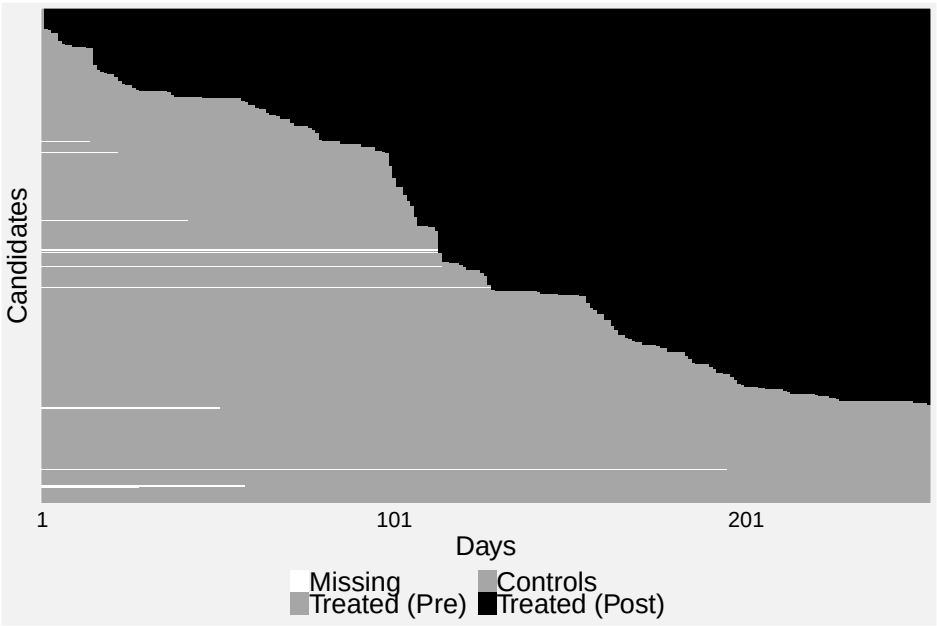
Date	States	Control	Treatment
Mar. 01	AR, AL, TX	346	0
Mar. 08	MS	319	27
Mar. 15	IL, NC (Senate), OH	318	29
Apr. 26	MD, PA	386	65
May 03	IN	279	73
May 10	NE, WV	272	80
May 17	ID, KY, OR	264	88
May 24	GA	256	96
Jun. 07	CA, IO, MT, NJ, NM, NC (House), SD	247	105
Jun. 14	ME, NV, ND, SC, VA	209	143
Jun. 28	CO, NY, OK, UT	170	185
Aug. 02	KS, MI, MO, WA, TN	148	208
Aug. 09	CT, MN, VT, WI	131	225
Aug. 13	HI	120	236
Aug. 16	AK, WY	116	240
Aug. 30	AZ, FL	108	248
Sep. 08	MA	96	260
Sep. 13	DE, NH, RI	91	266
Nov. 08	General Election	71	286

Chronological listing of 2016 primary election dates by state(s). Counts indicate cumulative number of candidates in control / treatment categories at the specified date. Treatment intervention occurs on the day following a candidate's primary election victory. Candidates enter the treatment condition upon authoring a a post with more than 100 likes after treatment intervention occurs. Panel data is unbalanced such that those with no prior record of posting to Facebook enter the study upon their initial post. Louisiana has no primary election, thus candidates remain in the control condition until the general election on Nov. 8.

Measuring the Dependent Variable: Daily Ideological Extremity

To measure the expressed ideology of individual social media posts I model social media messages as a network connected by user endorsements and estimate the latent ideal points expressed in those messages with an on-line data reduction technique. I ex-

Figure 1: Treatment Assignment Over Time



Visual representation of treatment assignment. Each row represents a candidate, whose treatment status is indicated by the shading of their cell at day t. Day 1 corresponds to March 1, 2016.

plain each of these steps abstractly (with precise details available in Appendix B), and validate the measure on multiple criteria. In treating the social media messages as a network, I follow Bond and Messing (2015), which formalizes the relationship between social media nodes (a message or a user account) and edges (engagements from users, such as replies or likes) as a network matrix.[8]. The network matrix under consideration herein is thus composed of individual social media messages in its rows and unique social media users in its columns. The cells of the matrix are populated by ones and zeros, which serve as binary indicators of whether user in column c liked the message in row r.

Substantively, this matrix represents the social connections between a set of specified messages and the users who have endorsed those messages with a like. Knowing that social networks are homophilic in nature (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015; Bond & Messing, 2015; McPherson, Smith-Lovin, & Cook, 2001), and that the unam-

[8]For operational definitions of social-media-specific terms, see Appendix A

Table 4: Balance Comparison by Treatment Assignment

	OLS	Logistic
House	0.03	0.20
	(0.08)	(0.48)
PartyR	-0.01	-0.08
	(0.04)	(0.27)
Safe	-0.02	-0.11
	(0.05)	(0.30)
Incumbent1	-0.04	-0.29
	(0.18)	(1.17)
(Intercept)	0.83*	1.62
	(0.17)	(1.11)
N	357	357

Balance comparisons of potential confounders on treatment assignment. The left model presents results using OLS regression and the right model presents results from logistic regression. Standard errors for both models in parentheses. No moderating covariate exhibits a statistically distinguishable difference between groups in either model.

biguous purpose of the like feature is to express a user's approval of social media content, then it is assumed that likes indicate similarity between a user's beliefs and the messages they choose to endorse. As such, when a user chooses to like a political message to the exclusion of some other, it indicates that the user is ideologically more proximate to the political position advocated in the liked message than the un-endorsed message. Given each individual user's decision to like some political messages and to ignore others, I can aggregate these individual endorsement decisions (using Online Dictionary Learning, the data reduction process described below) across all users in the network to find the average similarity between all posts *vis à vis* all users. This approach is conceptually similar to the crowd-sourced ideal point estimates of Ramey (2016), but relies on the implicit preferences exhibited by Facebook users' behavior instead of explicit answers to survey items.

In addition to the mathematical convenience of using the network matrix of social media messages to generate ideal point estimates, using endorsement data to scale social media posts solves the problem of multi-media applicability. As described, the network

matrix consists of the aggregate endorsement decisions for all social media users among a select set of messages. One can thus consider the network matrix to be a kind of human-coded dataset where each individual social media user — having their own ideological beliefs — is presented with a binary choice to endorse (or not) the messages to which they have been exposed. Importantly, users make these decisions whether to like messages based not only on the content within the message, but also from their prior knowledge about the offline political context of the message under their consideration. Therefore the presence of likes on a social media message is indicative of more than the message's literal denotation, but accounts for figurative content such as coded language, euphemisms, or irony, as well as non-text features such as images, audio-visuals, or linked content. Consequently, all types of social media messages can be reliably scaled with this method, regardless of content or platform, so long as user endorsement data is available at the level of the individual communication.

Estimating ideology scores from the networked message data requires computing the cross-product of the transpose network matrix and standardizing across columns (see Appendix B.1 for complete pre-processing explanation). The result of this calculation forms a square matrix, called the agreement matrix, with dimensions equal to the number of social media messages to be scaled. In conventional applications of this approach (Bond & Messing, 2015; Ramey, 2016), a data reduction technique such as singular value decomposition or principal component analysis would be applied to the agreement matrix to yield ideal points from the first dimensions of loadings. However this approach is intractable for scaling social media messages, where the volume of data results in massive agreement matrices. For example, analyzing ten-thousand messages requires decomposing an agreement matrix with 10^8 cells; analyzing one-million messages requires decomposing a matrix with 10^{12} cells. This big-data problem poses both hardware and software

constraints which limit the size of matrices which can be decomposed. [9]

To avoid these big-data constraints, I perform data reduction on the agreement matrix via online dictionary learning (ODL), a machine learning method imported from the field of computer vision (Mairal, Bach, Ponce, & Sapiro, 2010). ODL improves on the method in Bond and Messing (2015) by approximating the sparse principal components of the agreement matrix in an iterative, on-line algorithm that overcomes computer memory limitations by (1) analyzing the agreement matrix in an on-line, observation-by-observation approach that does not require the complete agreement matrix to exist in memory, and (2) estimating only the desired number of dimensions of principal components, thereby reducing what is otherwise an $r \times r$ matrix multiplication problem into a $r \times k$ multiplication problem, where the researcher may choose to extract $k \leq r$ dimensions of ideology (see appendix B.2 - B.3 for complete details).

I implement this procedure on a large set of Facebook posts (204,171 unique posts) authored by 425 House members and 97 Senators in the 115th U.S. Congress from July 2017 to the day in which each account was created. Each post in this set received at least 100 likes as of July 2017. Scaling posts within the larger set allows the data reduction technique to better discriminate between the precise ideological position of a message given that it learns more from wider range of available messages and associated patterns of user affiliations. In estimating the post-level ideology scores I ran ODL for 5,000 iterations, sampling 1,000 posts in each. I median-center and standardize the resulting scores using the full set of posts, and then extract the subset of posts in the year before the 2016 general election. The dependent variable, ideological extremity, is expressed as the absolute value of the average daily post scores, such that larger scores are more extreme and smaller scores are more moderate, regardless of a candidate's prior left-right ideological

[9] The constraint on random-access memory is exacerbated by modifying the integer-valued network matrix into a floating-point-valued agreement matrix.

orientation. Formally, the dependent variable is expressed as

$$\text{Ideological Extremity}_{i,t} = \left| \frac{\sum_{j=1}^{n} \text{Post Score}_{i,t,j}}{n} \right|$$

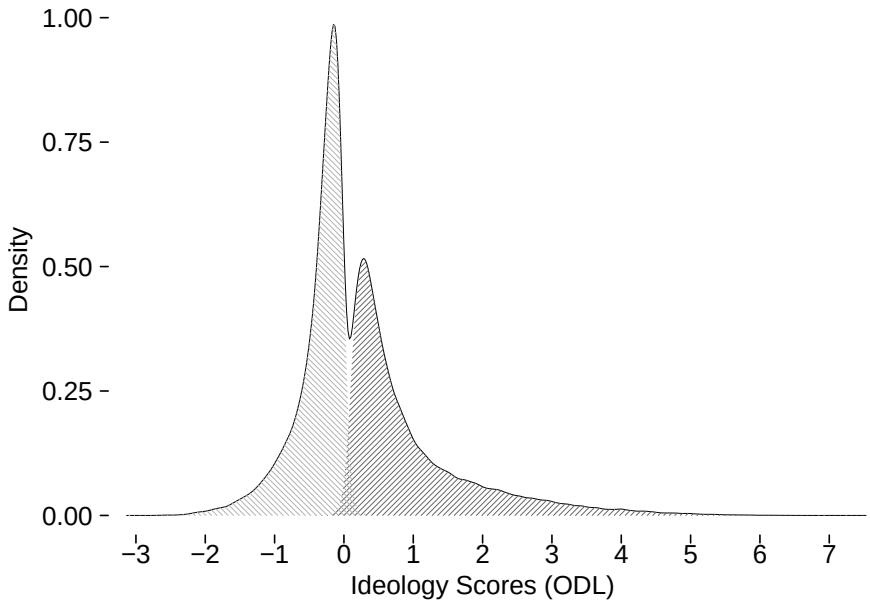
where $j \in \{1, ..., n\}$ indicates the individual scores assigned to posts authored by candidate i on day t.

Validation

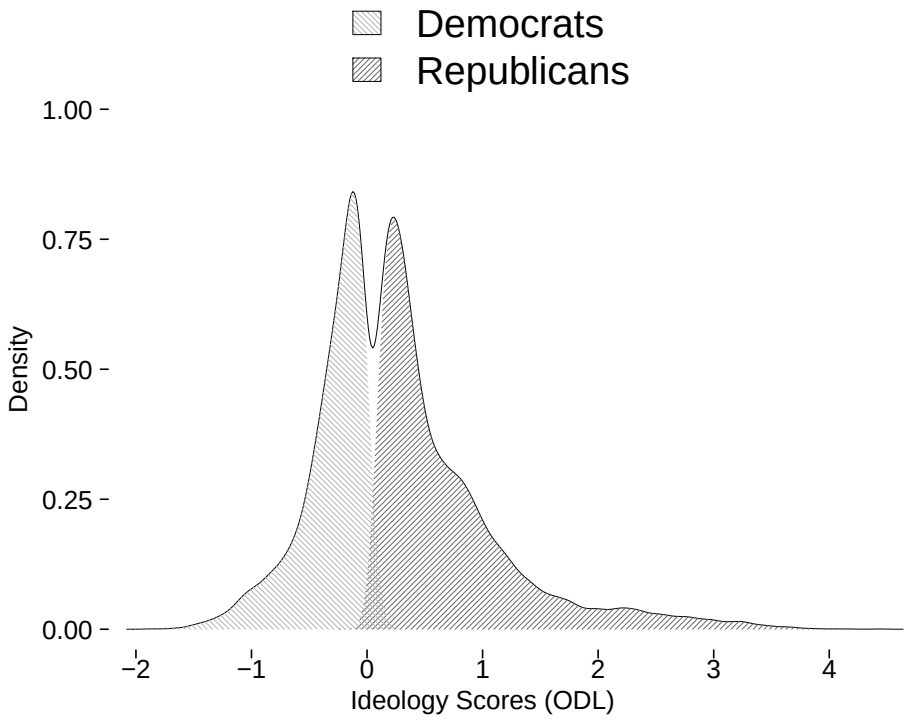
The measurement technique described above is novel in its application to specific social media messages. Therefore I present multiple validation exercises to demonstrate the properties of the Facebook post-level measure of expressed ideology. First, I present the density of the standardized post-level scores, both for the whole set of posts as well as for the subset analyzed herein (Figure 2). The distribution in Figure 2a indicates, that for the full set of posts, very few partisans author messages that cross the ideological divide, and there's a wide variety of ideological messages within parties. These trends are echoed in Figure 2b, which shows the density of ideology scores for the posts in the year preceding the 2016 general election. However, for this restricted set of posts, there is greater parity in the density of posts across parties. Furthermore, the bimodality of the distributions speaks to the face validity for the measure, as it accords with the expected ideological divide between parties. A sampling of posts and their corresponding scores is available in Appendix C. In general, these scored posts speak to the face validity of the measure, as scores correspond to the observable ideological content of the Facebook posts.

As a more rigorous test of the scores' validity I compare the average message-level scores for each candidate to (1) the Facebook-page-level ideal point estimates proposed

Figure 2: Distributions of Post Ideology Scores



(a) All Posts



(b) Analysis Posts

Density plot of post ideology scores. Figure 2.a (top) indicates density for all available posts from July 2017 to the creation of each candidate's respective page. Figure 2.b (bottom) indicates density for posts under analysis, which are created in the year before the November 8, 2016.

by Bond and Messing (2015) [10] and (2) the DW-NOMINATE scores for each legislator (Poole & Rosenthal, 1991, 1997), calculated after assuming office in the 115th Congress. Bond and Messing (2015) finds a Pearson correlation between Facebook-page-level ideology estimates and Dw-NOMINATE scores to be 0.94 overall, and within-party correlations of 0.47 for Democrats and 0.42 for Republicans. In the current analysis, the average post-level ideology scores for each candidate correlate with the Bond and Messing (2015) page-level scores at 0.832. This high correlation indicates the convergent validity of the measure, as it appears to measure the same ideological position expressed by candidates' Facebook pages in general. Importantly, the fact that the two measures do not correlate at 1 indicates that the measures are not identical, or redundant, and suggests that averaging over post ideologies weights the page-level estimate by the frequency with which users engage with a candidate's posts.

Comparing candidates' average post-level ideology scores to their DW-NOMINATE score produces a Pearson correlation of 0.787. The within-party correlation between the measures is 0.543 for Republicans and 0.203 for Democrats. As with the previous case, the high correlation for overall posts demonstrates the convergent validity of the post-level scores, which measure ideology in a similar sense to congressional voting. However the departure between within-party correlation between measures suggests that there is some distinction between the underlying latent dimension measured by roll call votes opposed to that measured by Facebook likes. I argue that this supports the discriminant validity of the measure, as it distinguishes candidates' communications from their concurrent voting behavior.

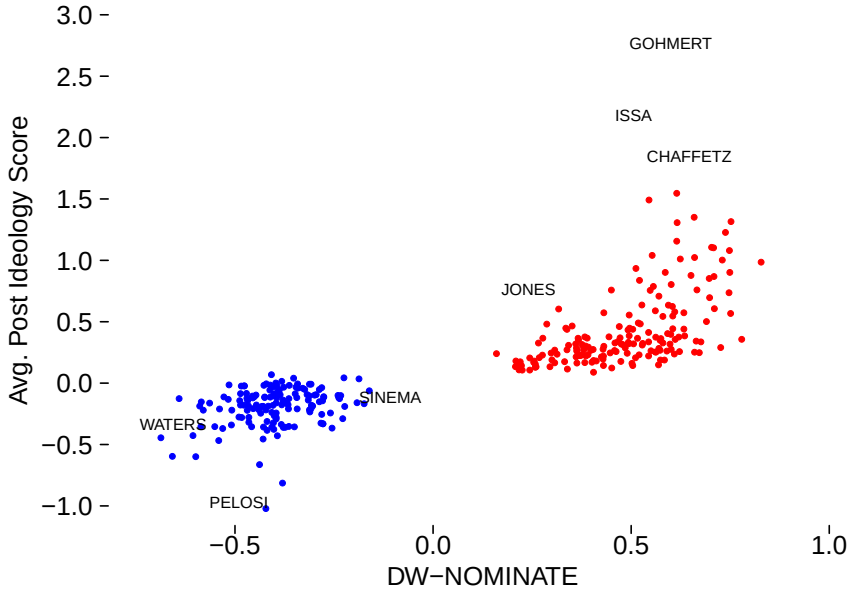
Both the convergent and discriminant validity of the measure are further supported

[10] To compute Bond and Messing (2015) scores for the candidates elected to the 115th Congress, I aggregate over posts in the user-post to form a user-page matrix indicating which users liked at least one post published on the Facebook page of the corresponding legislator in the 115th Congress. I then computed the agreement matrix for these pages and use the first left singular vector resulting from the singular value decomposition of the agreement matrix as the vector of candidate-level scores.

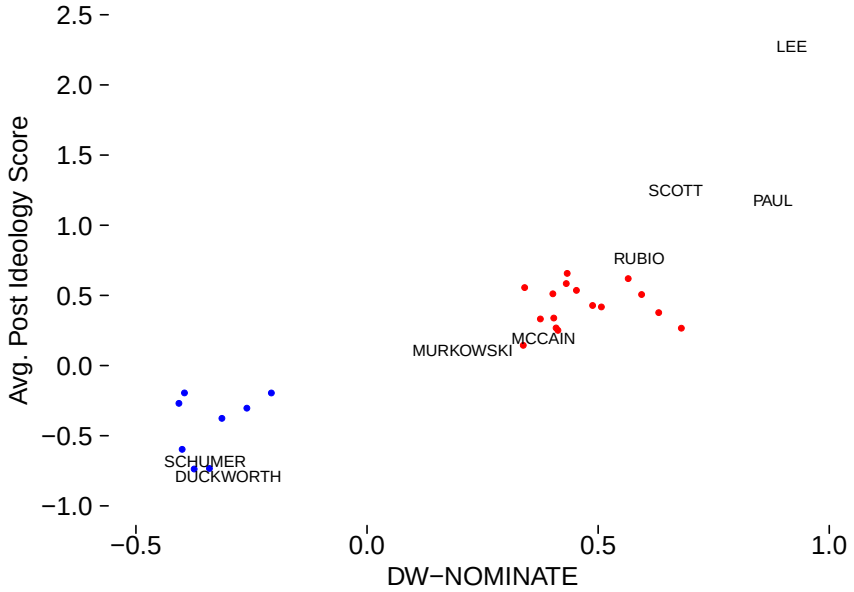
by Figure 3, which depicts some important similarities and differences between the post-level scores and DW-NOMINATE. Figure 3 plots the average first-dimension post-level scores against NOMINATE's first dimension. The graphical depiction of the post-level scores does well in discriminating between parties, while largely succeeding in separating out known extremists, such as Mike Lee (R-UT) and Louie Gohmert (R-TX 1st district), from known moderates, such as Lisa Murkowski (R-ME) and Kyrsten Sinema (R-AZ). An important distinction between the measures can be observed in Figure 3a, where Reps. Issa and Chaffetz score moderately among Republicans according to NOMINATE's voting record metric, whereas they are in the extremes on the rhetoric-based measure of expressed ideology via Facebook posts. Both Issa and Chaffetz, despite facing electoral and party constraints, offered vocal support for then-candidate Trump, thereby distinguishing themselves as more ideologically extreme than their congressional Republican counterparts. This difference between the average post scores and NOMINATE scores is indicative of the discriminant validity of the post-based measure. In general, the similarities between the NOMINATE scores and those estimated via ODL are striking considering that the former is based on legislative activity whereas the latter measures social media communication. Though intuition suggests that votes and rhetoric generate differing ideological representations for a single politician, the similarity may indicate the ability of Facebook users to confer likes upon a messages based on the qualities of both the content (post) and the subject (candidate). This speaks to the benefit of utilizing" human-coded" endorsement data for estimating ideological positions of Facebook content.

Finally, Table 5 demonstrates that the post-level ideology measure correlates with itself with relative consistency over time. Bonica (2014) demonstrates a similar property in CFscores, which suggests internal validity exists in the measure due to its ability to measure the same concept over time. Importantly, these correlation vary from year to year, thus permitting hypothesis testing to determine whether this temporal variability is

Figure 3: Correlation of Average Post Scores and NOMINATE Scores



(a) House



(b) Senate

Online Dictionary Learning (ODL) versus DW-NOMINATE for candidates elected to the 115th U.S. Congress. ODL scores are generated by averaging over each candidate's posts. Named legislators' scores are located at the center of their name's text.

Table 5: Correlation Between ODL Ideology Scores Over Time

	2017	2016	2015	2014	2013
All	0.939	0.962	0.988	0.999	0.976
2017		0.970	0.955	0.936	0.908
2016			0.979	0.960	0.940
2015				0.984	0.964
2014					0.978

Pearson correlation between Online Dictionary Learning ideology scores over time. Scores generated for posts published by candidates elected to the 115th U.S. Congress, and averaged for each candidate. Correlations represent similarity in average overall post ideology for each candidate (row 1), and average annual post ideology for each candidate (rows 2 - 5).

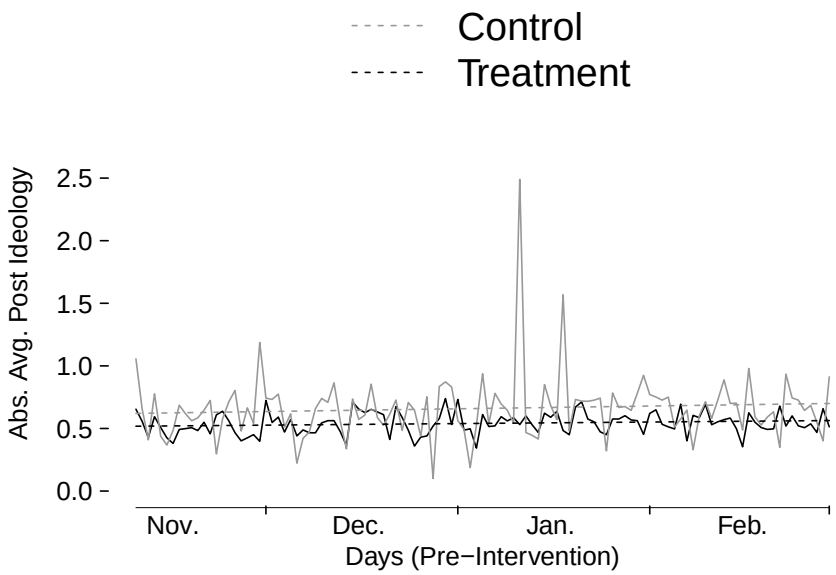
systematic.

Results

Having validated the measurement strategy of the dependent variable, I turn now to modeling the effect of primary elections on ideological moderation. I estimate the effect of primary victory on ideological extremity using the unit fixed effects, two-way fixed effects, and generalized synthetic control models. As described above, though the GSC estimator relaxes the parallel trends assumption for DID analysis, the two-way fixed effects model assumes parallel time trends for the outcome across treatment and control groups. To visually inspect these time trends, I present Figure 4. Inspection reveals that the pre-intervention regression lines for the respective groups appear approximately parallel. Though the fundamental problem of causal inference prevents us from ascertaining whether the post-treatment trends for both groups would remain parallel absent treatment, the pre-intervention trends offer no reasons to suspect a violation of the parallel trends assumption.

Given the plausibility of relevant assumptions, I estimate the effect of treatment using each model. The unit fixed effects model estimates treatment with an interaction on a one-day-lagged dependent variable in order to control for past outcomes' effects on current outcomes. The two-way fixed effects model estimates the ATT without any addi-

Figure 4: Parallel Trends Assessment



Pre-intervention trends in post ideology separated by eventual treatment status. Dashed lines indicate regression slopes for each group, which appear approximately parallel. Pre-intervention period ranges from November 9, 2015 to March 1, 2016.

tional controls. Finally, the GSC model contains no controls, and uses a 5-factor model — deemed optimal by leave-one-out cross-validation — to predict counterfactuals. I graphically present the respective treatment effect estimates from each model in Figure 5 with 95% confidence intervals for each.[11] Tables of regression results are available in appendix D. In general the results support the hypothesis that candidates moderate their instantaneous expressed ideological extremity upon winning their respective primary election. The unit fixed effects model estimates an ATE of -0.038 (p = 0.005), which indicates that candidates decrease the absolute value of the ideological extremity of their Facebook posts upon receiving treatment. To put the magnitude of the coefficient in perspective, the average variance of candidates' post ideology scores is 0.023. This implies that the treatment effect is greater than a squared standard deviation decrease in expressed ideology. Likewise, the average range of ideology scores for candidates is 0.542, which means the

[11]GSC confidence interval estimated via non-parametric bootstrap.

magnitude of the ATE is equivalent to an approximate 7% movement along the average candidate's ideological range. Results from the two-way fixed effects model reveal similar effects of treatment, and demonstrate the robustness of the results when imposing the addition of time fixed effects. The ATT under two-way fixed effects yields a similar effect of -0.025 ($p = 0.018$), which is also substantively large and significantly different from 0. Additionally, the GSC model estimates the ATT as -0.046 ($p = 0.000$), which is the largest magnitude among the models, and is approximately an 8.5% shift along the average candidate's ideological range. The consistency of these finding support the robustness of the treatment effect under additional restrictions and alternative specifications.

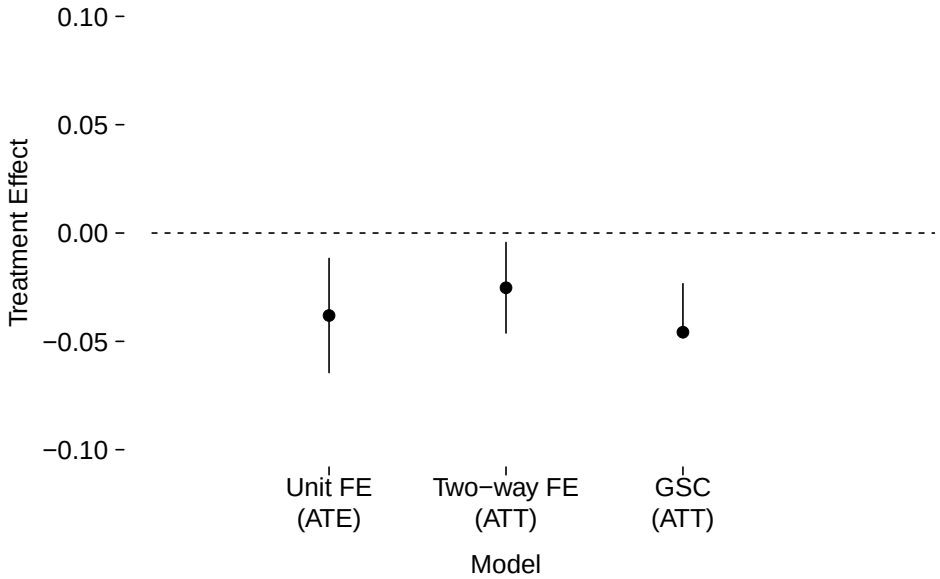
As an additional test of robustness I apply each fixed effects estimators to various cross-sections of the data to examine possible heterogeneous treatment effects related to candidate party, seat safety[12], and the chamber of Congress for which a candidate is running.[13] These results are available in Appendix D, and show that the treatment effects are robust to a variety of candidate types and model specifications. This suggests that the treatment effects described above apply broadly to U.S. congressional candidates, and that the statistical detection of average treatment effects is not due to the outsized influence of certain cross-sections of candidates.

Finally, the measure of a post's ideology is, in part, a function of a post's popularity. One concern for a popularity-based measure of ideology is that the ideal point estimates may become contaminated by a candidate's increasing popularity. In particular, the reported results that demonstrate ideological moderation might be caused by increased user engagement with a candidate's Facebook page after they win a primary. If

[12]Safe seats are coded as those in which a candidate's party received more than 60% of the vote in the previous election for that seat.

[13]The fixed effects models rely on matching and weighted linear regression to relax the assumption of linearity present in standard, linear fixed effects model. However the presence of unit fixed effects prohibits the direct inclusion of time-invariant observable candidate characteristics. Therefore heterogeneous effects are estimated by applying each estimator to relevant subsets of the data described in the main analysis.

Figure 5: Effect of Primary Victory on Ideological Extremity



Treatment effect estimates of primary victory on ideological extremity across multiple models. Unit fixed effect model (left) estimates the ATE to be -0.038 (p = 0.005). Two-way fixed effect model (center) estimates the ATT to be -0.025 (p = 0.018). Generalized synthetic control (right) estimates the ATT to be -0.046 (p = 0.000). Results suggest that candidates decrease the ideological extremity of their Facebook posts after winning a primary election.

a candidate wins their primary contest, voters who preferred a candidate's primary opponent may put their support behind the victorious candidate in the general election due to partisan loyalties. If social media users increasingly engage with primary victors over the course of an electoral cycle, this might alter candidates' computed post-level ideology scores, and might systematically cause the post-primary moderation effect found above. To allay this concern I perform an analysis using the models described in the main analysis, but replace the dependent variable with popularity. Specifically, I compute popularity as

$$\text{Popularity}_{i,t} = \frac{\sum_{j=1}^{n} \text{Post Likes}_{i,t,j}}{n}$$

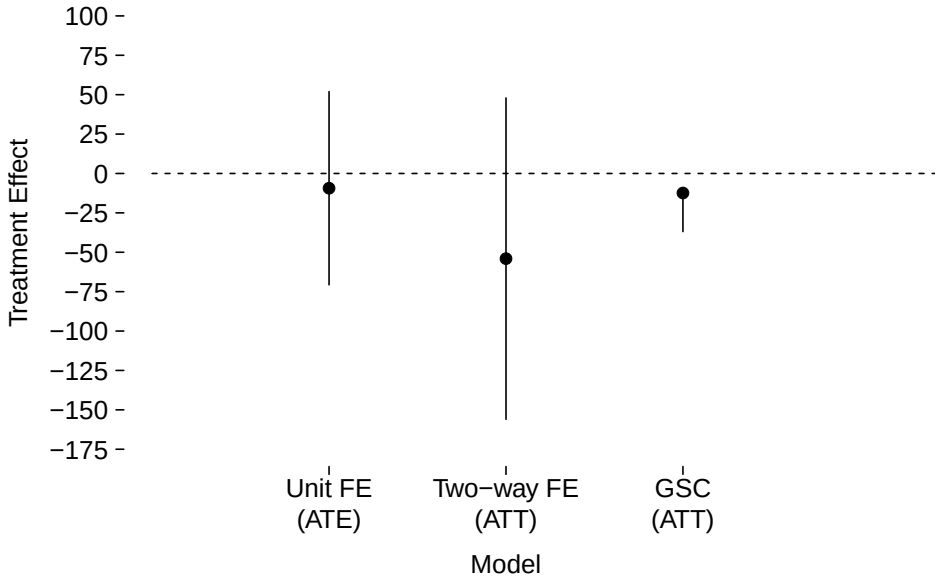
where $j \in \{1, ..., n\}$ indicates the total number of likes applied to each of n posts authored by candidate i on day t.

The results of these models are presented in Figure 6 along with 95% confidence intervals. They show no evidence that candidates become more popular on social media after winning a primary election. In general the evidence suggests the opposite scenario, whereby candidates' Facebook posts receive fewer likes after winning a primary contest, though both fixed effects models yield estimates that are indistinguishable from 0. The GSC estimate is negative (-12.9) and statistically significant (p = 0.000).

Conclusion

The role of ideological position-taking in elections has long remained an open question in political science, and likely will remain a topic of investigation. While the literature has traditionally focused on how candidates adopt static ideological positions that appeal to intersecting primary and general constituencies, political pundits have insinuated that candidate have more liberty to adapt and evolve their position-taking over the course of a campaign. The research described here joins a robust literature on campaign dynamics, but offers the first evidence of ideological dynamism among U.S. congressional candi-

Figure 6: Effect of Primary Victory on Popularity



Treatment effect estimates of primary victory on social media popularity across multiple models. Unit fixed effect model (left) estimates ATE to be -9.358 (p = 0.765). Two-way fixed effect model (center) estimates the ATT to be -54.041 (p = 0.299). Generalized synthetic control (right) estimates ATT to be -12.9 (p = 0.000) . Results indicate that candidates' Facebook posts do not have increased engagement after winning a primary contest.

dates. Using causal inference techniques for time-series data, I find that candidates do moderate the ideological tenor of their campaign messages after progressing from a primary to general election. Finding empirical evidence of post-primary moderation casts doubt on the fidelity of static models of candidate ideological position-taking and opens the door for additional research into how candidates strategically manipulate their instantaneous, expressed ideology over the course of the electoral calendar.

In addition to the substantive implications of this research, the methodological innovations reveal the value of social media data in evaluating longstanding questions in political science. Prior to the advent of social media, the ability to address the question of post-primary moderation was complicated by divided media markets, infrequent updates to campaign messages, and difficulty in quantifying the ideological extremity of political messages. With social media endorsement data, political scientist may now observe daily changes in the ideological extremity of politicians' messages which are made public to an international audience. Moreover, the social-networked nature of this endorsement data permits the measurement of ideology in novel ways, which do not rely on a researcher's preconceived determinations on what messages ought to be classified as liberal or conservative, but rather leverages the collective wisdom of social media users to identify messages that conform with their own ideological preferences. This method of ideal point estimation is not only robust across message mediums, but is dynamic in its ability to track alongside changing definitions of what it means to be liberal or conservative in American politics. The results detailed above demonstrate the utility and validity of endorsement-based measures of message ideology.

Finally, the findings here inject additional complications into the ongoing discussion about the polarizing effects of partisan primaries. If candidates are able to make extreme ideological appeals to primary voters while subsequently moderating their messages for the general electorate, the potential polarizing effects of primaries may not, themselves,

translate into polarized legislators or extreme policies in Congress. Conversely, if such ideological "cheap talk" is permissible to voters, partisan primaries may not sufficiently screen out party purists in a manner desirable to primary voters. In either event, these results are robust across a variety of model specifications and apply to multiple cross-sections of congressional candidates. Subsequent research must work to disentangle the representational and policy impacts of this apparently ubiquitous campaign behavior.

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A. SOCIAL MEDIA CHARACTERISTICS

A.1. *Terminology*

The following formally operationalizes common social media terminology referenced throughout the paper.

A Facebook user is defined as a personal account associated with an individual. Users have the ability to upload ("post") content to Facebook in a variety of media including text, image, video, links to other websites, and more. Users may post this content onto their public profile (their "wall") or interact with other users by posting content in response to others' posts. One common type of user interaction involves "liking" content generated by others.

In this context, a "like" is an action that users may take with respect to a wide variety of Facebook content - pages, posts, photos, etc. It is considered an endorsement of the material by the initiating user, and indicates that the user agrees with or supports the content that they have endorsed (Bond & Messing, 2015). Importantly, the like is distinct from a number of other reactions meant to send different signals about the content. In addition to the like, these reactions consist of emoticons representing "love," "haha," "wow," "sad," and "angry." [14]

Finally, a Facebook page is a publicly-accessible account for a public figure or organization. Users may interact with pages, and pages may interact with users, but generally pages are used for information dissemination to users who like and/or follow the page. The page does so through posts to its own profile, which interested users may view from their account. Pages are managed by users, who may have their own personal user accounts which post material that is not (necessarily) visible on the page. The formal distinctions between what pages and users can do on Facebook are few, though one key distinction is that pages can be "verified" by the social media platform. Verified pages

[14] In June of 2017, Facebook temporarily added a rainbow "pride" reaction in honor of Pride Month.

are noted by the symbol (a white checkmark circumscribed in blue) placed to the right of a page's name, and indicate that the page is an official representation of the person or organization for which the page is named.

B. METHOD DETAILS

B.1. *Data Pre-processing*

The network matrix does not explicitly model the relationship between one message and another. To do so requires computing the cross-product of the transpose network matrix, $\mathbf{E}_{r \times c}$, which results in a square affiliation matrix containing rows and columns equal to the number of unique messages, r.

$$\mathbf{F}_{r \times r} = \mathbf{E}\mathbf{E}'$$

The diagonals of **F** consist of the total number of likes for a given message, and the off-diagonals indicate the number of users who like both the message indicated by the row and the message indicated by the column (see Table A.1, middle panel). Rather than modeling the relationship between users and messages (as in E), F now explicitly models the relationships between each dyad of messages based on the number of users who like both messages. [15]

Though the affiliation matrix properly relates messages to one another, the entries of **F** vary widely as a consequence of each message's popularity. These differences in popularity effectively weight the ideology scores of messages by the number of users who like the message — pushing popular messages to the fringes of the ideological distribution (Bond & Messing, 2015). The final step, therefore, of pre-processing the social media data requires standardizing the affiliation matrix into an agreement matrix by dividing each column of F by its diagonal element.

$$\mathbf{G}^{c \times c} = \mathbf{f}_{ij} / diag(\mathbf{f}_j)$$

[15] Note that users who like only one page do not contribute any unique information to the affiliation matrix. As a result, they are removed prior to the construction of the network matrix in the interest of efficiency.

This standardizes the affiliation matrix such that, for each column $j \in \{1, ..., p\}$ of **G**, the entries represent the proportion of users that like the message in row $i \in \{1, ..., p\}$, given that they also like the message in the column j(see Table A.1, bottom panel). Naturally the values in **G** range from 0 (no common likes) to 1 (all common likes; the diagonal elements), and are irrespective of messages' popularities across columns. This matrix, **G**, contains all of the necessary information from which ideal points may be extracted using one's preferred data reduction technique.

Table 6: Pre-processing Social Media Data

Example Network Matrix, **E**

	"Repeal and replace"	"Obamacare works"	"Healthcare is a human right"
User 309	1	0	0
User 488	0	1	1
User 855	0	0	1
User ...	...	...	...
User 663	0	0	0
User 902	1	0	1
User 420	0	1	0

Example Affiliation Matrix, **F**

	"Repeal and replace"	"Obamacare works"	"Healthcare is a human right"
"Repeal ..."	4,784,474	135,603	36,201
"Obamacare ..."	135,603	171,686	3,456
"Healthcare ..."	36,201	3,456	47,951

Example Agreement Matrix, **G**

	"Repeal and replace"	"Obamacare works"	"Healthcare is a human right"
"Repeal ..."	1	0.790	0.755
"Obamacare ..."	0.028	1	0.072
"Healthcare ..."	0.008	0.020	1

B.2. *Data Reduction*

The canonical data reduction technique applied to the agreement matrix, $\mathbf{G}$, is singular value decomposition (SVD) (Bond & Messing, 2015). SVD factorizes the matrix of predictors $\mathbf{G}$ into three matrices $\mathbf{USV}'$, where $\mathbf{U}$ and $\mathbf{V}$ are orthonormal matrices, and $\mathbf{S}$ is a diagonal matrix with positive, real singular values (Eckart & Young, 1936). The columns of $\mathbf{U}$ consist of the eigenvectors of $\mathbf{GG}'$, $\mathbf{V}$'s columns are the eigenvectors of $\mathbf{G}'\mathbf{G}$, and the diagonal of $\mathbf{S}$ is populated by the non-zero square roots of the eigenvalues from both $\mathbf{GG}'$ and $\mathbf{G}'\mathbf{G}$. Substantively, SVD produces a low rank matrix that closely approximates the information contained in the original data matrix. Bond and Messing (2015, p. 68) compute ideology scores for Facebook pages using the "first rotated left singular [vector]" resulting from an SVD factorization of the transpose of the agreement matrix, $\mathbf{G}'$. This corresponds to the first column of $\mathbf{V}$ as demonstrated in Equation 1.

$$\mathbf{G}' = (\mathbf{USV}')' = \mathbf{VS}'\mathbf{U}' \tag{1}$$

Bond and Messing's (2015) approach is similar to the common dimension reduction technique of principal component analysis (PCA) (Jolliffe, 1986), which formulates the $\mathbf{USV}'$ factorization of SVD as consisting of principal components in the columns of the matrix formed by $\mathbf{US} = \mathbf{Z}$, and loadings in the rows of $\mathbf{V}'$ (Zou, Hastie, & Tibshirani, 2006). [16] The principal components are orthogonal linear combinations of the original data while the loadings represent the correlation between the underlying variables and the derived principal components. Therefore the first row contained in $\mathbf{V}'$ is proportional to the column of left singular values extracted by Bond and Messing (2015). Equation 2 shows this relationship between SVD and PCA for a matrix $\mathbf{G}$, with mean-centered

[16] This assumes that the columns of $\mathbf{G}$ are mean centered.

columns.

$$\mathbf{G} = \mathbf{USV}' = \mathbf{ZV}'. \tag{2}$$

Like SVD's singular vectors, the columns of the principal components are orthogonal with respect to one another, thus allowing for interpretation of one dimension of the data without regard for other possible related dimensions. Unlike SVD, PCA accounts for the variance in the dimensions of $\mathbf{G}$, and sequentially maximizes variability in the data as it constructs each row of loadings in $\mathbf{V}'$ so as to minimize information loss across successive dimensions. This property is useful for procuring nuanced, low-dimensional representations of data. With respect to the Facebook data utilized in this paper, as in Bond and Messing (2015), it is preferable to extract only the first principal component that describes the data, as this should represent the most salient consideration causing users to like political Facebook messages (i.e., ideology). A final advantage of PCA, particularly germane to the proposed methodological innovation of this paper, is that it can be estimated algorithmically in a regression-type framework as proposed in Zou, Hastie, and Tibshirani (2006), with the added benefit that such an estimation technique permits the reduction of erroneous component loadings.

The algorithmic approach to data reduction generalizes PCA into sparse principal component analysis (SPCA) - wherein the principal components are estimated in a regression-type optimization problem containing a quadratic penalty that induces sparsity among the loadings (dAspremont, Bach, & Ghaoui, 2008; dAspremont, Ghaoui, Jordan, & Lanckriet, 2007; Witten, Tibshirani, & Hastie, 2009; Zass & Shashua, 2007; Zou, Hastie, & Tibshirani, 2006). In practical terms this sparsity draws component loadings toward zero, thus improving the ease of principal components' interpretations as noisy loadings become nullified and legitimate loadings remain, sending clearer signals about

the data's variance-maximizing latent dimensions.

Formally, SPCA recasts conventional PCA as an optimization problem under an elastic net constraint (Zou & Hastie, 2005). To see how, first consider a ridge regression on principal component, $k \in \{1, ..., z\}$, given $\mathbf{Z}_k = \mathbf{U}_k \mathbf{S}_{kk}$ and a positive regularization term λ_{ridge}

$$\hat{\beta}_{\text{ridge}} = \arg\min_{\beta} ||\mathbf{Z}_k - \mathbf{G}\beta||_2 + \lambda_{ridge}||\beta||_2 \tag{3}$$

where $||\cdot||_2 = \sqrt{\sum |\cdot|^2}$ notes the ℓ^2-norm of the vector. The above equation expresses the regression of each principal component on the p columns contained in $\mathbf{G}$. Because each principal component is a linear combination of the p variables, the ridge estimates, $\hat{\beta}_{\text{ridge}}$ are proportional to the loadings recovered from the standard PCA approach expressed in Equation 2. Normalizing the ridge estimates yields the exact component loadings, $\mathbf{V}$. [17]

$$\mathbf{V}_k = \frac{\hat{\beta}_{\text{ridge}}}{||\hat{\beta}_{\text{ridge}}||} \tag{4}$$

To induce sparsity in the loadings, the lasso penalty is added to the regression as in Equation 5, where $||\beta||_1 = \sum_{k=1}^{z} |\beta_k|$ denotes the ℓ^1-norm of β.

$$\hat{\beta}_{\text{elastic}} = \arg\min_{\beta} ||\mathbf{Z}_k - \mathbf{G}\beta||_2 + \lambda_{ridge}||\beta||_2 + \lambda_{lasso}||\beta||_1 \tag{5}$$

This formulation of the SPCA regression is a naive elastic net (Zou & Hastie, 2005),

[17] Though $\mathbf{G}$ is a square $p \times p$ matrix, note the following for a matrix $\mathbf{X}$ with r rows and c columns: when $r > c$ and $\mathbf{X}$ is full rank, the regression does not require a positive value of λ_{ridge}. However when $c > r$ and $\lambda_{rridge} = 0$ or when $\mathbf{X}$ is not full rank, standard multiple regression fails to yield a unique solution exactly equal to $\mathbf{V}_k$. In order to eliminate this possible indeterminacy, the positive ridge penalty is applied in the regression equation to guarantee unique solutions for each $\mathbf{V}_k$. Importantly, once normalization of the ridge estimates is complete, the coefficients are independent of λ_{ridge}. Hence the ridge penalty does not penalize the coefficients, but merely ensures a proper reconstruction of the principal components (Zou, Hastie, & Tibshirani, 2006).

[18] where the lasso penalty imposes sparsity on $\hat{\beta}_{\text{elastic}}$ as a function of λ_{lasso}. As a result, $\frac{\hat{\beta}\text{elastic}}{||\hat{\beta}\text{elastic}||} = \mathbf{W}_k$ now constitutes a sparse approximation of $\mathbf{V}_k$, and $\mathbf{GW}_k$ approximates the kth principal component.

Each of the above steps moving from conventional PCA to the elastic-net constrained SPCA of Zou, Hastie, and Tibshirani (2006) has heretofore relied on the prior existence of principal components, $\mathbf{Z}$. The following formulation of SPCA presents the elastic net constraint implemented in Equation 5, but requires only the input of a complete predictor matrix $\mathbf{G}$, scalar λ_{ridge} and vector $\lambda_{lasso,k}$ containing respective sparsity constraints for each component loading.

$$(\hat{\mathbf{A}}, \hat{\mathbf{B}}) = \arg\min_{\mathbf{A},\mathbf{B}} \sum_{i=1}^{p} ||\mathbf{G}_i - \mathbf{AB}'\mathbf{G}_i||_2 + \lambda_{ridge} \sum_{k=1}^{z} ||\boldsymbol{\beta}_j||_2 + \sum_{k=1}^{z} \lambda_{lasso,k} ||\boldsymbol{\beta}_|||_1 \tag{6}$$

$$\text{subject to } \mathbf{A}'\mathbf{A} = \mathbf{I}^{z\times z}.$$

Above, $\mathbf{G}_i$ represents the ith row vector of $\mathbf{G}^{p\times p}$, $\mathbf{A}^{p\times z} = [\boldsymbol{\alpha}_1, ..., \boldsymbol{\alpha}_z]$ is an orthonormal matrix containing approximations of the principal components, and $\mathbf{B}^{p\times z} = [\boldsymbol{\beta}_1, ..., \boldsymbol{\beta}_z]$ contains the approximated component loadings. Estimation occurs through an iterative algorithm involving sequential optimizations of $\mathbf{A}$ and $\mathbf{B}$. [19]

The results of SPCA are comparable to standard PCA such that $\hat{\mathbf{A}} = \mathbf{UV}'$ from the SVD of $(\mathbf{G}'\mathbf{G})\mathbf{B}$ and $\hat{\mathbf{B}}$ is proportional to $\mathbf{W}$. As in Equations 3 and 5, the ridge penalty is required to prevent multicollinearity (see footnote 9), and per Equation 5, the lasso penalty imposes sparsity on the loadings. As a consequence, when the vector $\lambda_{lasso,k}$

[18] "Naive" because the complete elastic net contains a scaling factor of $(1 + \lambda_{ridge})$ (Zou & Hastie, 2005; Zou, Hastie, & Tibshirani, 2006). The use of normalized fitted coefficients (Equation 4) causes $\mathbf{V}_k$ to remain unaffected by scale.

[19] Interested readers are directed to Zou, Hastie, and Tibshirani (2006, pp. 270-272) for complete details. For the current paper, an abstract understanding of the SPCA approach is sufficient for ascertaining the merits of the on-line SPCA algorithm described in Section 3.3

contains all zero values, the resulting estimates of the principal components and loadings are identical to a standard, algorithmic calculation of PCA. The notable exception to the results of SPCA is that the principal components are no longer uncorrelated due to approximated values of the principal components and loadings. Though this property potentially complicates the interpretation of the various principal components, it more accurately depicts the underlying latent dimensions driving the data generating process. [20]

Apart from the potential correlation between dimensions, estimating the ideal points of social media data via SPCA has a number of additional desirable properties. First, since PCA is closely related to SVD, the technique herein builds on existing valid approaches to the social media ideal point problem (Bond & Messing, 2015). Second, SPCA induces sparsity among loadings which may otherwise erroneously take on non-zero values in the standard PCA approach. In practice, the addition of zero-valued elements within principal components permits interpretation of what a single dimension explains (i.e., which observations load high or low) in addition to what it does not explain (i.e. which observations fail to elicit distinct loadings on certain dimensions). In theory, this property should aid in the interpretation of principal components that describe variability in the data under circumstances where existing theory is silent. Finally, though the conventional computational implementation of SPCA described above requires input of an entire matrix of predictors at runtime, the algorithmic nature of the estimation procedure is readily adaptable to an on-line approach for estimating principal components.

[20] Consider, for instance, the potentially confounding motivations that might cause a Facebook user to like a politician's page. Though the politician's political leaning is likely the most salient factor driving a user to click the like button, geographic considerations (whether a politician hails from the user's district, state, or region) might also cause a user to like a page. Though ideology and geography remain distinct underlying motivations, the two are not uncorrelated. One would expect a user's geographic surroundings to inform their political beliefs, and perhaps *vice versa*.

B.3. *Online Dictionary Learning*

To approximate the sparse principal components from large-n social media data, I employ the on-line dictionary learner (ODL) developed by Mairal, Bach, Ponce, and Sapiro (2010). The ODL allows for the estimation of sparse principal components from i.i.d draws of individual vectors (or small sets of vectors, η) from within a matrix of data $\mathbf{G}^{p \times p}$. It follows Zou, Hastie, and Tibshirani (2006) in formulating SPCA as a linear optimization problem, but estimates the principal component loadings in two stages: sparse coding and dictionary updating.

The sparse coding step occurs prior to the estimation of the sparse principal components, wherein it (1) calculates the optimal effective sparsity of each principal component based on observed data and (2) represents the data as a sparse linear combination in order to reduce computational cost. [21] Equation 7 describes the sparse coding step at iteration $t \in \{1, ..., T\}$, given a column vector j of data, $\mathbf{G}_{j,t}$, an initial matrix of z component loadings (the dictionary) $\mathbf{D}_{t-1}^{p \times k}$, and effective sparsity parameter, γ_{lasso} and γ_{ridge}

$$\boldsymbol{\theta}_t = \underset{\boldsymbol{\theta} \in \mathbb{R}}{\arg\min} ||\mathbf{G}_t - \mathbf{D}_{t-1}\boldsymbol{\theta}||_2 + \gamma_{lasso}||\boldsymbol{\theta}||_1 + \gamma_{ridge}||\boldsymbol{\theta}||_2. \tag{7}$$

Numerically, the least-squares problem presented by Equation 7 is evaluated via a Cholesky-based implementation of the LARS-Lasso algorithm (Efron, Hastie, Johnstone, Tibshirani, et al., 2004, provides deatiled explanations of the algorithm and its efficienct modifications). Substantively, the utility of this approach is that it provides the full regularization path, solving for all possible values of γ_{lasso}, at higher accuracy and speed than compara-

[21] Formally, the sparse coding step minimizes the expected empirical cost of the loss function, where the expectation is evaluated with respect to the probability distribution of the data (Mairal, Bach, Ponce, & Sapiro, 2010).

ble approaches (Mairal, Bach, Ponce, & Sapiro, 2010).[22]

Upon calculating $\boldsymbol{\theta}_t$, the ODL algorithm stores all information necessary for the estimation of the sparse principal component loadings in the updates of matrices $\mathbf{M}^{z\times z} = \mathbf{M}_{t-1} + \boldsymbol{\theta}_t\boldsymbol{\theta}_t'$ and $\mathbf{N}^{p\times z} = \mathbf{N}_{t-1} + \mathbf{G}_t\boldsymbol{\theta}_t'$. This step permits the algorithm to discard all past information about $\mathbf{G}_t$ and $\boldsymbol{\theta}_t$ simply maintain continual updates of $\mathbf{M}$, $\mathbf{N}$ and $\mathbf{D}$ in memory. These three matrices are sufficient for completing the update step of the ODL algorithm, wherein the approximations of the component loadings are updated according to the SPCA criterion discussed in the previous subsection. Specifically, the dictionary update step sequentially revises the loadings for each component dimension k by first estimating the unconstrained component loadings, and then projecting those estimates onto the elastic net constraint. Formally, given the kth columns of matrices $\mathbf{M}$, $\mathbf{N}$, and $\mathbf{D}$, the unconstrained estimate of the component loadings is

$$\mathbf{c}_k = \frac{1}{\mathbf{M}_{k,k}}\left(\mathbf{N}_k - \mathbf{D}\mathbf{M}_k\right) + \mathbf{D}_k, \tag{8}$$

and the projection of the unconstrained loadings onto the constraint set is

$$\mathbf{D}_k = \underset{\mathbf{d}\in\mathbb{R}^k}{\arg\min}||\mathbf{c}_k - \mathbf{d}||_2 \text{ such that } ||\mathbf{d}||_2 + \lambda_{lasso}||\mathbf{d}|| \leq 1. \tag{9}$$

The dictionary update step repeatedly iterates across each individual component loading, k, until convergence of the entire matrix of approximated loadings, $\mathbf{D}$. At each step, the optimization of $\mathbf{c}_k$ via the elastic net is achieved through an efficient projection algorithm (describes the complete algorithm Mairal, Bach, Ponce, & Sapiro, 2010, p. 53). Once $\mathbf{D}$ has converged, the ODL algorithm begins its next iteration by drawing a new i.i.d subsample of size η from the data and estimating a new $\boldsymbol{\theta}_t$. This process continues until completing

[22]Mairal, Bach, Ponce, and Sapiro (2010) use only the $\ell - 1$ regularization term in the sparse coding step of SPCA. For the purpose of inducing greater sparsity among the principal component scores, and for the superior results returned from this approach, the sparse coding step above uses both the $\ell - 2$ and $\ell - 2$ regularization terms.

the desired number of total iterations, T. Pseudo-code outlining the algorithm's steps as described above is available in Algorithm 1.

This iterative, observation-wise approach to estimating component loadings allows the application of SPCA to large data sets which would otherwise be impossible to analyze because of an inability to fit into a computer's working memory. Since SPCA, like SVD, offers a low-dimensional representation of political social media data, the ODL offers the opportunity to scale ideal point estimates for vast quantities of Internet-based political communication.

Algorithm 1: Online Dictionary Learning

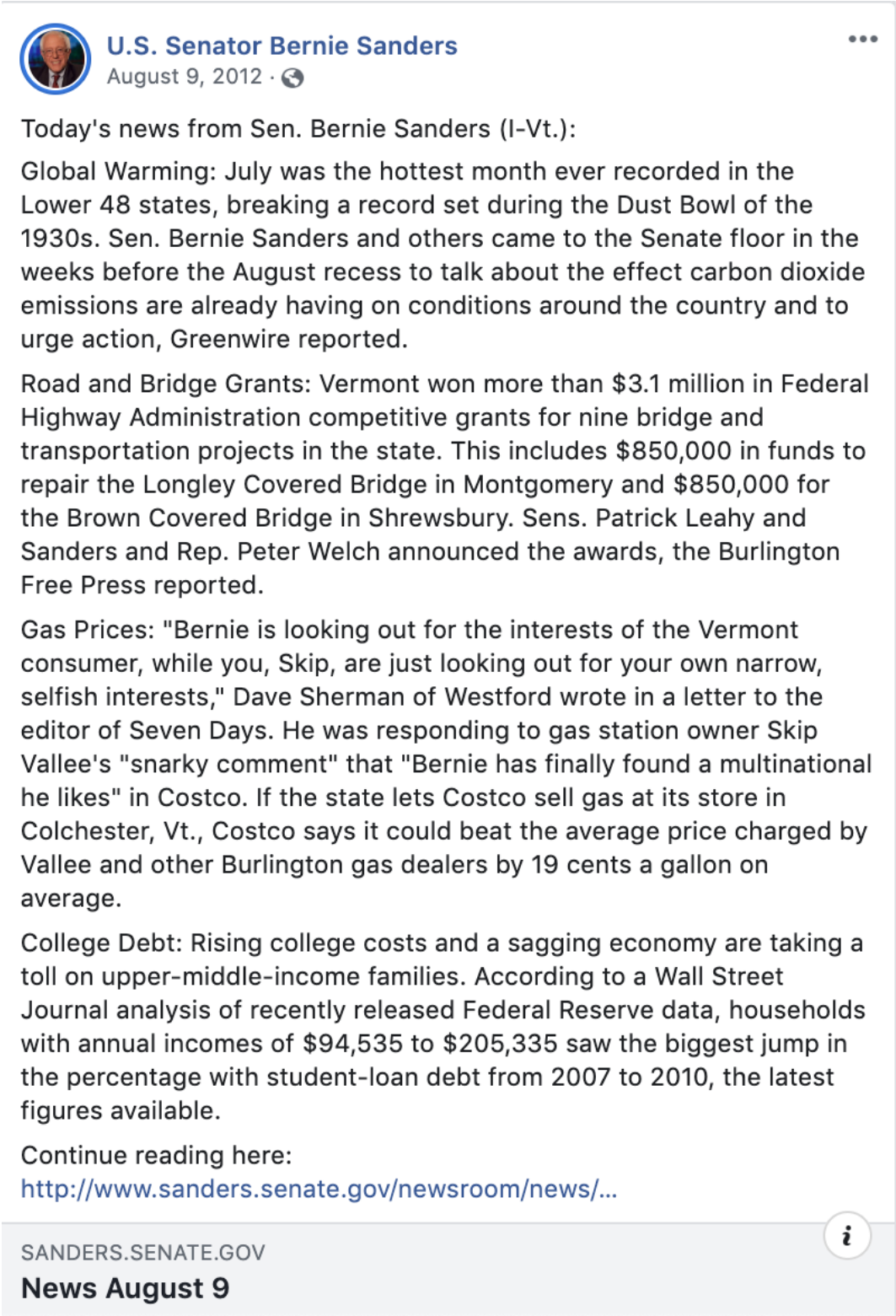
Given:
Data $\mathbf{G}^{p \times p}$ with iid observations distributed $p(\mathbf{G})$
Regularization parameters γ_{lasso} and λ_{lasso}
Initial matrix of loadings $\mathbf{D}_0^{p \times z}$

1. Reset past information: $\mathbf{M}_0 \leftarrow \mathbf{0}^{z \times z}$, $\mathbf{N}_0 \leftarrow \mathbf{0}^{p \times z}$
2. For t in iterations 1 to T
3. Subset $\mathbf{G}^{p \times \eta}$ by sampling η iid observations from $p(\mathbf{G})$
4. Optimize $\boldsymbol{\theta}_t^{z \times \eta}$ for fixed $\mathbf{D}_{t-1}$ (Equation 7)
5. $\mathbf{M_t} \leftarrow \mathbf{M}_{t-1} + \frac{1}{\eta} \sum_{n=1}^{\eta} \boldsymbol{\theta}_{t,n} \boldsymbol{\theta}'_{t,n}$, $\mathbf{N_t} \leftarrow \mathbf{N}_{t-1} + \frac{1}{\eta} \sum_{n=1}^{\eta} \mathbf{G}_{t,n} \boldsymbol{\theta}'_{t,n}$
6. Repeat
7. For k in dimensions $1 : z$
8. Evaluate $\mathbf{c}_k$ for fixed $\mathbf{M}$, $\mathbf{N}$, and $\mathbf{D}$ (Equation 8)
9. Optimize $\mathbf{D}_k$ for fixed $\mathbf{c}_k$ (equation 9)
10. Continue until convergence of $\mathbf{D}$
11. Return $\mathbf{D}_t$
12. Return $\mathbf{D}_T$

C. MEASUREMENT

The main text offers correlational evidence of the validity of the post-level measure of expressed ideology. This appendix offers additional insight into the face validity of the measure. Figure 7 displays the posts located at the 2.5, 25, 45, 55, 75, and 97.5 percentiles of the sorted post-level ideology scores. Figure 7a displays the post located at the 2.5th percentile of sorted post scores. The post is authored by Senator Bernie Sanders (I-VT) and engages in non=partisan credit claiming for Vermont's infrastructure grants as well as position-taking on gas prices. Sanders's post also takes an affirmative stance on reducing global-warming-inducing carbon emissions and references contemporaneous statistics on national student loan debt. In aggregate, Sanders's post expresses a left-of-center ideological position. The post's reference to global warming is evocative of Sander's support for government intervention in environmental protection, while its mention of student loans speaks to the senator's role as an exponent of student loan forgiveness and government-funded college. Figure 7b is posted by Senator Gary Peters (D-MI). It is located at the 25th percentile of sorted post scores and is left-of-center in expressed ideology, as it describes Peters's meeting with, and support for, Supreme Court nominee Merrick Garland. Though the post is devoid of explicit policy content, the praise for President Obama's Supreme Court nominee is subtly supportive of the Democratic president's administration. Figure 7c is drawn from the 45th percentile of post-level scores. It depicts a post on the Facebook page of Congressman Jim McGovern (D-MA 2nd District) in which Rep. McGovern holds a sign in support of the Charlie Hebdo magazine. The expressed ideology of the post is ambiguous, as the Democratic congressman's sign implicitly offers support for the satirical magazine in the aftermath of violent attacks directed against its staff. The post's message is simultaneously evocative of support for free speech and condemnation of Islamic terrorism. The post at the 55th percentile of scores (Figure 7d) is authored by Congresswoman Kirti Noem (R-SD). The expressed ideology is centrist, as

its message lacks explicit policy content. Instead the message adopts a non-partisan message of congratulations directed at the Congresswoman's husband. Figure 7e shows a post by Senator James Lankford (R-OK) which contains a right-of-center policy message. It is drawn from the 75th percentile of scores. In the post Lankford frames the 2012 fiscal cliff debate as a "SPENDING problem" rather than a "REVENUE problem." This position is consistent with a fiscally-conservative view on government spending. Finally, Figure 7f contains a post by Senator Ted Cruz (R-TX), which is located at the 97.5th percentile of post scores. The message links viewers to a YouTube video where Senator Cruz appeals to the constitutional sanctity of the First Amendment. The expressed ideology of the message indicates the senator's ideology as a constitutional conservative.



U.S. Senator Bernie Sanders
August 9, 2012 ·

Today's news from Sen. Bernie Sanders (I-Vt.):

Global Warming: July was the hottest month ever recorded in the Lower 48 states, breaking a record set during the Dust Bowl of the 1930s. Sen. Bernie Sanders and others came to the Senate floor in the weeks before the August recess to talk about the effect carbon dioxide emissions are already having on conditions around the country and to urge action, Greenwire reported.

Road and Bridge Grants: Vermont won more than $3.1 million in Federal Highway Administration competitive grants for nine bridge and transportation projects in the state. This includes $850,000 in funds to repair the Longley Covered Bridge in Montgomery and $850,000 for the Brown Covered Bridge in Shrewsbury. Sens. Patrick Leahy and Sanders and Rep. Peter Welch announced the awards, the Burlington Free Press reported.

Gas Prices: "Bernie is looking out for the interests of the Vermont consumer, while you, Skip, are just looking out for your own narrow, selfish interests," Dave Sherman of Westford wrote in a letter to the editor of Seven Days. He was responding to gas station owner Skip Vallee's "snarky comment" that "Bernie has finally found a multinational he likes" in Costco. If the state lets Costco sell gas at its store in Colchester, Vt., Costco says it could beat the average price charged by Vallee and other Burlington gas dealers by 19 cents a gallon on average.

College Debt: Rising college costs and a sagging economy are taking a toll on upper-middle-income families. According to a Wall Street Journal analysis of recently released Federal Reserve data, households with annual incomes of $94,535 to $205,335 saw the biggest jump in the percentage with student-loan debt from 2007 to 2010, the latest figures available.

Continue reading here:
http://www.sanders.senate.gov/newsroom/news/...

SANDERS.SENATE.GOV
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(a) 2.5th Percentile

(b) 25th Percentile

(c) 45th Percentile

(d) 55th Percentile

(e) 75th Percentile

(f) 97.5th Percentile

Figure 7: A sampling of post authored by legislators in the 115th U.S Congress. Posts are ordered by percentile of post scores sorted from most liberal to most conservative. Sampled posts broadly construe the face validity of the post-level ideology score.

D. MODELS

I use both models proposed by Imai and Kim (2019, n.d.) to estimate the conditional treatment effects for candidates in each chamber of congress, of each party, and in safe versus marginal districts. In the unit fixed effects model, candidates for the U.S. House evince negative, statistically significant effects on ideology upon treatment (Coef: -0.032, p = 0.023;). Compared to candidates for U.S. Senate, the treatment effects on House candidate are attenuated. The unit fixed effects model estimates the effect of treatment on Senate candidates to be -0.100 (p = 0.009). These findings suggest that the degree of ideological moderation is affected by the office for which candidates run. A number of features distinguish the House from the Senate, though which factors might encourage moderation among Senate candidates requires additional research.

Among Democrats and Republicans, the unit fixed effects model finds that treatment has negative, statistically significant effects on the ideological extremity of candidates in both parties. However the effects are exaggerated for Republicans (Coef: -0.051, p = 0.009) compared to Democrats (Coef: -0.020, p = 0.041). Finally, unit fixed effects find that candidates in safe districts moderate their ideology more substantially than the unconditional ATE (Coef: -0.043, p = 0.007). However, there is no statistically discernible difference from 0 for the effect of treatment on candidates in marginal districts (Coef: -0.027, p = 0.052). This finding indicates that candidates in safe districts may have greater latitude to modify their expressed ideology in order to stave off primary challengers while subsequently making appeals to the general electorate.

The two-way fixed effects model yields similar results for conditional ATTs, though the added imposition of time fixed effects reduces the statistical discernibility of some treatment effects. It finds a negative, statistically significant treatment effect for House candidates (Coef: -0.027, p = 0.012), but does not produce a statistically distinct estimate for Senate candidates (Coef: -0.011, p = 0.841). Similarly, the models finds Republicans to

engage in more severe post-primary ideological moderation (Coef: -0.037, p = 0.029) compared to the unconditional ATT, however the estimated effect for Democratic candidates is not statistically significant (Coef: -0.007, p = 0.541). Finally, as in the unit fixed effects case, the two-way fixed effects model finds a greater effect of treatment on candidates in safe districts (Coef: -0.037, p = 0.011) relative to the unconditional ATT, yet once again the effects for candidates in marginal districts is indistinguishable from 0 (Coef: 0.002, p = 0.880).

Table 7: Unit Fixed Effects Results

	ATE	House	Senate	Democrat	Republican	Safe	Marginal
Treatment	-0.038^*	-0.032^*	-0.100^*	-0.020^*	-0.051^*	-0.043^*	-0.027
	(0.013)	(0.014)	(0.038)	(0.010)	(0.019)	(0.016)	(0.014)
Ideology_{t-1}	0.086	0.094	0.049	0.171^*	0.057	0.083	0.099^*
	(0.090)	(0.100)	(0.104)	(0.053)	(0.117)	(0.107)	(0.040)
Treatment	0.018	0.014	0.071	0.007	0.018	0.015	0.098^*
$\times\text{Ideology}_{t-1}$	(0.048)	(0.051)	(0.119)	(0.042)	(0.056)	(0.053)	(0.050)
N units	357	325	32	158	199	245	112
White's p	1.000	1.000	1.000	1.000	1.000	1.000	1.000

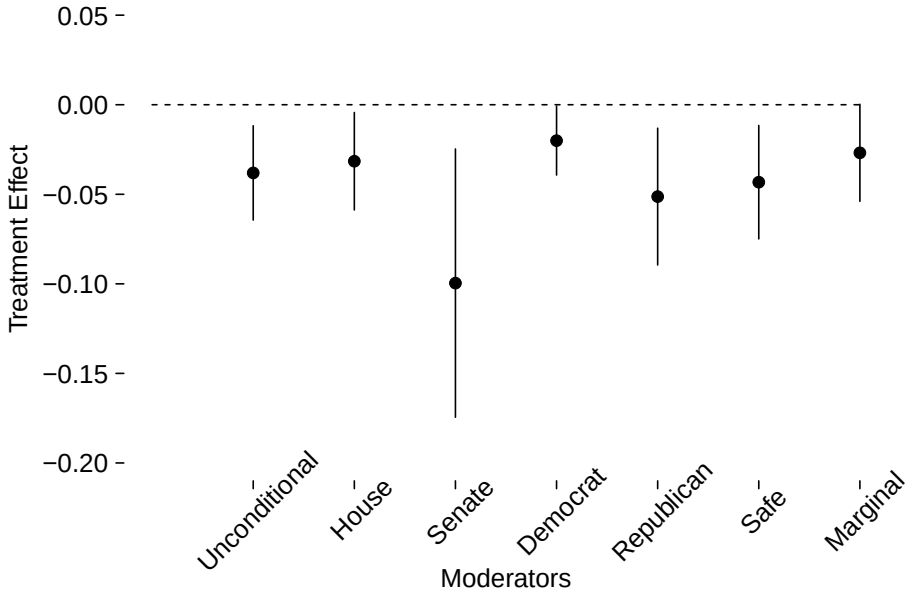
Matched, weighted unit fixed effects regression results. White's p indicates p-value of White's misspecification test, the null hypothesis of which is no misspecification compared to a linear fixed effects regression. Coefficients denoted with asterisks are statistically significant at the 0.05 level.

Table 8: Two-way Fixed Effects Results

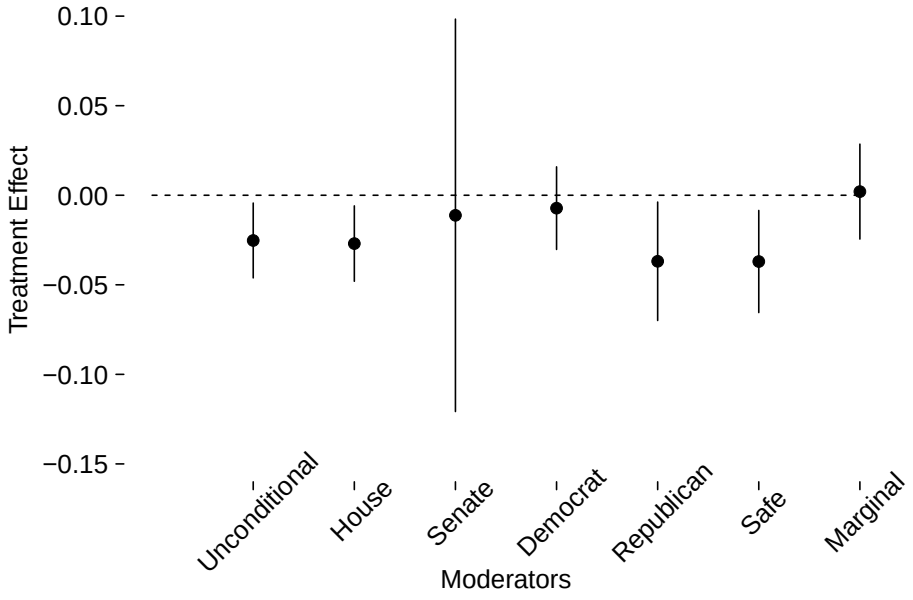
	ATT	House	Senate	Democrat	Republican	Safe	Marginal
Treatment	-0.025^*	-0.027^*	-0.011	-0.007	-0.037^*	-0.037^*	0.002
	(0.011)	(0.011)	(0.056)	(0.012)	(0.017)	(0.015)	(0.014)
N units	357	325	32	158	199	245	112
White's p	1.000	1.000	1.000	0.000	1.000	1.000	1.000

Matched, weighted two-way fixed effects regression results. White's p indicates p-value of White's misspecification test, the null hypothesis of which is no misspecification compared to a linear fixed effects regression. Coefficients denoted with asterisks are statistically significant at the 0.05 level.

Figure 8: Treatment Effects



(a) Unit Fixed Effects



(b) Two-way Fixed Effects

Table 9: Generalized Synthetic Control Results

	ATT
Treatment	-0.046^{*}
	(0.006)
N units	353
N periods	365
N factors	5

Generalized synthetic control difference in difference results. Analysis spans the year before the 2016 general election. Candidate included in analysis are those who have at least 5% of valid periods in control before undergoing treatment.