

test

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## Introduction

Since 2015 through today, calls to increase government regulation of social media tech companies have grown. Social media companies have an inherent interest in limiting increased regulations which can disrupt many aspects of business models and growth strategies.

Public opinion is an important motivator of politicians' actions, and the public's views towards social media companies and the extent to which they are regulated can either motivate or prevent politicians from altering existing frameworks. Political ideology and identities are inherently related to individuals' opinions about regulation and government intervention, with those identifying as more conservative favoring less government involvement and those identifying as more liberal favoring a more active government. While political persuasion is likely to remain a critically important determinant in individuals' views on regulating the tech sector, individuals' experiences directly interacting with social media sites and products may also influence their views.

This analysis utilizes Bayesian methods to test if public opinion on regulating social media companies can be explained entirely as a function of one's political views or if the types of content and experiences users interact with on social media sites is also associated with their views on regulation. Put another way, are opinions towards regulating big tech all just politics, or can altering aspects of the social media experience increase the public's favorability towards social media companies?

If opinions towards regulation are associated with aspects of the social media experience or engaging with specific types of social media content, social media companies may be able to structure algorithmic changes that downregulate these types of content as a means of increasing their favorability and preventing increased government intervention.

## The Data

In 2018 the Pew Research Center surveyed a representative sample of Americans on their use of and feelings toward social media. Participants were asked whether the government should regulate social media companies more than they already are, about the same as they are now or less than they are now. This item was dichotomized such that respondents indicating current or lower levels of regulation were coded as being against expanding regulation and compared against those favoring expanding regulation. After dichotomizing, this item was used as the outcome variable in all subsequent analyses. Favoring more regulation was coded as 1 while being against an expansion of regulations was coded as 0.

Demographic items respondents indicated their political identity, race and age were used as measures of political persuasion and identity. Political ideology was described as either very conservative, conservative, moderate (reference class), liberal or very liberal. Age was divided by users who were 18-29, 30-49 (reference class), 50-64 or 65 and above. Respondents could indicate their race as either white (reference class), black, Asian, mixed race or other.

User experiences with social media content was measured through three separate variables: the frequency of encounter posts that increased negative affect, the frequency of encountering politically charged, triggering and controversial content and the frequency of encountering disinformation.

Factor analysis was used to combine 3 separate items about the frequency of seeing content that made users feel angry, depressed and lonely into a single continuous latent variable representing negative affect. Similarly, a factor scores were used to combine a series of 4 separate items asking about the frequency that users encountered posts about race relations, sexual harassment/assault, gun control/gun violence and immigration into a single continuous latent variable representing politically charged content. A single item where respondents were asked to describe if they saw more posts protesting deception, saw more posts trying to point out misinformation or an equal amount each (reference class) was included as a measure of disinformation.

To understand the relationship between political identity, social media content and views on regulation 3 candidate models were created and compared against each other.

## Hypotheses: comparing 3 separate models

### Model 1: Views on regulation as a function of political ideology, age and race

Model 1 is the uses only political identification, race and age to predict whether a given individual factors expanding existing regulations of social media companies or believes current regulatory practices are sufficient. If model fits the data the best, this implies that opinions on the regulation of social media companies are an extension of already existing political beliefs.

$$\begin{aligned} regulation_i &\sim Binomial(n, p_i) \\ logit(p_i) &= \alpha + \beta_{veryconservative_i} + \beta_{conservative_i} + \beta_{liberal_i} + \beta_{veryliberal_i} + \\ &\beta_{age : 18 - 29_i} + \beta_{age : 50 - 64_i} + \beta_{age : 65 and up_i} + \\ &\beta_{black_i} + \beta_{asian_i} + \beta_{mixedrace_i} + \beta_{race : other_i} \end{aligned}$$

### Model 2: Views on regulation as a function of political ideology, identity and features of social media sites

Model 2 includes the same political and identity predictors as model 1 but adds the measures of social media based features (negative affect, charged content and deceptive vs corrective information).

If model 2 fits the data better than the other models this supports the hypothesis that views towards the regulation of social media companies is not a purely political issues but is also related to the content and types of experiences encountered by users.

$$\begin{aligned} regulation_i &\sim Binomial(n, p_i) \\ logit(p_i) &= \alpha + \beta_{veryconservative_i} + \beta_{conservative_i} + \beta_{liberal_i} + \beta_{veryliberal_i} + \\ &\beta_{age : 18 - 29_i} + \beta_{age : 50 - 64_i} + \beta_{age : 65 and up_i} + \\ &\beta_{black_i} + \beta_{asian_i} + \beta_{mixedrace_i} + \beta_{race : other_i} + \\ &\beta_{negativeaffect_i} + \beta_{chargedcontent_i} + \beta_{deception_i} + \beta_{correctingmisinformation_i} \end{aligned}$$

**Model 3: Views on regulation as a function of identity and features of social media sites with the role of user experience varying across different political ideologies**

Model 3 allows the relationship between social media content and opinions on regulation to vary across different political ideologies. The opinions of those with less extreme political opinions may be more malleable than those who identify as highly ideological. By estimating different slopes for each political identity, model 3 allows for these differential effects. If model 3 fits the data best, this implies that for some political identities, views on social media are only a function of political identity, but for other political identities views on regulation vary with different experiences on social media sites.

$$\begin{aligned}
& regulation_i \sim \text{Binomial}(n, p_i) \\
& \text{logit}(p_i) = \alpha_{ideology_i} + \\
& \beta_{ideology_i} \text{negative affect}_i + \beta_{ideology_i} \text{charged content}_i + \\
& \beta_{ideology_i} \text{deception}_i + \beta_{ideology_i} \text{correct misinformation}_i + \\
& \beta_{age : 18 - 29}_i + \beta_{age : 50 - 64}_i + \beta_{age : 65 \text{ and up}}_i + \\
& \beta_{black}_i + \beta_{asian}_i + \beta_{mixed race}_i + \beta_{race : other}_i \\
& \begin{bmatrix} \alpha_{ideology} \\ \beta_{ideology} \end{bmatrix} \sim \text{MVNormal} \left( \begin{bmatrix} \alpha \\ \beta \end{bmatrix}, S \right) \\
& S = \begin{pmatrix} \sigma_\alpha & 0 \\ 0 & \sigma_\beta \end{pmatrix} \quad R = \begin{pmatrix} \sigma_\alpha & 0 \\ 0 & \sigma_\beta \end{pmatrix} \\
& \alpha \sim \text{Normal}(0, 2) \\
& \beta_{\text{negative affect}} \sim \text{Normal}(0, .25) \\
& \beta_{\text{charged content}} \sim \text{Normal}(0, .25) \\
& \beta_{\text{deception}} \sim \text{Normal}(0, 1.5) \\
& \beta_{\text{correct misinformation}} \sim \text{Normal}(0, 1.5) \\
& (\sigma_{\alpha}, \sigma_{\beta}) = \text{Exponential}(1) \\
& R = \text{LKJcorr}(1)
\end{aligned}$$