Political Donor Motivations and Social Media: A Time-Series Analysis

The two predominant theories of political donor motivations are the access-oriented model (Fouirnaies and Hall 2015) and the consumption model (Ansolabehere, Figueiredo, and Snyder 2003). In the access-oriented model, individual political donors and political action committees (PACs) are assumed to contribute to campaigns in an effort to acquire access and influence politicians into supporting specific policy issues (Fouirnaies and Hall 2015). The consumption model of donors views political contributions as being an extension of voting along a participatory spectrum, and that donors support candidates who they already know support policy issues that the donors care about or are ideologically motivated (Barber 2016; Johnson 2010). Previous studies have posited these two models of political donor motivations against each other (Heerwig 2016).

This paper combines political donation records and Twitter and Facebook posts from politicians. These two datasets are analyzed together to examine if politicians' public support of various policy issues on social media precede, lag, or have no relationship with donations from various communities of political donors. The access-oriented model of political donors predicts that donations from specific groups of donors will precede public support of certain policies. In contrast, the consumption model of political donors predicts that donations from various groups of donors would lag in response to public support of certain policy issues by candidates. This paper sets these two models of political donors against each other to see if evidence of either model is found in observational data.

Data

Data for this research comes from two primary sources: politicians' social media posts and political donation data. For social media posts, this paper used the Facebook (Barbera, Geisler, and Atteveldt 2017) and Twitter (Kearney 2019) APIs to collect social media posts from all candidates for the Wisconsin State Senate and Wisconsin State Assembly during the 2016 election cycle (n = 82,851). A subset of these posts were hand-coded into 27 topical categories. This subset was used to train a BERT deep learning transfer model that was used to predict the topic of the remainder of the posts (training dataset = 8,242, 10% of total posts; testing dataset = 4,122, 5% of total posts). Political donation data for all candidates to the Wisconsin State Legislature during the 2016 election cycle were collected from the Wisconsin Campaign Information System (CFIS). These donations were used to create a network of political donations with candidates and donors serving as nodes and donations between them as edges. This network was clustered into distinct communities so that donors in each community are most similar to one another based on which campaigns they contributed to. I theorize that these clusters of donors represent *latent coalitions* of donors who, whether they operate in an organized fashion or not, are working toward the goal of electing the same candidates. Studying political fundraisers as members of political coalitions has been studied in the past (Adams 2007; Heerwig 2016), and this paper's statistically-driven definition of latent coalitions seeks to add to the coalition literature.

Methodology

These two datasets were analyzed against each other using the Granger causality time-series methodology This methodology has been used by other researchers to study social media (Freelon, McIlwain, and Clark 2018; Lukito 2020). Similar to political donations, this methodology has been used to study non-social media events such as offline protests (Bastos, Mercea, and Charpentier 2015) and stock prices (Park, Leung, and Ma 2017). This methodology detects whether movements in one time series precedes, lags, has a confounding variable, or is not related to another time series. Specifically, this paper compares time series of donations from clusters of political donors and times series of the number of social media posts by each topic that were made by campaigns that each donor cluster contributed to. For example, a time series of donations from a donor cluster was compared to the aggregate count of posts about a given topic made by candidates that the donor cluster contributed to.

Results

Initial results provide some evidence consistent with both the access-oriented and consumption models, but more coalitions of donors exhibit behavior that is consistent with the consumption model of donor motivations. In about 31% (4/13) of coalitions, donations from the coalition lagged social media posts about at least one specific topic by the candidates that they donated to–behavior that is predicted by the consumption model of donor motivations. About 15% (2/13) of coalitions showed behavior inline with the access-oriented model of donors where their donations preceded social media posts about at least one specific topic made by candidates that they contributed to. Specific results can be found in Figure 1.

The next step is to analyze potential confounding factors that could describe the motivations of political donors, such as geographic proximity or competitiveness of the races the cluster contributed to in aggregate. These factors are especially important for the coalitions that the model identified as having a confounding variable or not having a relationship.

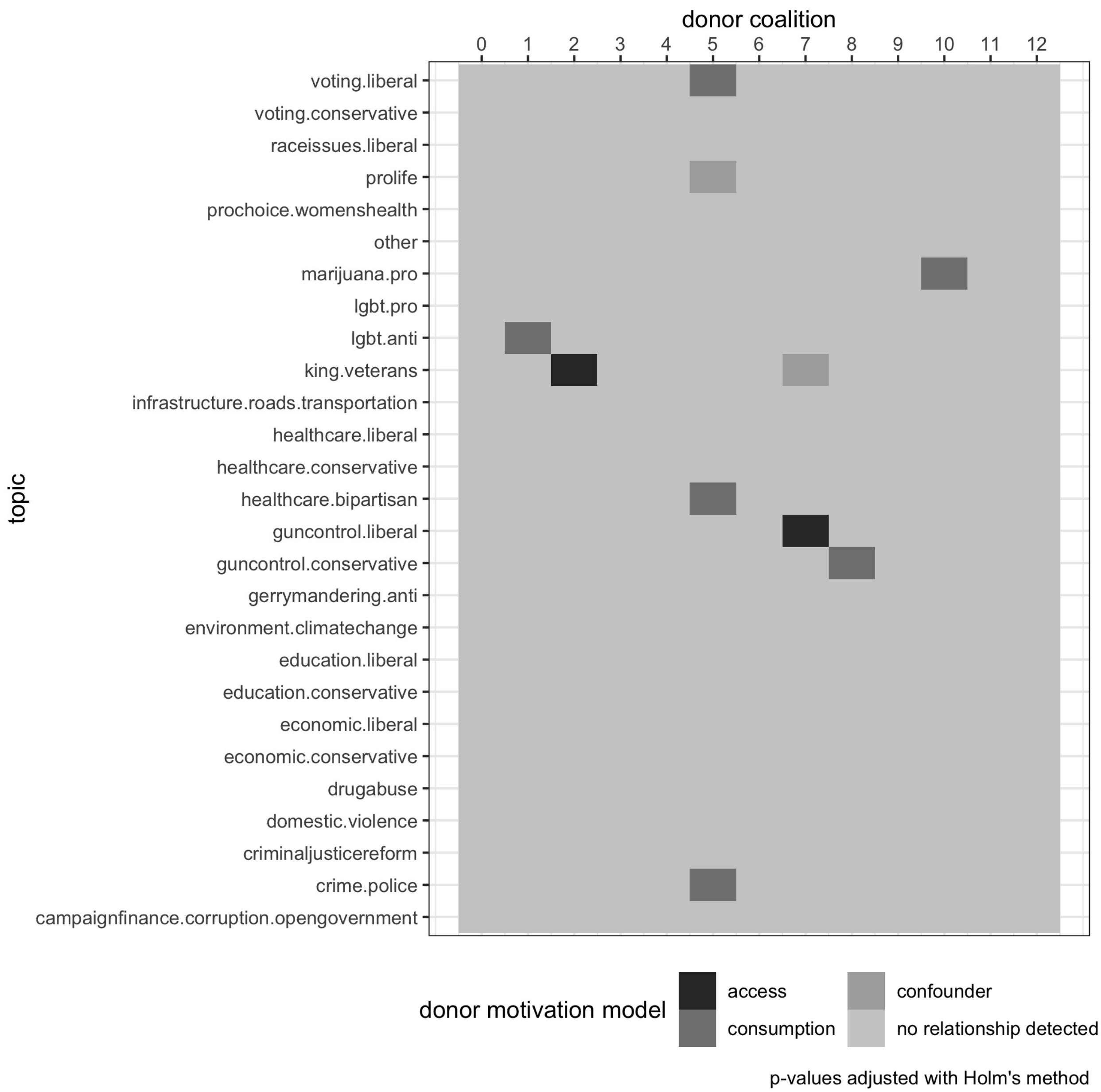

Figure 1: Donor Motivation Models

Word Count

Method	koRpus	stringi
Word count	791	780
Character count	5263	5262
Sentence count	34	Not available
Reading time	4 minutes	3.9 minutes

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