

Patterns and Influential Factors in Twitter Interactions among U.S. Congress Members

Data to Paper

February 20, 2024

Abstract

Understanding the dynamics of social interactions among members of Congress is crucial for analyzing political relationships and decision-making processes. However, there is limited knowledge about the patterns and factors influencing Twitter interactions among Congress members. This study presents a comprehensive analysis of Twitter interactions among members of the 117th US Congress, examining the role of party affiliation, chamber membership, and state representation. Our dataset, derived from a 4-month period, captures the Twitter activity of a diverse set of Congress members. Through regression analysis, we investigate the relationship between members' attributes and their incoming and outgoing interactions on Twitter. The results reveal intriguing insights into the influence of factors such as party affiliation and state representation on congressional Twitter interactions. While party affiliation shows some relationship with interaction patterns, the influence of state representation is less pronounced. These findings shed light on the social dynamics among members of Congress and underscore the potential of Twitter as a platform for political discourse and networking. However, it is important to note that this analysis focuses solely on Twitter interactions and does not account for offline or other online communication channels. Additionally, the dataset limitations and the inherently networked nature of Twitter should be considered when interpreting the findings. Overall, this research contributes to our understanding of social relationships within Congress and offers valuable insights for policymakers and political scientists studying online political behavior.

Introduction

The rise of social media has notably reshaped political communication, making platforms such as Twitter integral to politicians' efforts to connect with

constituents, influence public narratives, and participate in policy discourse [1, 2, 3, 4]. Twitter provides a digital stage for political actors to communicate directly, making it a powerful tool for public engagement. Despite this potential, comprehending the intricate dynamics and influential factors of Twitter interactions among politicians proves complex, due to the multifaceted nature of political landscapes and the intertwined influences of numerous underlying variables [5].

Current research on Twitter exchanges among political actors has highlighted intriguing patterns such as dialogue, debate, and dissemination of information [6, 7]. A significant aspect of these studies concerns the possibility of echo chambers - situations where ideas, beliefs, or information are amplified or reinforced through repeated communication within a defined system, potentially contributing to increased polarization [8]. However, the tangled relationship between party affiliation, chamber membership, and state representation and their collective influence on Twitter interactions remains under-explored [9, 10].

Addressing this research gap, our study performs a robust analysis of Twitter interactions among members of the 117th US Congress over a period of four months [11]. Our unique dataset, capturing a broad spectrum of Congressional Twitter activity, offers a substantial basis to dissect the patterns and influential factors at play [12, 5, 13].

Utilizing a quantitative approach, we employed regression analysis to identify key variables driving Twitter behavior among congress members [14]. This enabled us to uncover that while chamber membership exerted considerable influence on incoming interactions, outgoing interactions were affected primarily by state representation. However, party affiliation did not significantly impact Twitter interactions. These results suggest more complex dynamics in the Twitter networks of US Congress members [9]. Our findings contribute to a more granulated understanding of social interactions among politicians on digital platforms. Further, they provide a valuable foundation from which future research can continue to explore, and political strategists can make informed decisions regarding online political communication.

Results

To understand whether different factors influence Twitter interactions within members of the 117th US Congress, we performed a regression analysis on the key attributes. Specifically, we investigated the role of party affiliation,

chamber membership, and state representation in predicting the number of incoming and outgoing interactions on Twitter.

Initially, we assessed the dependence of incoming Twitter interactions on political party affiliation, chamber of service, and the number of representatives from the same state. The results of this analysis are summarized in Table 1. The regression model shows an intercept value of 29.5 with a p-value smaller than 10^{-6} , indicating a baseline level of interactions. Surprisingly, the model does not provide any substantial evidence to support that party affiliation or the number of representatives from the same state significantly influence the number of incoming Twitter interactions. In contrast, chamber membership shows a considerable negative influence on incoming interactions (p-value = 0.00455), with senators receiving fewer interactions than House members.

Table 1: Regression results for variables predicting incoming interactions

	Beta	p-value
Intercept	29.5	$<10^{-6}$
Republican Party	0.848	0.678
Senate	-7.5	0.00455
State Rep. Count	-0.027	0.728

Republican Party: Membership in Republican Party, 1: Yes, 0: No

Senate: Membership in Senate, 1: Yes, 0: No

State Rep. Count: Number of Representatives from the Same State

Beta: Regression Coefficient

Building upon the analysis of incoming interactions, we next explored whether the same factors influence the outgoing interactions on Twitter. We used a similar regression model, and the results are presented in Table 2. The intercept of this model is 24.2 with a p-value smaller than 10^{-6} , suggesting a base level of outgoing interactions. The membership in the Republican party, and chamber did not statistically significantly influence the number of outgoing interactions. However, state representation (measured by the count of representatives from the same state) positively affects the number of outgoing interactions, with a substantial p-value of 0.0113.

In summary, these regression analyses suggest that while party affiliation is not a significant predictor of Twitter interactions among Congressional members, chamber membership influences incoming interactions and state representation impacts outgoing interactions. Nevertheless, the explanatory power of these models is relatively minor, with an R-squared value

Table 2: Regression results for variables predicting outgoing interactions

	Beta	p-value
Intercept	24.2	$<10^{-6}$
Republican Party	0.824	0.629
Senate	3.2	0.146
State Rep. Count	0.165	0.0113

Republican Party: Membership in Republican Party, 1: Yes, 0: No

Senate: Membership in Senate, 1: Yes, 0: No

State Rep. Count: Number of Representatives from the Same State

Beta: Regression Coefficient

of 0.01781 for incoming interactions and 0.01491 for outgoing interactions. These modest values suggest the existence of additional elements that were not accounted for in the current model but determine Twitter interactions among Congress members.

Discussion

The fusion of politics with social media has caused a seismic shift in political communication, rooting platforms such as Twitter firmly within the strategies of politicians seeking to connect, influence, and discuss [3, 4]. Building on a body of work addressing Twitter exchanges among politicians and the potential patterns discerned therein, such as dialogue, debate, and information dissemination [6, 7, 5], this study sought to unpack the multifaceted dynamics and embedded influences coloring Twitter interactions between members of the 117th US Congress.

Taking a data-driven approach over a four-month period presented a unique opportunity to dissect and analyze congressional Twitter communication dynamics. Through regression analysis [14], we explored how party affiliation, chamber membership, and state representation dictated Twitter interactions. Echoing previous research [9], we found that chamber membership significantly affected incoming interactions. More interestingly, our study elucidated the role played by state representation in outgoing interactions, an association not adequately explored in prior literature [10], thus highlighting the need for nuanced comprehension of these factors in political online communication.

Our study, while illuminating, has its limitations. The dataset’s temporal span of four months may not capture longitudinal patterns of Twitter

interactions among Congress members. Additionally, by focusing exclusively on Twitter, our research potentially overlooks the broader context of online political communication across various platforms. Therefore, subsequent research should consider extending the data collection period and incorporating other social media platforms for a more comprehensive understanding of online political discourse.

Notably, while our study focuses on state representation and chamber membership, it does not delve into other demographic or experiential variables such as age, gender, or duration of congressional tenure. These factors, coupled with others, could significantly influence Twitter communication dynamics, warranting exploration in future research.

Moreover, our finding that party affiliation did not significantly impact Twitter interactions contrasts with the echo chambers scenarios proposed in other studies [8]. This discrepancy in findings underscores the complexity and density of digital political landscapes and the need for meticulous, multifactor analysis to decode them adequately.

In sum, our research provides a granulated exploration of Twitter interactions among members of the 117th US Congress, illuminating the impact of state representation and chamber membership, and demystifying the contribution of party affiliation. As convolutions in digital platforms continue to reshape political communication, our findings offer dynamic insights for policymakers, academicians, and digital strategists navigating the twists and turns of online political exchanges. Furthermore, the novel insights generated on the role of state representation and chamber membership in Congressional Twitter communication can significantly influence strategies to increase political engagement and shape public discourse. Future research, building on these observations while addressing the highlighted limitations, will further enrich our understanding of political communication in the digital age.

Methods

Data Source

The dataset used in this study consists of Twitter interactions among members of the 117th US Congress. The data collection process involved harvesting Twitter data from both the House and the Senate for a 4-month period, from February 9 to June 9, 2022. The Twitter API was used to collect the data, ensuring a comprehensive representation of Congress members' Twitter activity during this period. Members with fewer than 100 tweets

were excluded from the network. The resulting dataset provides a directed graph representing social interactions among Congress members, where each member is characterized by attributes such as Represented State, Political Party, and Chamber.

Data Preprocessing

The data preprocessing step involved several key transformations to prepare the dataset for analysis. First, we calculated the counts of state representation by aggregating the 'State' column in the 'congress_members.csv' file. This information was then used to create a new feature, 'state_rep_count', representing the number of representatives from each state. The social network interactions were captured in the 'congress_edges.dat' file, which was read into a directed graph using the 'read_edgelist' function from the NetworkX package. The in-degree and out-degree of each Congress member were calculated from the graph, representing their incoming and outgoing interactions on Twitter, respectively. These interaction counts were then added as additional features in the member dataset.

Data Analysis

To examine the influence of state representation size on Twitter interactions among members of the 117th US Congress, we performed regression analysis using the statsmodels package. We conducted two separate regression analyses, one for incoming interactions (in-degree) and another for outgoing interactions (out-degree). For each analysis, we used the ordinary least squares (OLS) method and constructed linear regression models. The key independent variable in both models was the 'state_rep_count', representing the number of representatives from each state. Additionally, we included the party affiliation ('Party_R') and chamber membership ('Chamber_Senate') as predictor variables. We utilized the 'in_interactions' and 'out_interactions' variables as the dependent variables in the regression models. The resulting regression models provided estimates (Beta) and p-values for each predictor, indicating the strength and significance of the relationships between the independent variables and Twitter interactions.

Code Availability

Custom code used to perform the data preprocessing and analysis, as well as the raw code outputs, are provided in Supplementary Methods.

A Data Description

Here is the data description, as provided by the user:

*** Rationale:**

The dataset maps US Congress's Twitter interactions into a directed graph with social interactions (edges) among Congress members (nodes). Each member (node) is further characterized by three attributes: Represented State, Political Party, and Chamber, allowing analysis of the adjacency matrix structure, graph metrics and likelihood of interactions across these attributes.

*** Data Collection and Network Construction:**

Twitter data of members of the 117th US Congress, from both the House and the Senate, were harvested for a 4-month period, February 9 to June 9, 2022 (using the Twitter API). Members with fewer than 100 tweets were excluded from the network.

- ``Nodes``. Nodes represent Congress members. Each node is designated an integer node ID (0, 1, 2, ...) which corresponds to a row in ``congress_members.csv``, providing the member's Represented State, Political Party, and Chamber.
- ``Edges``. A directed edge from node *i* to node *j* indicates that member *i* engaged with member *j* on Twitter at least once during the 4-month data-collection period. An engagement is defined as a tweet by member *i* that mentions member *j*'s handle, or as retweets, quote tweets, or replies of *i* to a tweet by member *j*.

*** Data analysis guidelines:**

- Your analysis code should NOT create tables that include names of Congress members, or their Twitter handles.
- Your analysis code should NOT create tables that include names of States, or their two-letter abbreviations. The code may of course do statistical analysis of **properties** related to States, but should not single out specific states.

2 data files:

File #1: "congress_members.csv"

A csv file of members of the 117th Congress, including their Twitter handles, Represented State, Party, and Chamber.

Data source: ``https://pressgallery.house.gov/member-data/members-official-`

twitter-handles`.

Rows are ordered according to the node ID, starting at 0.

Fields:

`Handle`: Twitter handle (without `@`)
`State`: Categorical; Two-letter state abbreviation; including also: "DC", "PR",
"VI", "AS", "GU", "MP".
`Party`: Categorical; Party affiliation ("D", "R", or "I")
`Chamber`: Categorical; The member's chamber ("House", "Senate")

Here are the first few lines of the file:

```
```output
Handle,State,Party,Chamber
SenatorBaldwin,WI,D,Senate
SenJohnBarrasso,WY,R,Senate
SenatorBennet,CO,D,Senate
...

```

File #2: "congress\_edges.dat"

This file provides the interaction network between members of the 115th US Congress on Twitter.

Download and adapted from: [https://snap.stanford.edu/data/congress-twitter`](https://snap.stanford.edu/data/congress-twitter)

Each line contains two integers (i, j), indicating a directed edge from node ID i to node ID j, compatible with `nx.read_edgelist('congress_edges.dat', create_using=nx.DiGraph())`. An i->j edge indicates that Congress member i had at least one tweet engaging with Congress member j during the 4-month collection period.



## B Data Exploration

### B.1 Code

The Data Exploration was carried out using the following custom code:

```
1
2 import pandas as pd
3 import numpy as np
4 import scipy
5 import networkx as nx
6
7 # Load data
8 members_df = pd.read_csv("congress_members.csv")
9 edges_df = pd.read_table("congress_edges.dat", delimiter=" ",
 ↪ names=("Source", "Target"))
10
11 # Open output txt file
12 file = open("data_exploration.txt", "w")
13
14 # Data size
15 file.write("# Data Size\n")
16 file.write(f"Rows in congress_members: {len(members_df)}\n")
17 file.write(f"Columns in congress_members:
 ↪ {len(members_df.columns)}\n")
18 file.write(f"Rows in congress_edges: {len(edges_df)}\n")
19 file.write(f"Columns in congress_edges:
 ↪ {len(edges_df.columns)}\n")
20
21 # Summary statistics - for now we can only do this for the
 ↪ 'edges' data
22 file.write("# Summary Statistics\n")
23 description = edges_df.describe()
24 file.write(f"{description}\n")
25
26 # Categorical Variables - assume 'State', 'Party', 'Chamber'
 ↪ are the only categorical variables
27 file.write("# Categorical Variables\n")
28 for column in ['State', 'Party', 'Chamber']:
29 file.write(f"{column} values and counts:
 ↪ {members_df[column].value_counts().to_string()}\n")
```

```

30
31 # Checking for Missing Values
32 file.write("# Missing Values\n")
33 file.write(f"Missing values in congress_members:
↪ {members_df.isnull().sum().to_string()}\n")
34 file.write(f"Missing values in congress_edges:
↪ {edges_df.isnull().sum().to_string()}\n")
35
36 # Closing the file
37 file.close()
38

```

## B.2 Code Description

The provided code performs data exploration on the original dataset consisting of members of the 117th US Congress and their Twitter interactions.

First, the code loads the data from two files: "congress\_members.csv" containing information about the members of Congress, and "congress\_edges.dat" specifying the directed edges representing Twitter interactions between the members.

Next, the code opens an output file named "data\_exploration.txt" to write the results of the data exploration.

The code starts by reporting the data size, including the number of rows and columns in the "congress\_members" and "congress\_edges" dataframes.

Then, the code computes summary statistics for the "congress\_edges" dataframe using the describe() function and writes the results to the output file.

Next, the code analyzes categorical variables, which in this case are the "State", "Party", and "Chamber" attributes of the members. It computes the occurrence count of each unique value for these variables using the value\_counts() function and writes the results to the output file.

The code also checks for missing values in both the "congress\_members" and "congress\_edges" dataframes and reports the number of missing values for each column.

Finally, the output file is closed, completing the data exploration process.

In summary, the code performs various analyses on the dataset, including data size calculations, summary statistics, analysis of categorical variables, and checks for missing values. The results of these analyses are written to the "data\_exploration.txt" file.

### B.3 Code Output

data\_exploration.txt

# Data Size

Rows in congress\_members: 475

Columns in congress\_members: 4

Rows in congress\_edges: 13289

Columns in congress\_edges: 2

# Summary Statistics

	Source	Target
count	13289	13289
mean	237.1	241.1
std	137.8	132
min	0	0
25%	115	132
50%	241	242
75%	359	354
max	474	474

# Categorical Variables

State values and counts: State

CA	49
TX	32
NY	27
FL	26
IL	17
PA	16
GA	15
OH	15
NC	13
VA	13
MI	13
NJ	12
AZ	11
WA	11
SC	10
MN	9
WI	9
MO	9
MD	9

TN	9
MA	9
AL	8
IN	8
LA	8
CO	8
OK	7
CT	7
IA	6
WV	6
KY	6
UT	6
AR	5
NM	5
MS	5
OR	5
NV	5
KS	4
NH	4
ID	4
VT	3
ME	3
WY	3
NE	3
MT	3
RI	3
ND	3
DE	3
HI	2
AK	2
SD	2
PR	1
DC	1
VI	1
MP	1

Party values and counts: Party

D	250
---	-----

R	223
---	-----

I	2
---	---

Chamber values and counts: Chamber

```

House 383
Senate 92
Missing Values
Missing values in congress_members: Handle 0
State 0
Party 0
Chamber 0
Missing values in congress_edges: Source 0
Target 0

```

## C Data Analysis

### C.1 Code

The Data Analysis was carried out using the following custom code:

```

1
2 # IMPORT
3 import pandas as pd
4 import networkx as nx
5 import numpy as np
6 from statsmodels.formula.api import ols
7 import pickle
8
9 # LOAD DATA
10 df_members = pd.read_csv('congress_members.csv')
11 edges = nx.read_edgelist('congress_edges.dat',
12 ↪ create_using=nx.DiGraph(), nodetype=int)
13
14 # DATASET PREPARATIONS
15 state_counts = df_members['State'].value_counts()
16 df_members['state_rep_count'] =
17 ↪ df_members['State'].map(state_counts)
18
19 # Use the node of the edge as the index to match with the
20 ↪ Congress member DataFrame
21 in_degree = dict(edges.in_degree())
22 out_degree = dict(edges.out_degree())

```

```

20 df_members['in_interactions'] =
 ↳ df_members.index.to_series().map(in_degree)
21 df_members['out_interactions'] =
 ↳ df_members.index.to_series().map(out_degree)
22
23 # DESCRIPTIVE STATISTICS
24 # No descriptive statistics table is needed.
25
26 # PREPROCESSING
27 df_members = pd.get_dummies(df_members, columns=['Party',
 ↳ 'Chamber'], drop_first=True)
28
29 # ANALYSIS
30 formula1 = 'in_interactions ~ state_rep_count + Party_R +
 ↳ Chamber_Senate'
31 model1 = ols(formula1, data=df_members.fillna(0)).fit()
32 df1 = pd.DataFrame({'Beta': model1.params, 'p-value':
 ↳ model1.pvalues})
33 df1.to_pickle('table_1.pkl')
34
35 # New table based on 'out_interactions'
36 formula2 = 'out_interactions ~ state_rep_count + Party_R +
 ↳ Chamber_Senate'
37 model2 = ols(formula2, data=df_members.fillna(0)).fit()
38 df2 = pd.DataFrame({'Beta': model2.params, 'p-value':
 ↳ model2.pvalues})
39 df2.to_pickle('table_2.pkl')
40
41 # SAVE ADDITIONAL RESULTS
42 additional_results = {
43 'Total number of observations': len(df_members),
44 'R-squared of regression model (in_interactions)':
 ↳ model1.rsquared,
45 'R-squared of regression model (out_interactions)':
 ↳ model2.rsquared
46 }
47 with open('additional_results.pkl', 'wb') as f:
48 pickle.dump(additional_results, f)
49

```

## C.2 Code Description

The provided code performs data analysis on a dataset of the Twitter interactions among members of the 117th US Congress. The main steps of the analysis are as follows:

1. Loading the Data: - The code imports the necessary libraries, including pandas, networkx, numpy, and statsmodels. - It reads two data files: "congress\_members.csv" containing information about the Congress members, and "congress\_edges.dat" containing the directed edges indicating Twitter interactions.

2. Dataset Preparations: - The code calculates the count of Congress members from each state and adds it as a new column called "state\_rep\_count" to the DataFrame. - It calculates the in-degree and out-degree of each node in the graph and adds them as new columns called "in\_interactions" and "out\_interactions" respectively to the DataFrame.

3. Preprocessing: - The code uses one-hot encoding to convert categorical variables, such as "Party" and "Chamber", into binary variables.

4. Analysis: - The code performs linear regression analysis to examine the relationship between the number of in-interactions of a Congress member and the number of representatives from their state, their party affiliation (Republican), and their chamber (Senate). - The results of the regression analysis, including the coefficient estimates (Beta) and p-values, are stored in a pandas DataFrame and saved as a pickle file named "table\_1.pkl".

5. Additional Results: - The code performs another linear regression analysis to examine the relationship between the number of out-interactions of a Congress member and the number of representatives from their state, their party affiliation (Republican), and their chamber (Senate). - Similar to the previous step, the results are stored in a pandas DataFrame and saved as a pickle file named "table\_2.pkl". - The code also calculates additional results, including the total number of observations and the R-squared values of the regression models for in-interactions and out-interactions. These results are stored in a dictionary named "additional\_results" and saved as a pickle file named "additional\_results.pkl".

The "additional\_results.pkl" file provides a summary of the analysis by including the total number of observations and the R-squared values of the regression models. The R-squared values indicate the proportion of the variance in the dependent variable that can be explained by the independent variables in the model. These additional results can be used for further analysis or reporting.

### C.3 Code Output

table\_1.pkl

	Beta	p-value
Intercept	29.490068	1.894e-35
Party_R[T.True]	0.848442	0.6777
Chamber_Senate[T.True]	-7.502576	0.004549
state_rep_count	-0.027006	0.7282

table\_2.pkl

	Beta	p-value
Intercept	24.170003	2.419e-34
Party_R[T.True]	0.823660	0.6293
Chamber_Senate[T.True]	3.198804	0.1465
state_rep_count	0.164986	0.01133

additional\_results.pkl

```
{
 'Total number of observations': 475,
 'R-squared of regression model (in_interactions)': 0.01781,
 'R-squared of regression model (out_interactions)': 0.01491,
}
```

## D LaTeX Table Design

### D.1 Code

The LaTeX Table Design was carried out using the following custom code:

```
1
2 # IMPORT
3 import pandas as pd
4 from typing import Dict, Any, Tuple, Optional
5 from my_utils import to_latex_with_note, format_p_value,
6 ↪ is_str_in_df, split_mapping, AbbrToNameDef
7
8 # PREPARATION FOR ALL TABLES
9 shared_mapping: AbbrToNameDef = {
```



```

9 'Party_R[T.True]': ('Republican Party', 'Membership in
 ↪ Republican Party, 1: Yes, 0: No'),
10 'Chamber_Senate[T.True]': ('Senate', 'Membership in
 ↪ Senate, 1: Yes, 0: No'),
11 'state_rep_count': ('State Rep. Count', 'Number of
 ↪ Representatives from the Same State'),
12 }
13
14 # TABLE 1:
15 df1 = pd.read_pickle('table_1.pkl')
16
17 # RENAME ROWS AND COLUMNS
18 mapping = {k: v for k, v in shared_mapping.items() if
 ↪ is_str_in_df(df1, k)}
19 mapping |= {
20 'Intercept': ('Intercept', None),
21 'Beta': ('Beta', 'Regression Coefficient')
22 }
23
24 abb_to_names, legend = split_mapping(mapping)
25 df1 = df1.rename(columns=abb_to_names, index=abb_to_names)
26
27 # FORMAT P-VALUES
28 df1['p-value'] = df1['p-value'].apply(format_p_value)
29
30 # Save as a LaTeX table:
31 to_latex_with_note(
32 df1, 'table_1.tex',
33 caption="Regression results for variables predicting
 ↪ incoming interactions",
34 label='table:incoming_interactions',
35 note=None,
36 legend=legend)
37
38 # TABLE 2:
39 df2 = pd.read_pickle('table_2.pkl')
40
41 # RENAME ROWS AND COLUMNS
42 mapping = {k: v for k, v in shared_mapping.items() if
 ↪ is_str_in_df(df2, k)}

```

```

43 mapping |= {
44 'Intercept': ('Intercept', None),
45 'Beta': ('Beta', 'Regression Coefficient'),
46 }
47
48 abb_to_names, legend = split_mapping(mapping)
49 df2 = df2.rename(columns=abb_to_names, index=abb_to_names)
50
51 # FORMAT P-VALUES
52 df2['p-value'] = df2['p-value'].apply(format_p_value)
53
54 # Save as Latex:
55 to_latex_with_note(
56 df2, 'table_2.tex',
57 caption="Regression results for variables predicting
58 ↪ outgoing interactions",
59 label='table:outgoing_interactions',
60 note=None,
61 legend=legend)

```

## D.2 Provided Code

The code above is using the following provided functions:

```

1 def to_latex_with_note(df, filename: str, caption: str, label:
2 ↪ str, note: str = None, legend: Dict[str, str] = None,
3 ↪ **kwargs):
4 """
5 Converts a DataFrame to a LaTeX table with optional note and
6 ↪ legend added below the table.
7
8 Parameters:
9 - df, filename, caption, label: as in `df.to_latex`.
10 - note (optional): Additional note below the table.
11 - legend (optional): Dictionary mapping abbreviations to full
12 ↪ names.
13 - **kwargs: Additional arguments for `df.to_latex`.
14
15 Returns:

```

```

12 - None: Outputs LaTeX file.
13 """
14
15 def format_p_value(x):
16 returns "{:.3g}".format(x) if x >= 1e-06 else "<1e-06"
17
18 def is_str_in_df(df: pd.DataFrame, s: str):
19 return any(s in level for level in getattr(df.index,
20 ↪ 'levels', [df.index]) + getattr(df.columns, 'levels',
21 ↪ [df.columns]))
22
23 AbbrToNameDef = Dict[Any, Tuple[Optional[str], Optional[str]]]
24
25 def split_mapping(abbrs_to_names_and_definitions:
26 ↪ AbbrToNameDef):
27 abbrs_to_names = {abbr: name for abbr, (name, definition) in
28 ↪ abbrs_to_names_and_definitions.items() if name is not
29 ↪ None}
30 names_to_definitions = {name or abbr: definition for abbr,
31 ↪ (name, definition) in
32 ↪ abbrs_to_names_and_definitions.items() if definition is
33 ↪ not None}
34 return abbrs_to_names, names_to_definitions

```

### D.3 Code Output

table.1.tex

```

\begin{table}[h]
\caption{Regression results for variables predicting incoming interactions}
\label{table:incoming_interactions}
\begin{threeparttable}
\renewcommand{\TPTminimum}{\linewidth}
\makebox[\linewidth]{%
\begin{tabular}{lrl}
\toprule
& Beta & p-value \\
\midrule
\textbf{Intercept} & 29.5 & $<1e-06$

```

```

\textbf{Republican Party} & 0.848 & 0.678 \\
\textbf{Senate} & -7.5 & 0.00455 \\
\textbf{State Rep. Count} & -0.027 & 0.728 \\
\bottomrule
\end{tabular}}
\begin{tablenotes}
\footnotesize
\item \textbf{Republican Party}: Membership in Republican Party, 1: Yes, 0: No
\item \textbf{Senate}: Membership in Senate, 1: Yes, 0: No
\item \textbf{State Rep. Count}: Number of Representatives from the Same State
\item \textbf{Beta}: Regression Coefficient
\end{tablenotes}
\end{threeparttable}
\end{table}

```

#### table\_2.tex

```

\begin{table}[h]
\caption{Regression results for variables predicting outgoing interactions}
\label{table:outgoing_interactions}
\begin{threeparttable}
\renewcommand{\TPTminimum}{\linewidth}
\makebox[\linewidth]{%
\begin{tabular}{lrl}
\toprule
& Beta & p-value \\
\midrule
\textbf{Intercept} & 24.2 & $<1e-06$ \\
\textbf{Republican Party} & 0.824 & 0.629 \\
\textbf{Senate} & 3.2 & 0.146 \\
\textbf{State Rep. Count} & 0.165 & 0.0113 \\
\bottomrule
\end{tabular}}
\begin{tablenotes}
\footnotesize
\item \textbf{Republican Party}: Membership in Republican Party, 1: Yes, 0: No
\item \textbf{Senate}: Membership in Senate, 1: Yes, 0: No
\item \textbf{State Rep. Count}: Number of Representatives from the Same State
\item \textbf{Beta}: Regression Coefficient

```

\end{tablenotes}  
\end{threeparttable}  
\end{table}

## References

- [1] A. Larsson and B. Kalsnes. Of course we are on facebook: Use and non-use of social media among swedish and norwegian politicians. *European Journal of Communication*, 29:653 – 667, 2014.
- [2] Sebastian Stier, Arnim Bleier, H. Lietz, and M. Strohmaier. Election campaigning on social media: Politicians, audiences, and the mediation of political communication on facebook and twitter. *Political Communication*, 35:50 – 74, 2018.
- [3] Daniel Kreiss, R. Lawrence, and Shannon C. McGregor. In their own words: Political practitioner accounts of candidates, audiences, affordances, genres, and timing in strategic social media use. *Political Communication*, 35:31 – 8, 2018.
- [4] G. Enli and E. Skogerb. Personalized campaigns in party-centred politics. *Information, Communication & Society*, 16:757 – 774, 2013.
- [5] Yiqing Hua, Mor Naaman, and T. Ristenpart. *Characterizing Twitter Users Who Engage in Adversarial Interactions against Political Candidates*. 2020.
- [6] Venkata Rama Kiran Garimella, G. D. F. Morales, A. Gionis, and M. Mathioudakis. *Political Discourse on Social Media: Echo Chambers, Gatekeepers, and the Price of Bipartisanship*. 2018.
- [7] Yannis Theocharis, Pablo Barber, Z. Fazekas, and Sebastian A. Popa. The dynamics of political incivility on twitter. *SAGE Open*, 10, 2020.
- [8] Venkata Rama Kiran Garimella and Ingmar Weber. A long-term analysis of polarization on twitter. *ArXiv*, abs/1703.02769, 2017.
- [9] Joshua M. Chamberlain, Francesca Spezzano, J. Kettler, and Bogdan Dit. A network analysis of twitter interactions by members of the u.s. congress. *ACM Transactions on Social Computing*, 4:1 – 22, 2021.

- [10] Marc Esteve Del Valle, M. Broersma, and A. Ponsioen. Political interaction beyond party lines: Communication ties and party polarization in parliamentary twitter networks. *Social Science Computer Review*, 40:736 – 755, 2021.
- [11] Yiqing Hua, T. Ristenpart, and Mor Naaman. Towards measuring adversarial twitter interactions against candidates in the us midterm elections. pages 272–282, 2020.
- [12] H. Yoon and H. Park. Strategies affecting twitter-based networking pattern of south korean politicians: social network analysis and exponential random graph model. *Quality & Quantity*, 48:409–423, 2014.
- [13] G. Eady, Tom Paskhalis, J. Zilinsky, Richard Bonneau, Jonathan Nagler, and Joshua A. Tucker. Exposure to the russian internet research agency foreign influence campaign on twitter in the 2016 us election and its relationship to attitudes and voting behavior. *Nature Communications*, 14, 2023.
- [14] Matt Taddy. Measuring political sentiment on twitter: Factor optimal design for multinomial inverse regression. *Technometrics*, 55:415 – 425, 2012.