

Tweet It Like You Mean It: Relationships Between Police Reform Legislation and Governor Twitter Behavior

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Abstract

We investigate whether state governors' twitter habits regarding the Black Lives Matter (BLM) movement correlates with passage of police reform laws in the state policy adoption network. Politicians have been increasingly using Twitter to communicate their stances on important issues such as the BLM movement, but little work has been done to investigate whether they follow up on these stances with legislative action. Tweets were classified as either related to BLM and/or pro-BLM or not using gradient-boosted trees. By investigating the passage of police reform laws from May 2020-May 2021, we find no significant impact of BLM and/or pro-BLM tweeting rates when treating states/governors as a network or as independent observations. Future research should focus on refining tweet topic classification and broadening the scope of tweet/legislation topics studied.

Keywords: BLM, Twitter, Social network analysis

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1 Introduction

Twitter users often observe elected officials communicating their stance on political issues or making promises of policy change via Twitter. Politicians and their teams invest significant effort into curating a tweets and communicating with the public via online social networking sites. When evaluating the political performance of politicians, we expect that they “practice what they preach” and at least make good-faith attempts to pass legislation regarding issues they have publicly tweeted their support for. However, it is difficult to know whether tweeting about an issue predicts passage of legislation without actively seeking out this information. In the context of the Black Lives Matter movement, politicians were facing unprecedented societal pressure to crack down on police violence and enact substantial police reform laws. Though a controversial issue that saw many bills die in committee in Congress, the states had more power to pass police reform legislation if pursued. This provides the motivation of our work investigating whether tweeting similarly and at all about the Black Lives Matter movement correlates with similar police reform policy adoption.

We employed a gradient-boosted tree topic-classification algorithm to classify tweets as either BLM and/or pro-BLM or not. We then employed network regression models regressing state shared police reform bills on difference in proportion of BLM and pro-BLM tweets, contiguity, difference in % Black population, difference in % white population, difference in state % urban, difference in median income, and difference in state ideology. We find no significant relationships between number of shared bills and any of the predictors included. This prompted further monadic analyses regressing number of police reform laws passed on BLM and pro-BLM tweeting proportion, urban index, % white, % Black, median income, population size, and ideology score for all states and only states that passed at least one police reform law. We find significant relationships between BLM tweeting and police reform law passage only when filtering for states that passed at least one bill, pointing to the need for further study and inclusion of police reform bills passed outside the studied window.

2 Literature Review

2.1 Politician use of Twitter

Social media has become an increasingly pervasive presence in our daily lives and its impact has been far-reaching. Consequently, social media has been increasingly used in a political context. There are several studies regarding the use of social media in general and in a political context. Many studies have focused on the way politicians use social media, finding that common motivations are a desire to grow their support base (sometimes by inciting an extreme reaction), to disseminate information, and to network with other politicians. Hemsley (2019) finds that in the context of the U.S. 2014 gubernatorial election, candidates for governor used Twitter to advocate for themselves, their policies, what they believe in, and calls-to-action in addition to attacks on their opponents and their policies. Further, Hemsley finds that the the most popular tweets that reach the widest audience are call-to-action and attack tweets. Therefore political candidates wishing to broaden their support base may disproportionately send out attack or call-to-action tweets. In the Korean political context, Park et al. (2016) find that Tweets from leading government officials are more likely to increase citizen perceptions of credibility in a government Twitter feeds and government overall. This use of Twitter as a mechanism for politicians to increase trust in government also appears in the U.S., where Song & Lee (2015) find that government use of social media websites increases perceived government transparency and citizens' trust in government. Notably, Song and Lee's work used 2009 survey data, and may not be consistent with current public perception of government Twitter feeds, and Park et al.'s work may not be applicable in the U.S. political context. Former U.S. president Donald Trump, the highest elected official in the U.S. from 2016-2020, frequently made false or misleading claims on Twitter, and these false or misleading tweets were among his most popular (Rattner, 2021).

The way politicians are using Twitter can also be broken down by party, gender, and incumbency, among other factors. Evans et al. (2014) offer a more granular analysis of how politicians are using Twitter in their study of candidates for the 2012 U.S. House. They find that women tweet more overall and are more likely to criticize their opponents.

It may be true that female candidates have to work harder to grow their support base, as they are underrepresented in many areas of U.S. government, and may face gender-specific roadblocks to getting elected (Bos et al., 2018). Paired with Hemsley’s findings, it is possible that female political candidates tweet more opponent-criticizing or “attack” messages in an attempt to produce more viral tweets and grow their support base. However, our study focuses on state governor Tweeting during the height of the Black Lives Matter movement, and thus the findings of Evans et al. may not correlate with trends observed in our data. Additionally, our data was not collected during an election cycle, and thus opponent-attacking and campaigning tweets are likely not as prevalent in the dataset. Pivoting to studying politician use of Twitter specific to the BLM movement, Panda et al. (2020) find that in a study of Tweets from 520 U.S. Congress members that Democrats are more likely to tweet about the movement in general and express their concern for police brutality, while Republicans are less likely to tweet about the movement overall and more likely to express concern about perceived protest violence associated with the movement. Because of these findings, we hypothesize that Democrat (and possible female) governors will be more likely to tweet about BLM and police reform overall.

2.2 Black Lives Matter movement and Twitter

The Black Lives Matter (BLM) movement, which peaked in support following the murder of George Floyd, and declined in support from June 2020 - August 2020, has had a steady support level since (Horowitz). Twitter and social media websites played critical roles in helping the movement build momentum during this time period. Mundt et al. (2018) note that Twitter was critical in helping the BLM movement expand and strengthen its internal ties by decreasing roadblocks to organizing and amplifying narratives, among other mechanisms. Freelon et al. (2018) find that BLM, categorized as a powerful Twitter social movement, was correlated with increased mainstream news coverage of issues relevant to the movement, such as police brutality, which is the strongest attention driver for political elites. Americans look to their elected officials for leadership and support regarding contentious and relevant public issues, and this is often portrayed by citizens and organizations communicating with politicians via Twitter and calling on them to take action on

important issues. For example, The Campaign to End Qualified Immunity [@campaign-toendqi] (2023) recently tweeted that Congress should revive efforts to pass the Justice in Policing Act, a call to action that is not uncommon among social movements active on Twitter. Additionally, the Black Lives Matter [@Blklivesmatter] (2021) tagged Nancy Pelosi in a tweet responding to her commentary on the death of George Floyd, showcasing that Twitter is a direct communication line to public officials that is more convenient and public than traditional methods of citizen-politician communication such as letter-writing or emailing.

Citizens rely on elected officials to implement policy and make change when the public is faced with injustices. It is important for politicians to tweet support for certain policies or ideas, but besides declarations of signing bills into law or cosponsoring legislation, how does the public know if this support holds up when it comes time to vote? For example, Governor Jay Inslee [@GovInslee] (2020), governor of the state of Washington, tweeted during the height of the BLM movement’s popularity that Washington’s state government is “going to take a hard look at how we manage independent investigations of police use of force in WA”. However, it is not known empirically whether this show of support resulted in legislative action being taken unless citizens seek it out or he publicly communicates the passage of a law, as Massachusetts governor Charlie Baker [@MAGovArchive] (2020) and California governor Gavin Newsom [@GavinNewsom] (2019) did when they passed comprehensive police reform legislation in 2020 and new standards for police use of force in 2019, respectively.

2.3 State Policy Adoption

State policy reform is a complex process that cannot be captured by the actions of an individual state governor alone. There has been much scholarship in the field of policy diffusion and investigation of the factors and underlying network that cause states to adopt certain policies. In their study of the correlation between perceived state similarity and similar policy adoption, Bricker & LaCombe (2021) find that factors like perceived state similarity, legislative professionalism, population size differences, and different partisan control of state legislatures can significantly impact whether a state will adopt a policy

similar to a policy previously adopted by another state. Desmarais et al. (2015) model a latent underlying state policy diffusion network that correlates with media state policy emulation stories, finding that California tops the list, especially in more recent years (2005-2009), as a leading policy innovator. Overall, we know that there is non-independence among states regarding choice of policy adoption, which is something we control for in our analysis by treating state policy adoption as a network object.

In addition to the independent variable of governor Twitter behavior, we use state control variables as identified by Bricker and LaCombe, 2020. Their pooled dyadic event history analysis predicting similar policy adoption features 9 state level attributes, of which we selected contiguity, percent white, median income, population, percent urban, and census region. (variables may change) Contiguity is defined as a binary value of shared state borders. (more codebook definitions) We additionally include a measure of percent Black to account for Black Lives Matter movement interests. The state level attributes are sourced from the Correlates of State Policy dataset, which contains over 3000 variables representing political, social, and economic impacts on policy. The dataset covers all 50 states and spans the time period approximately 1900-2020.

2.4 The Relationship Between Twitter and Police-Reform Policy Adoption

From the selected studies and tweets, we’ve found that politicians use Twitter for increasing credibility and transparency, building a support base, and communicating their support for policies and ideas, and that Twitter has immense power in helping social movements expand their reach and influence, and communicate with political elites. However, no studies have been found that investigate whether promises made, stances declared, or movements talked about by politicians via Twitter correlate with how they implement policies. Because policy adoption has an underlying non-independent network structure, we transformed our governor Tweeting habits into a network object to understand if these networks are correlated.

We investigate if similar governor tweeting habits regarding the Black Lives Matter movement during its peak correlate with police reform policy adoption in their respective

states. We hypothesize that state governors tweeting similarly about BLM will positively correlate with their states adopting similar police reform policies. But tweeting similarly can mean different things. We specifically hypothesize that states with governors who tweet about BLM more in general will be more likely to adopt similar police reform policies, given the results that tweeting more frequently about BLM often goes hand-in-hand with being more pro-BLM. We also hypothesize that states with governors who tweet positively about the BLM movement more often will likely adopt similar police reform policies, as these state governors are likely more sympathetic towards the movement and more willing to make change. Lastly, we hypothesize that states with governors who tweet negatively about the BLM movement more often will likely adopt few police reform policies, as these state governors are likely less sympathetic towards the movement and less willing to make change.

3 Hypotheses

Hypothesis₁ : Democrat and female governors will be more likely to tweet about BLM and police reform overall.

Hypothesis₂ : States with governors who tweet about BLM more in general will be more likely to adopt similar police reform policies.

Hypothesis₃ : States with governors who both tweet positively about the BLM movement more often will likely adopt similar police reform policies.

Hypothesis₄ : States with governors who tweet negatively about the BLM movement more often will likely adopt few police reform policies.

4 Methods

Our governor Twitter dataset contains full Twitter data of US state governors over the period of May 1, 2020 to October 31, 2020. It was acquired from the open dataset by Zhaozhi Li and Chenglin Zhang from an article titled “Senators’ Response to Black Lives Matter during the 2020 Election Campaign: Evidence from Twitter”. The original web scraping was conducted using the Selenium Python package. The dataset includes 30,490 tweets with the associated governor name, party, Twitter account, time, and text. The text contains the main body of the tweet as well as any hashtags (e.g. #BackTheBlue, #BlackLivesMatter, #COVID19).

The time period of the tweet data overlaps with the murder of George Floyd by police officer Derek Chauvin on May 25, 2020, an event that incited nationwide and global protests in the following months against police brutality, white supremacy, and structural racism under the common message: Black Lives Matter. The demands of these community-led uprisings included calls to “Defund the Police,” restructuring local budgets and law enforcement and instead invest in community programs such as mental health responders, supportive housing, and violence prevention.

Joint methods of key term identification and binary classification were used to label the full set of tweets with the binary designation of content relating to George Floyd, the Black Lives Matter movement, or policing. From here, we will use “on topic” to refer to text that represents any of these connected topics.

```
on_topic <- c('Floyd', 'Breonna', 'Breonna Taylor', 'BLM', 'blm', 'Black Lives Matter',
'lack lives matter', 'protest', 'justice', 'racis', 'law enforcement', 'police', '#BackTheBlue')
off_topic <- c('COVID', 'virus', 'social distanc', 'nurse', 'hospital', 'health', 'mask', 'test-
ing', 'unemployment', 'schools', 'positive', 'PPE', 'ballot', 'vote', 'census', 'symptom', 'pan-
demic', 'econom', 'octor')
```

These were then sub-categorized as aligned with or against the broad demands of the Black Lives Matter movement. Pro- tweets encompassed those sympathetic to George Floyd, Breonna Taylor, and other victims of police brutality; messaging regarding police reforms or defunding; anti-racist and pro-equality statements. Anti- tweets decried the need for mass protest and civil unrest; contained expressions of support for law enforcement; or denigrated the legitimacy of the movement.

We employed a topic classification algorithm using gradient-boosted trees and 5-fold cross validation. Gradient-boosted trees are a boosted sum of trees model that are able to integrate gradient descent to improve accuracy. We used the methods outline in [CITE] with binary classifications (pro-BLM vs not, BLM vs not). Topic classification, otherwise known as text classification, is a supervised text mining method and a sub-field of natural language processing (NLP) machine learning. As a supervised The model was trained on a sample of approximately 3,500 hand-labeled tweets. Each instance could be a) on topic, b) pro-BLM/pro-reform/anti-police, and/or c) pro-police/anti-BLM. Most tweets could be

categorized into either of the latter two groups.

@(Jay Inslee): “Together, we grieve for the death of George Floyd, and many, many others. The events in Minnesota and across the nation the past few nights have been stunning and illustrate how inequity causes people to lose faith in their public institutions.”

@(Bill Lee): “Approaches that would result in the total upheaval of police are not the right approach to these real and challenging issues. We support law enforcement in Tennessee, and I have the utmost respect for these men and women who serve their communities every day.”

Some politicians expressed sentiments from both groups at the same time.

@NC_Governor (Roy Cooper): “It’s critical that our state law enforcement be leaders in repairing this breach. They have a tough job and I’m grateful for so many of them who are doing their best to protect and serve with fairness. Many are now acknowledging that systemic and cultural changes must be made.”

Due to the sometimes ambiguous nature and expression of political ideologies, these categories do not fully encompass all that is put forth in a politician’s social media content. A tweet advocating for policing transparency may also encourage additional support for the law enforcement branch making those changes in the same breath. Would such a tweet be aligned with the movement calls for reform, or against the demands for defunding? Such contradictions fall within the mixed goals of a grassroots-organized movement. We ran a binary classification algorithm on each of the three topic groups to annotate tweets with none, one, or multiple labels.

The state legislative data is sourced from the Brennan Center for Justice, a nonpartisan law and policy institute. The dataset contains records of state-by-state enactment of bills within three areas of policing reform: use of force; duty for officers to intervene, report, or render medical aid in instances of police misconduct; and policies relating to law enforcement misconduct reporting and decertification. All 50 states have adopted some form of legislation relating to at least one of the identified policy areas within the time period of May 25, 2020 to May 21, 2021. The use of force category of bills restricts or specifies the type of physical force police officers are allowed to employ in certain situations. Duty to intervene policies establish responsibility for officers to intervene in cases where they

witness use of excessive force, and penalties for failure to do so. Finally, decertification & centralized misconduct reporting bills establish or centralize state misconduct reports that may result in an officer being decertified and removed from duty.

The 50 states are represented as an undirected network, with the degree of similarity between the states computed as the number of shared policies of 15 potential policing reform policies. Similar to policy diffusion networks, weighted ties connect states with shared state policies. We investigate the relationship between our dependent variable of inter-state legislative similarity with independent variable attributes of the social media agenda setting of state governors. We find the frequency of on topic tweeting, relative ratio to total tweets, and amount of positive or negative opinion. While increased frequency is hypothesized to correlate with adoption of legislation, certain legislators produce a much greater volume of tweets than others. The topical makeup of their social media statements may signify legislative priorities, and whether or not that politician is highly motivated to take action on issues of criminal justice.

To measure similarity of BLM tweeting frequency between governors, we measured the absolute difference in estimated proportion of tweets relating to BLM. To measure pro-BLM tweeting similarity, we repeated this process for proportion of tweets that were estimated to be pro-BLM. State

We ran a network regression with 1000 repetitions, regressing the shared police reform bills network on. The Quadratic Assignment Procedure (QAP) permutation test, using Dekker’s “semi-partialling plus” procedure was used, as it is recommended for multivariate analyses.

Because BLM and pro-BLM tweeting proportions are correlated (see Figure 1), we ran models with either one or the other, but not both.

5 Results

The top five states that adopted the most police reform laws from May 25, 2020-May 21, 2021 were Illinois, Washington, Colorado, Massachusetts, and Virginia.

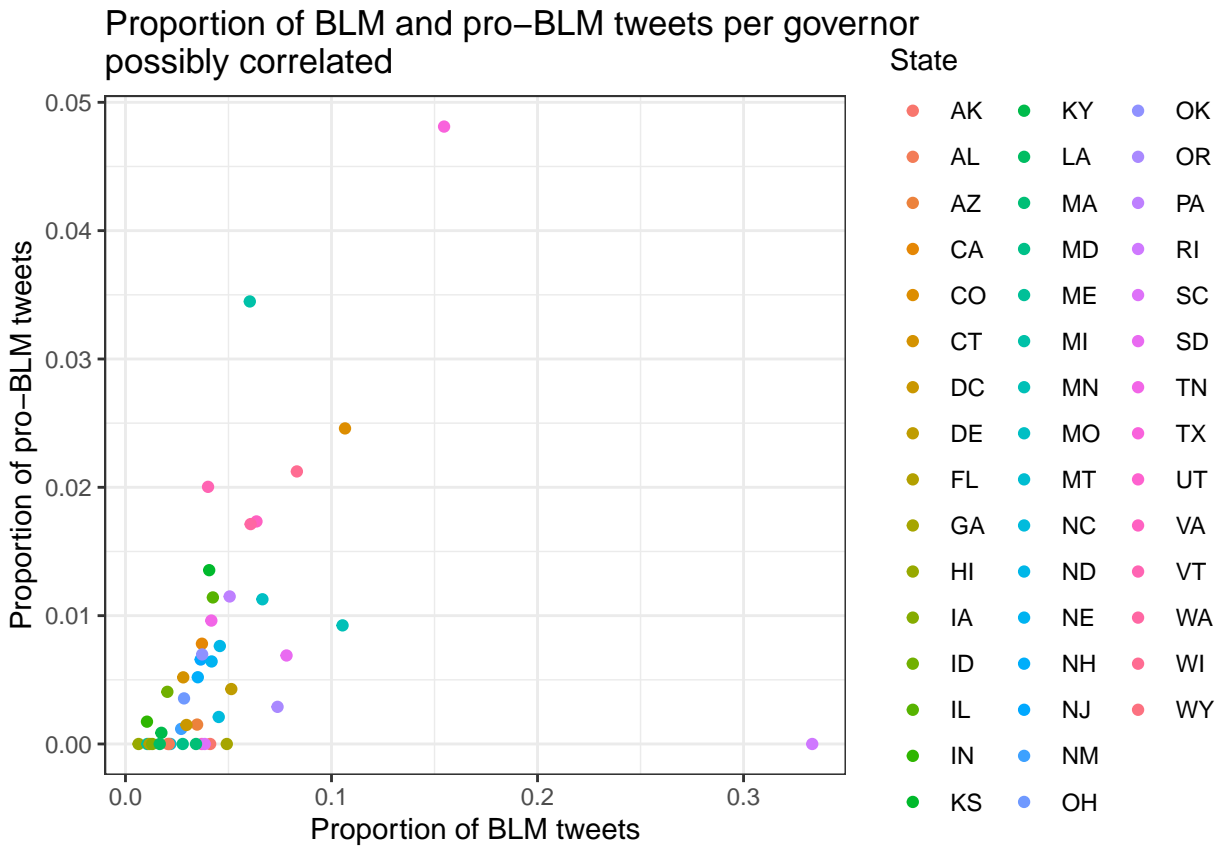


Figure 1: Plot of predicted BLM vs pro-BLM tweets per governor

Table 1: Regression of BLM tweeting proportion on governor gender and party

Variable	Estimated Coefficient	Standard Error	t-value	$\Pr(> t)$
Intercept	0.073	0.017	4.369	0.000
Male	-0.021	0.019	-1.121	0.269
Republican	-0.015	0.015	-0.951	0.347

Table 2: Regression of pro-BLM tweeting proportion on governor gender and party

Variable	Estimated Coefficient	Standard Error	t-value	$\Pr(> t)$
Intercept	0.007	0.003	2.106	0.041
Male	0.002	0.004	0.569	0.572
Republican	-0.003	0.003	-0.981	0.332

Table 3: Network regression of shared police reform policies on difference in proportion of BLM tweets between governors, contiguity, difference in % Black population, difference in % white population, difference in state % urban, difference in median income, and difference in state ideology

Variable	Estimated Coefficient	$\Pr(<=b)$	$\Pr(>=b)$	$\Pr(>= b)$
Intercept	0.9582214	1.00	0.00	0.00
BLM	-0.8957513	0.41	0.59	0.60
Contiguity	0.1317323	0.81	0.19	0.34
Black	-1.1746500	0.15	0.85	0.28
White	-0.9403489	0.08	0.92	0.25

Variable	Estimated Coefficient	Pr($\leq b$)	Pr($\geq b$)	Pr($\geq b $)
Urban	-0.1329542	0.10	0.90	0.22
Income	0.0000018	0.75	0.25	0.84
Ideology	-1.0208221	0.02	0.98	0.06
Population	0.0000000	0.69	0.31	0.69

Table 4: Network regression of shared police reform policies on difference in proportion of pro-BLM tweets between governors, contiguity, difference in % Black population, difference in % white population, difference in state % urban, difference in median income, and difference in state ideology

Variable	Estimated Coefficient	Pr($\leq b$)	Pr($\geq b$)	Pr($\geq b $)
Intercept	0.9131001	1.00	0.00	0.00
pro-BLM	0.3992253	0.56	0.44	0.96
Contiguity	0.1383964	0.86	0.14	0.32
Black	-1.0930636	0.15	0.85	0.33
White	-0.9175984	0.11	0.89	0.24
Urban	-0.1252649	0.20	0.80	0.33
Income	0.0000013	0.55	0.45	0.89
Ideology	-1.0799296	0.04	0.96	0.12
Population	0.0000000	0.66	0.34	0.74

None of our estimated coefficient values were significantly different from their predicted null hypothesis values in our police reform legislation-adoption network regressions, and neither gender nor party were significant predictors in the model predicting BLM and pro-BLM tweeting frequency. This is contrary to our original hypotheses, and pointed to a need for further analysis. We wondered, does tweeting about BLM and tweeting pro-BLM sentiments correlate with police reform policy adoption in a non-network context (monadic

analysis)? How does this relationship change if we filter for states who passed at least one police reform law? We filter for states that passed at least one law because we know these states had some gap in their policing legislation that needed to be filled, whereas we did not know whether states that didn't pass any reform laws in the period studied had already passed police reform laws prior.

5.1 Follow-up Hypotheses

H_5 : Increased governor BLM and pro-BLM tweeting will correlate with more police reform policies being passed in their state.

H_6 : Increased governor BLM and pro-BLM tweeting will correlate with more police reform policies being passed in their state when filtering for states with at least one bill passed.

5.2 Follow-up Results

Table 5: Monadic regression of police reform laws on proportion of BLM tweets, urban index, % white, % Black, median income, population size, and ideology score

Variable	Estimated Coefficient	Standard Error	t-value	Pr(> t)
Intercept	-10.200	8.189	-1.246	0.221
BLM	-11.052	8.106	-1.364	0.181
Urban	0.065	0.752	0.086	0.932
White	6.514	3.879	1.679	0.102
Black	3.443	5.652	0.609	0.546
Income	0.000	0.000	2.093	0.043
Population	0.000	0.000	-0.364	0.718
Ideology	-9.367	3.898	-2.403	0.021

Table 6: Monadic regression of police reform laws on proportion of pro-BLM tweets, urban index, % white, % Black, median income, population size, and ideology score

Variable	Estimated Coefficient	Standard Error	t-value	Pr(> t)
Intercept	-7.597	8.122	-0.935	0.356
pro-BLM	33.781	45.177	0.748	0.459
Urban	-0.085	0.754	-0.112	0.911
White	4.893	3.966	1.234	0.225
Black	3.593	5.748	0.625	0.536
Income	0.000	0.000	1.908	0.064
Population	0.000	0.000	-0.569	0.573
Ideology	-9.005	3.980	-2.262	0.030

Table 7: Monadic regression of police reform laws on proportion of BLM tweets, urban index, % white, % Black, median income, population size, and ideology score, filtered for states where laws passed > 0

Variable	Estimated Coefficient	Standard Error	t-value	Pr(> t)
Intercept	-10.417	12.136	-0.858	0.405
BLM	45.075	24.268	1.857	0.084
Urban	0.479	1.183	0.405	0.692
White	6.569	5.043	1.303	0.214
Black	3.013	7.628	0.395	0.699
Income	0.000	0.000	0.488	0.633
Population	0.000	0.000	-0.666	0.516
Ideology	-8.346	5.524	-1.511	0.153

Table 8: Monadic regression of police reform laws on proportion of pro-BLM tweets, urban index, % white, % Black, median income, population size, and ideology score, filtered for states where laws passed > 0

Variable	Estimated Coefficient	Standard Error	t-value	Pr($> t $)
Intercept	-7.597	10.249	-1.703	0.111
pro-BLM	33.781	76.245	2.991	0.010
Urban	-0.085	1.033	1.208	0.247
White	4.893	4.274	1.508	0.154
Black	3.593	6.669	0.234	0.818
Income	0.000	0.000	0.573	0.576
Population	0.000	0.000	-1.444	0.171
Ideology	-9.005	5.034	-0.881	0.393

6 Discussion

Interestingly, once we stop treating our data as a network object, more significant relationships emerge. BLM and pro-BLM become significant at the 10% level only when filtering for states who passed at least one police reform law. Is this because the states we excluded passed police reform legislation outside the specified window or were those excluded states contributing valuable and accurate information to our model?

Our network regression models both explain $\sim 5\%$ of the variation in shared police reform laws when accounting for difference in proportion of BLM and pro-BLM tweets and relevant control variables. This is 35% and 32% for monadic regression models with BLM and pro-BLM, respectively.

Among states who passed police reform legislation, every 1% increase in proportion of BLM tweets is expected to result in a 0.45 increase in bills passed on average when controlling for urban index, % white, % Black, median income, population size, and ideology score. Similarly among states who passed police reform legislation, every 1% increase in

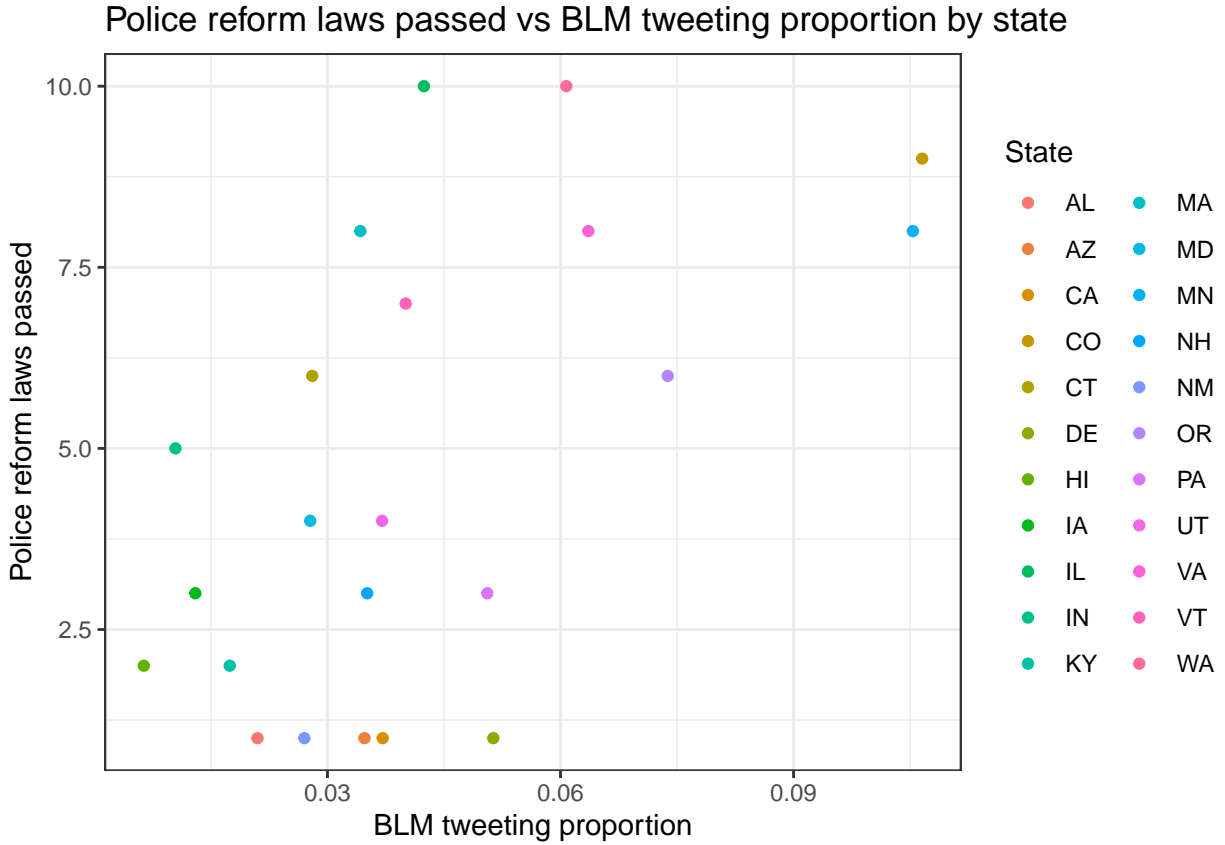


Figure 2: Plot of proportion of BLM tweets vs police reform laws passed by state

proportion of pro-BLM tweets is expected to result in a 0.34 increase in bills passed on average when controlling for urban index, % white, % Black, median income, population size, and ideology score.

Looking at Figure 2, we can see that by filtering for states that passed at least one police reform policy (i.e. removing the 5 dots on the y-intercept), a clearer relationship between BLM tweeting proportion and police reform laws passed starts to emerge. However, we would like to restate that we are unsure if these observations are adding signal or noise to our data set. In Figure 3, removing the observations where no bills were passed has a less clear effect on the relationship between pro-BLM tweeting proportion and police reform laws passed.

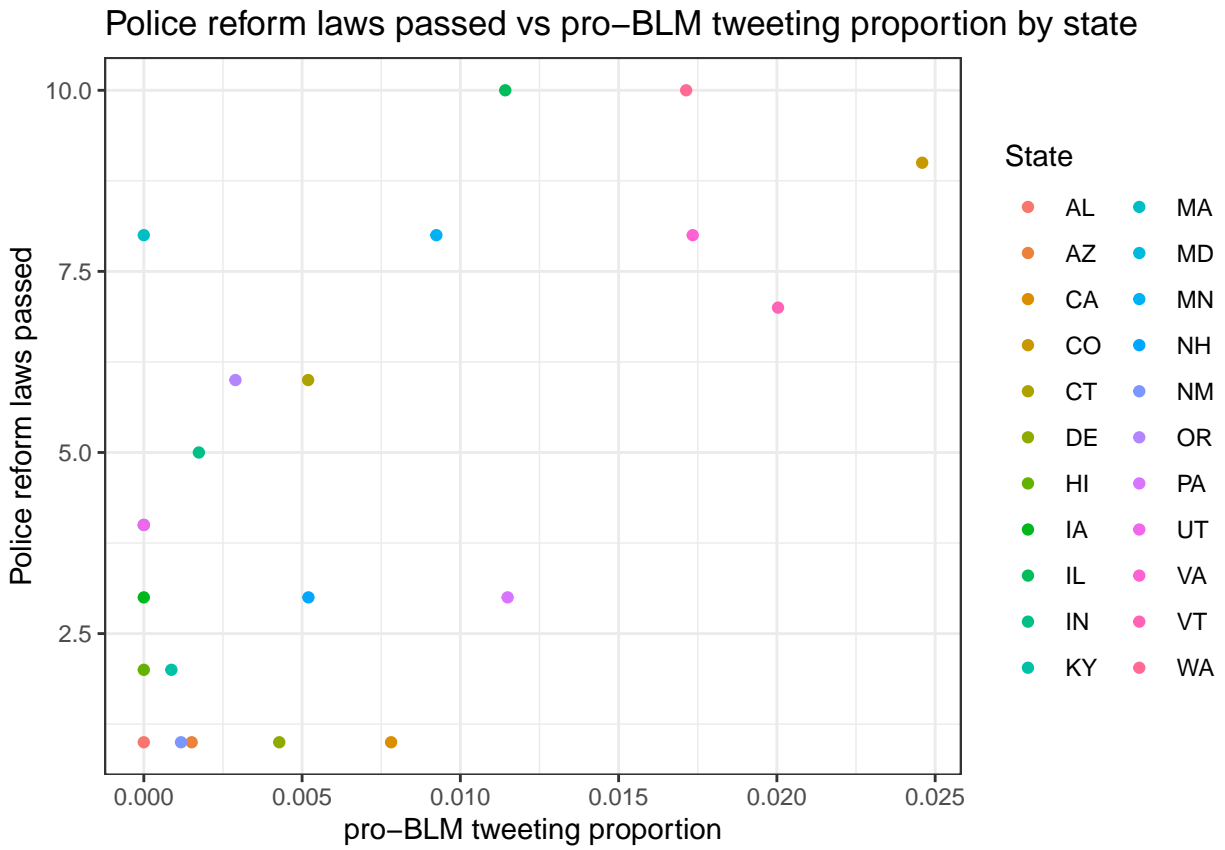


Figure 3: Plot of proportion of pro-BLM tweets vs police reform laws passed by state

7 Limitations and Future Work

Because our data is censored, in that we don’t know what happened regarding state police reform policy adoption post-May 21 2021. It is possible that states continued to adopt police reform policies in after this timepoint, though we hypothesize it is less likely given the decline in popularity of the BLM movement. We additionally do not know if states adopted police reform policies prior to the period studied. It is possible that states did not adopt police reform policies during the given period because they already had robust police reform laws in place.

With limited data, i.e. 15 possible bills for our states to adopt, it is difficult to understand the relationship between BLM tweeting and police reform policy adoption. Though other bills in this area may have been adopted at other points in time, this general question should be expanded to other policy topics not only be more generalizable but also to provide our models with more predictive power and a stronger conclusion. Generally, does tweeting support (or opposition) for a specific topic correlate with passing or not passing policies in that topic area? This also implies extending to other legislative contexts (i.e. Congress, international politics).

Policy adoption is often not the result of just one person (i.e. governor’s) decisions, but often the result of the efforts and opinions of the state legislature as a whole. Future work should focus on investigating the relationship between state congressperson or senator tweeting habits and their voting habits and controlling for their impact, if the sole goal is to understand the relationship between state governor tweeting/social media use and state policy adoption.

We also would like to investigate the relationship between “anti-BLM” tweets and “anti-BLM” bills in the future. In response to the BLM protests that took place in the wake of George Floyd’s death, many (Republican) lawmakers pushed anti-protest laws (CITE). Unfortunately our anti-BLM classifier was not accurate enough for us to use in this research, but future studies could investigate other more accurate NLP topic-classifiers that would hopefully offer better performance in this area. It is important to note however that anti-BLM sentiment may be “fuzzier” and harder to classify in general than pro-BLM sentiment.

It would be interesting to run a time-series dyadic analysis, to understand who the

policy innovators are in our network. For example, in Gavin Newsom’s tweet regarding California’s passage of new standards for police use of force in 2019, he says the passage “[makes California] a model for the rest of the nation”, highlighting that he likely expects the rest of the states to observe the efficacy of this legislation and adopt it if successful. This showcases an important factor in state policy adoption, learning (proposed by Shipan & Volden (2008)), in which states may observe policy efficacy in other states before deciding to implement it themselves. Given the results of Desmarais et al. and Governor Newsom’s statement, it is possible that California to be a big policy adopter in our network, adopting more police reform policies than other states. It would be worthwhile to attempt to investigate and validate these claims (though it is unlikely California is a major policy innovator for May 25, 2020-May 21, 2021 police reform legislation considering they passed one law.)

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