CSMaP Data Report 2020:03

Influential Users in the Common Core and Black Lives Matter Social Media Conversation

December 16, 2020

Authors:
Zhanna Terechshenko,
Sean Kates,
Fridolin Linder,
Joshua A. Tucker,
Richard Bonneau,
Mona Vakilifathi,
Jonathan Nagler

CENTER FOR SOCIAL MEDIA AND POLITICS
NYU

CSMaP Data Report 2020:03
December 2020

Influential Users in the Common Core and Black Lives Matter Social Media Conversation

Zhanna Terechshenko[1]*, Sean Kates[1], Fridolin Linder[2], Joshua A. Tucker[1,3], Richard Bonneau[1,4], Mona Vakilifathi[5], Jonathan Nagler[1,3]

Abstract
This Data Report aims to map the pathways leading to issue politicization through identifying influential users within politically contentious topics on Twitter, using the online discussion over the Common Core State Standards (CCSS) and the Black Lives Matter (BLM) movement. We find that politically motivated popular users are the most influential users in both CCSS and BLM online conversations.

Keywords
Politicization — Social Media — Black Lives Matter — Common Core State Standards

[1] *Center for Social Media and Politics, New York University*
[2] *Siemens Mobility, Munich, Germany; fridolin.linder@siemens.com*
[3] *Department of Politics, New York University*
[4] *Departments of Biology and Computer Science, New York University*
[5] *Robert F. Wagner Graduate School of Public Service, New York University*
***Corresponding author**: zt10@nyu.edu

Contents

1. Introduction

This project aims to map the underlying "information ecosystem" discussion of politically contentious issues and identify the most influential users in the online conversation. This Data Report looks to address two research questions: 1) What types of users engage in conversations on contentious issues online? 2) What are the characteristics of the most influential users in such online discussions? Through analyzing Twitter data and the examples of the Common Core State Standards (CCSS) policy debate and Black Lives Matter (BLM) movement in particular, we seek to identify the characteristics of users who become influential in online discussions over time. Our approach consists of two parts. First, we categorize users into seven types within two groups (*politically motivated* and *apolitical* users) based on Twitter activity and status. In addition, we categorize them into sixteen types based on their level of engagement with the topic (CCSS or BLM). Having developed the framework for user categorization, we then developed a method for measuring user influence in discussions on Twitter, namely, measures of *reach*, or impact, of the content produced by a group, as well as the measure of the *influence* of one group of users on another group of users. We find that majority of *users* who participated in CCSS ans BLM online conversations are users, who are not invested in politics and have a relatively low number of followers. In contrast, the majority of *tweets* were from users who tweeted much more often about politics more broadly. Finally, we find that, for both issues, *politically motivated* users, who tweeted a lot about these issues, were the most influential in the online conversation.

2. Case Studies

In this Data Report, we use the examples of the online discussion over the Common Core State Standards and the Black Lives Matter movement. In this section, we briefly describe the issues, including the major events that shaped the movements and the most important participants.

Black Lives Matter

Black Lives Matter is a decentralized movement advocating primarily for the end of police violence against Black people. It first surfaced online with the use of the #BlackLivesMatter hashtag after the acquittal of George Zimmerman in the shooting death of African-American teen Trayvon Martin in

February 2012, and rose to national prominence in the period immediately following the killing of Michael Brown, a Black man, and the ensuing protests in Ferguson, Missouri.

The movement as a whole has no centralized hierarchy, though the Black Lives Matter Network (BLMN) was founded in 2013 in hopes of creating a core group of principles that local chapters and proponents might use as guiding lights. These principles have developed over time, and the BLM movement has frequently partnered with other advocacy groups to lend support for causes outside the primary focus of police violence against Black people.

From a policy perspective, the movement specifically calls for community control of the police, a reduction in the incarceration rate (especially for young, Black men), and a refocus on funding public education. The focus of the movement is on political expression through action, particularly in rallies and protests. This in-person agitation on the streets is combined with a massive social media presence in hopes of garnering attention and enacting change.

The immediate response to the movement was mixed, particularly along racial lines, and critics were quick to portray protests as riots harmful to the movement's goals. Counter-movements coined the terms "All Lives Matter" (to suggest that BLM was itself racist in its focus on Black people) and "Blue Lives Matter" (in support of police officers and their actions). However, the continuous displays of police brutality, captured on video and distributed widely through social media, spurred the movement and slowly won public opinion to its side. By 2020, polls showed that the majority of all races at least somewhat supported the movement (Pew 2020). The recent deaths of George Floyd, Ahmaud Arbery and Breonna Taylor have sparked a new wave of protests under the Black Lives Matter (BLM) banner.

Common Core State Standards

CCSS is the name given to a set of state K-12 English-language arts and mathematics standards in the United States to prepare students for college and careers in the global workforce [1]. The Standards, adopted by a large majority of states, have become a source of contention inside and outside of the education policy world.

In the United States, state governments have the legal authority to regulate a state's K-12 education standards, which results in a large variation in the rigor of states' K-12 education standards and, ultimately, student achievement. The federal government has the legal authority to provide federal funding to state governments to incentivize state governments to adopt favorable policies, including K-12 education standards, upon receipt of funding.

In 2009, following the Great Recession, the federal government used the opportunities presented by crisis to tie stimulus and infrastructure funding to the adoption of a core set of education policies. President Obama signed the American Recovery and Reinvestment Act of 2009 in February 2009, which created the Race to the Top Fund. This fund was set up to provide state and local governments with federal funding to invest in education reform relating to standards and assessments, data systems, teacher development, and school improvement. State governments were awarded grants on the basis of adopting a series of education reforms, including "developing and adopting common standards" and "developing and implementing common, high-quality assessments." State governments adopted suggested education reforms in order to apply for this grant and increase K-12 education revenue during the Great Recession.

The Standards were the natural extension of this plan. In order to have a consistent set of standards that states accepting the funds would adopt, the National Governors Association's Center for Best Practices and the Council of Chief State School Officers created the Standards, starting in April 2009, and finalizing them in June 2010 [2]. The Standards were touted as a product of collaboration among state government stakeholders, including governors, state education commissioners, researchers, curriculum experts, and educators [2].

In order to receive Race to the Top funds, 45 states and the District of Columbia initially adopted CCSS in 2010 and 2011 [3]. In addition, the Department of Education awarded grants to two state government coalitions to develop state assessment programs aligned with CCSS, the Partnership for Assessment of Readiness for College and Careers (PARCC) and the Smarter Balanced Assessment Consortium (SBAC), both in September 2010 [4]. 26 states initially adopted PARCC and 31 states adopted SBAC [4].

State governments implemented CCSS and PARCC or SBAC as early as the 2011-12 academic year [5]. Starting in 2010, Americans' support for CCSS decreased over time among all voters, Democrats and Republicans ([6]; [7]; [8]), with Republican voters' support declining at a larger rate than others. Democratic voters and teachers generally opposed CCSS because CCSS constrains a teacher's ability to tailor their curriculum to their students' needs, and incentivizes teachers to "teach to the test" rather than improve student achievement. In addition, CCSS represents an increase in the privatization of education or influence of philanthropic organizations in education. Republican voters, especially Tea Party Republican voters, generally opposed CCSS because CCSS represents an increase in the size of the federal government, or the federal government's role in K-12 education, and therefore, from the conservative perspective, a threat to Americans' freedom and culture. In addition, the Standards were tied to President Obama, a Democrat widely distrusted by Republicans. This general dissatisfaction with the standards spread widely, and the Standards became a controversial topic in the 2016 presidential election, especially among Republican presidential candidates [9]. As a result of the public backlash, by the 2018-19 academic year, only 41 states and the District of Columbia used CCSS and only 15 states and the District of Columbia used PARCC or SBAC ([10]; [11]).

3. Influential Users Categorization

In order to identify the influential users in the online discussions of the CCSS and BLM, we, first, developed a theoretical framework for social media user categorization. For major political issues, one can expect to see political elites (e.g., politicians, journalists, and political pundits), activists, as well as politically engaged, non-professional individuals participating in the online debate. While prior work on social media users has studied this composition, and these individuals are likely to engage by virtue of their professional roles or personal interest in politics [12], we are also particularly interested in those individuals who engage in discussions about these issues prior to their politicization.[1] That is, we are interested in understanding the role of individuals who are involved in the early stages of these discussions and whose involvement is tied to a personal interest in the topic beyond its political aspect. For instance, for Common Core, these individuals may be concerned parents who are exposed to the topic through their children's experiences, teachers who are directly affected by Common Core curricula, or experts on education. For Black Lives Matter, these individuals may be witnesses to a police shooting, friends or family of an affected person, or a "citizen journalist" [13] who wants to document an event. Beyond these directly invested individuals, the one-to-many broadcast nature of platforms such as Twitter increase the likelihood of an otherwise unconcerned individual's incidental exposure to these topics who then react to this exposure [14]. Therefore, our first step is to categorize the users into two groups: *politically motivated* users and *apolitical* users.

By *politically motivated users*, we mean users who are generally interested in politics, and tweet about a specific topic as one of many political discussions in which they choose to participate.

In order to identify influential users in the discussion, we refine these groups of users further. Within the set of *politically motivated users* we can distinguish between *elites*, *pros*, and *amateurs*. *Political elites* are defined as those who participate broadly in politics and are well known, such as members of congress. *Political pros* are people who participate broadly in politics, have some status within the world of politics, but are not necessarily as well known as elites. In the world of Twitter, these *political pros* would be people with enough standing in the political world to be credentialed on Twitter, but with many fewer followers than *political elites*. Finally, *political amateurs* are those who contribute frequently to political discussions, but are neither well known nor have any particular status in the political world.

We have four groups among the *apolitical users*. *Media elites* are users with large audiences, such as celebrities, prominent athletes, and social media activists or 'influencers'. If they were not sufficiently well known on Twitter, but have enough standing in the real world to be credentialed on Twitter, they would be *pros*. *Citizen journalists*, or *allies*, can be individuals who are exposed to the topic through personal/their children's experiences, witnesses, or citizen journalists. Finally, *reactors* are similar to *citizen journalists*, except they tend to retweet the content of other users rather than produce original political or topical content.

As shown in Table 1, we categorized users into each of these 7 categories based on a combination of the content of their tweets, their number of followers, the proportion of their tweets that included original content, and whether or not they had achieved 'credentialed' status on Twitter. Political tweets are classified more broadly as tweets relating to any political topic. In particular, we followed the definition proposed by [15] and classified tweets as political if they are about politics, including 'politicized issues', such as vaccination, sexual harassment, or global warming. In order to identify *politically motivated* users, we collected the latest 3,200 tweets[2] from the timelines of the users who tweeted about CCSS or BLM at least once and classified each of the tweets as political or not. Similarly, these users were categorized as *politically motivated* if the proportion of political tweets exceeded 0.5 of their total tweets. To distinguish between the users who produce original content from those who spread the information through the retweets, we calculated the proportion of original tweets from the user to the number of total tweets (tweets plus retweets) posted by the user. We identified users as *reactors* if the proportion of their retweets exceeds 0.95 of their tweets. We measure whether the user is credentialed or not using their Twitter verification status. Finally, we distinguished between users with high number of followers, labeled here as *elites*, and other users, who we put in the 'low number of followers' category. We categorized users as *elites* if their number of followers placed them in the top 5% of users based on number of followers in the set of users who tweeted about the topic.

In addition to the account types described above, we also classify users based on their engagement level with a topic, which we measure through the number of times a user has tweeted about the topic (Table 2). In particular, we distinguish between users who tweeted about the topic once, from 2 to 10 times, from 11 to 100 times, and over 100 times. Within each category we categorize users into account types similar to the ones describe above: *elites*, *pros*, *amateurs*, and *reactors*. We label users as *elites*, if they have high number of followers; *pros* - if they are credentialed on Twitter; *amateurs* - if they are neither well known nor have a verified status, and reactors - if they are similar to *amateurs* but tend to retweet the content of other users.

4. Data and Methodology

In this section, we describe our dataset and explain the process of users categorization as well as the way we measure their influence.

[1] By 'politicization' we mean that the issue enters the political agenda, note that this is distinct from the issue becoming polarized where the conflict over the issue coincides with general left-right or Democrat vs Republican conflicts.

[2] The Twitter API returns only up to 3,200 of a user's most recent tweets.

Table 1. Account Types

	% Political Tweets	% Original Tweets	Credentialed	Number of Followers
Politically Motivated				
Political Elites	High	n/a	n/a	High
Political Pros	High	n/a	Yes	Low
Political Amateurs	n/a	n/a	No	Low
Apolitical				
Media Elites	Low	n/a	n/a	High
Pros	Low	n/a	Yes	Low
Citizen Journalists/Allies	Low	High	No	Low
Reactors	Low	Low	No	Low

4.1 Dataset

In order to identify the universe of tweets relevant to CCSS and BLM discussions, we performed a census of relevant social media data within the Center for Social Media lab's extant archives and identified gaps in coverage. We constructed high-recall queries that fill these gaps and capture both sides of a topic's discussion. These queries were used to purchase data from Twitter containing the topical terms we identified. The purchased dataset contains 12,764,541 tweets with terms related to CCSS and 231,457,543 tweets related to BLM, and covers the time period of January 1, 2010 - December 31, 2018.

We then developed a classifier to identify if tweets containing the set of terms we chose were in fact about each of our two issues.[3] Out of these tweets we classified 6,331,690 tweets as relevant to the CCSS issue and 149,411,817 to BLM. There are 896,936 and (aproximately) 13,000,000 unique users in the CCSS and BLM discussions, respectively.[4] The percentage of tweets about Common Core with original content, rather than re-tweeted content, is 58%, while original tweets about BLM account for only 31% of the total BLM discussion.

Figure 1 shows the distribution of tweets per user in CCSS and BLM conversations. As can be seen from this figure, a plurality of users in both collections tweeted about these issues only once. However, the proportion of users who tweet about the topic more often than once is higher in the BLM conversation (54.7%) than in the case of CCSS (39.2%). Figure 2 shows the number of unique users who engage in the discussions of these topics in each year. The number of users discussing CCSS jumped substantially in 2013 and 2014, and was then relatively stable until declining in 2017 - though to a level well above the 2012 number of users. For BLM, the number of users jumped in 2014, which coincides with the number of demonstration against the deaths of numerous African Americans by police actions, including the deaths of Eric Garner and Michael Brown, and was then relatively stable from 2014 through 2018, though the numbers in 2016 and 2017 were somewhat higher.

[3] The information on relevance classifier is presented in the Appendix A

[4] Due to high computational costs as well as missing data, the results presented here at the user-level are based on an analysis of a sample of 772,106 users who tweet about BLM.

4.2 Methodological Framework

We described above how we categorized users into the account types. Here we discuss how we assess the influence of each group of users. In order to assess influence, we developed two measures: **production** and **reach**. We operationalize **production** as the proportion of tweets in period t sent by group g:

$$P_{tg} = \frac{|S_{tg}|}{\sum_{g \in G} |S_{tj}|}$$

where S_{tg} is a set of tweets sent by group g in time period t and $|S|$ is the size of set S. We then calculate the **reach** of each account type with the following measure:

$$R_{tg} = \frac{RT(S_{(\leq t)g}, t) + |S_{tg}|}{\sum_{j \in G}(RT(S_{(\leq t)j}, t) + |S_{tj}|)}$$

where $S_{(\leq t)g}$ is the set of tweets sent by group g up to (and including) time period t, $RT(S,t)$ is the number of retweets of tweets in set S, $T_{\leq t}$ is the union of all tweets sent by all groups up to time period t, and G is the set of all groups.[5].

That is, the **reach** of group g at time t is the number of tweets they sent in that period plus the number of times they have been retweeted in the time period, divided by the total number of tweets and retweets in that period.

[5] The number of retweets of a set of tweets is measured at time of retweet creation

Table 2. Engagement Levels

	% Original Tweets	Credentialed	Number of Followers
Number of Tweets (1)			
Elites	n/a	n/a	High
Pros	n/a	Yes	Low
Amateurs	High	No	Low
Reactors	Low	No	Low
Number of Tweets (2-10)			
Elites	n/a	n/a	High
Pros	n/a	Yes	Low
Amateurs	High	No	Low
Reactors	Low	No	Low
Number of Tweets (11-100)			
Elites	n/a	n/a	High
Pros	n/a	Yes	Low
Amateurs	High	No	Low
Reactors	Low	No	Low
Number of Tweets (100)			
Elites	n/a	n/a	High
Pros	n/a	Yes	Low
Amateurs	High	No	Low
Reactors	Low	No	Low

Finally, we are interested in measuring who is influenced by whom, or, in other words, who is responsible for retweets. The **influence** that group g has on group h is the proportion of tweets of group h in time period t that are retweets of original tweets by members of group g :

$$I_{g \to h} = \frac{RT(S_{(\leq t)g}, t, h)}{|S_{th}|}$$

where $RT(S_{(\leq t)g}, t, h)$ is the number of retweets of tweets in set S in time period t by users in group h, and as before $S_{th}$is the set of tweets sent by group h in time period t.

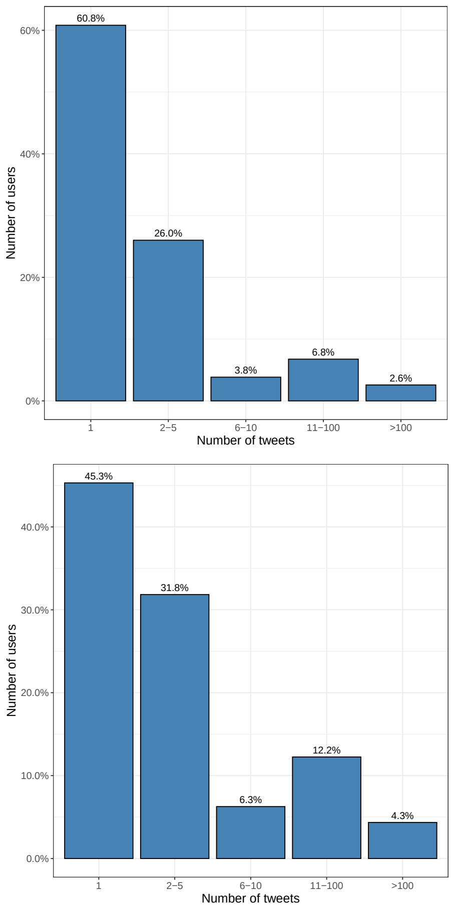
In the first part of our presentation of our finding, we analyze the data at the user-level, thus looking at the influence of the account types introduced above during the whole time period. In the second part, we disaggregate our results to the user-year level of analysis in order to see the changes in the influence of the groups over time.

5. Results and Discussion

Table 3 shows the distribution of users across account types during the entire time period. For both CCSS and BLM, the majority of users (73% and 82%) fall into the *apolitical* category, almost all of them as *citizen journalists/allies* and *reactors*. In other words, the majority of users who tweet about CCSS and BLM are people who are not particularly interested in politics and do not have a large audience or an expertise but are exposed to the topic through personal experiences or conversations on Twitter.

Table 4 gives the proportion of *tweets* in each collection from each type of user. Interestingly over the half of tweets in both collections (57% for CCSS and 55% for BLM) come from *politically motivated* users: users for who political tweets across all issues make up a large fraction of their overall tweets.[6] While *apolitical* people make up 73% of users on

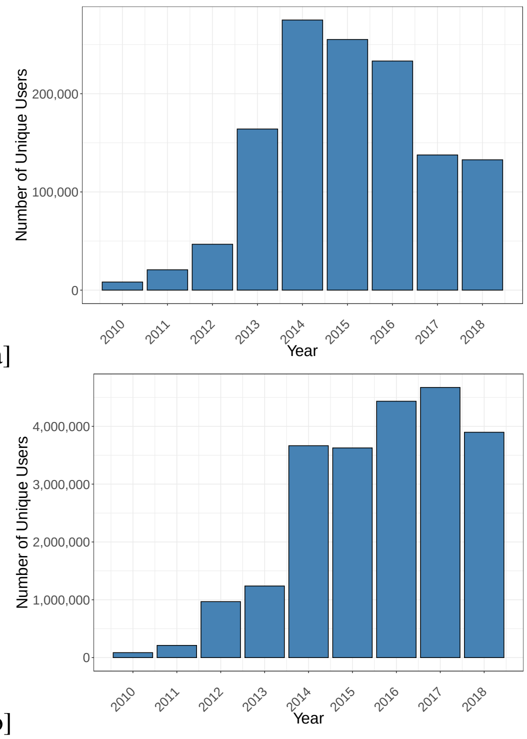
[6] This includes retweets.



[a]

[b]

Figure 1. Distribution of Tweets per User in Common Core (a) and Black Lives Matter (b) Conversation



[a]

[b]

Figure 2. Number of Unique Users per year in Common Core (a) and Black Lives Matter (b) Conversations

CCSS, they only account for 43% of tweets. That is because the *politically motivated* users (who make up 27% of users), clearly tweet much more than the *apolitical* users do about Common Core – and account for 57% of tweets about the issue. So while *apolitical* people participate in the discussion, they are drowned out by *politically motivated* people. So the schoolteachers or parents or educators who may have expertise are being overwhelmed in volume by *politically motivated* tweeters. We observe a similar pattern in the BLM collection, where 18% of *politically motivated* users account for 55% of all the tweets.

Table 5 shows the distribution of users across different engagement levels. According to this Table (and in line with Figure 1), a majority of users tweeted about the topics once (in case of CCSS) or fewer than 5 times (in case of BLM). Table 6 gives the proportion of *tweets* in each collection from each engagement level and it shows that the majority of tweets comes from *amateurs* who tweet about the topics more than 100 times. In other words, the majority of tweets in our collection were tweeted by the 1% of users who are either frequent tweeters or are highly interested in the topic.

Moving to the discussion of the influence of these users, Table 7 shows the reach of each account type. As defined above, reach is a measure of what proportion of the overall volume of tweets and retweets a given group is responsible for. We can see that *politically motivated* accounts have the most reach in both topics. This is perhaps not surprising since *politically motivated* users also account for the majority of tweets in each corpus. In BLM, *political elites* as a group account for almost six times as much reach as their number of tweets suggest, whereas in CCSS the proportion of reach to tweets for *political elites* is only one and a half. In the case of *political amateurs*, however, in both BLM and CCSS, their fraction of tweets exceeds their reach. In other words, while the influence of *political amateurs* or *citizen journalists* can be explained by the sheer volume of their tweets, the influence of political elites is more likely to be explained by the attributes of these accounts (ex. high number of followers) or the content of their tweets. The fact that for *media elites* in BLM, the group's reach four times their proportion of tweets provides an additional support to this argument.

If we look at the reach of accounts with different engagement levels (Table 8), we can see that *elites* and *amateurs* who tweeted about the topics more than 100 times had the most influence in the conversation. Therefore, the influence of the users in this conversations can be explained both by their level of engagement and the size of their audience.

Table 9 and Tables 10 list the examples of top-influential users[7] within each account type and across different engagement levels. For CCSS, this includes Diane Ravitch and Lynne

[7] We estimated the influence of a user by calculating their reach

Table 3. Percentage of people who fit each account type (over the whole time period)

Account type	Proportion of users	
	CCSS	BLM
Politically motivated	0.27	0.18
Political Elites	0.02	0.01
Political Pros	0.00	0.01
Political Amateurs	0.25	0.17
Apolitical	**0.73**	**0.82**
Media Elites	0.03	0.04
Pros	0.00	0.02
Citizen Journalists/Allies	**0.44**	**0.44**
Reactors	0.25	0.32

Taylor - prominent opponents of Common Core - as well as accounts such as AboutCommonCore and "Cuomo Core's Gottago", suggesting that the CCSS discussion on Twitter is dominated by the CCSS opponents. In line with the results from Table 3, the majority of top accounts in CCSS focus on education issues, while accounts tweeting about BLM are more diverse. Furthermore, a relatively high number of top influential users in the BLM discussion belong to news media and journalists.

Finally, Table 11 and Table 12 show the 12 account types' pairs with the highest *influence* score within CCSS and BLM.[8] Recall that the *influence* of one group on another is measured by the proportion of tweets in one group that are retweets of the influencing group. We see that in both cases *elites* and have the strongest influence on other groups. If we look at the users with different engagement levels (Table 13 and Table 14), we observe that unsurprisingly elites who are highly engaged with the topic, i.e. tweeted about it more than 100 times are more likely to influence other groups.

Table 4. Fraction of tweets, which comes from each type

Account type	Proportion of users	
	CCSS	BLM
Politically motivated	**0.57**	**0.55**
Political Elites	0.19	0.06
Political Pros	0.00	0.01
Political Amateurs	**0.37**	**0.48**
Apolitical	0.43	0.45
Media Elites	0.07	0.04
Pros	0.00	0.02
Citizen Journalists/Allies	0.30	0.31
Reactors	0.06	0.09

[8]For the full list see Appendix C.

Table 5. Percentage of people who fit each engagement level (over the whole time period)

Account type	Proportion of users	
	CCSS	BLM
Number of Tweets (1)	**0.61**	**0.46**
Elites	0.02	0.01
Pros	0.00	0.00
Amateurs	**0.31**	**0.15**
Reactors	**0.28**	**0.30**
Number of Tweets (2-10)	0.32	0.41
Elites	0.02	0.02
Pros	0.00	0.0
Amateurs	0.21	0.20
Reactors	0.08	0.19
Number of Tweets (11 - 100)	0.07	0.11
Elites	0.01	0.01
Pros	0.00	0.00
Amateurs	0.05	0.07
Reactors	0.01	0.03
Number of Tweets (>100)	0.01	0.01
Elites	0.00	0.00
Pros	0.00	0.00
Amateurs	0.01	0.01
Reactors	0.00	0.00

Table 6. Fraction of tweets, which comes from each engagement level

Account type	Proportion of users	
	CCSS	BLM
Number of Tweets (1)	0.08	0.04
Elites	0.00	0.00
Pros	0.00	0.0
Amateurs	0.04	0.01
Reactors	0.04	0.03
Number of Tweets (2-10)	0.16	0.14
Elites	0.01	0.01
Pros	0.00	0.00
Amateurs	0.11	0.07
Reactors	0.04	0.06
Number of Tweets (11 - 100)	0.27	0.31
Elites	0.05	0.04
Pros	0.00	0.00
Amateurs	0.19	0.18
Reactors	0.03	0.09
Number of Tweets (>100)	**0.49**	**0.52**
Elites	0.20	0.17
Pros	0.00	0.00
Amateurs	**0.27**	**0.23**
Reactors	0.02	0.12

Table 7. Reach of account types

Account type	Reach	
	CCSS	BLM
Politically motivated	**0.61**	**0.61**
Political Elites	**0.29**	**0.37**
Political Pros	0.00	0.01
Political Amateurs	**0.32**	**0.22**
Apolitical	0.39	0.39
Media Elites	0.09	**0.17**
Pros	0.08	0.03
Citizen Journalists/Allies	**0.26**	**0.17**
Reactors	0.04	0.03

Table 8. Reach of engagement levels

Account type	Proportion of users	
	CCSS	BLM
Number of Tweets (1)	0.07	0.04
Elites	0.00	0.00
Pros	0.00	0.00
Amateurs	0.04	0.01
Reactors	0.03	0.03
Number of Tweets (2-10)	0.14	0.14
Elites	0.02	0.01
Pros	0.00	0.00
Amateurs	0.09	0.07
Reactors	0.03	0.06
Number of Tweets (11 - 100)	0.25	0.31
Elites	0.08	0.04
Pros	0.00	0.00
Amateurs	0.16	0.18
Reactors	0.02	0.09
Number of Tweets (>100)	**0.53**	**0.50**
Elites	**0.27**	**0.17**
Pros	0.00	0.00
Amateurs	**0.25**	**0.22**
Reactors	0.01	0.11

Table 9. Top-influential users in each type

Account type	Users	
	CCSS	BLM
Political Elites	Michelle Malkin,	Shaun King,
	DianeRavitch	AJ+, Bipartisan Report
Political Pros	Benjamin Wood, Gary Stern,	Jon Ziegler “Reb Z”,
	American Principles	Alice Speri, NYCLU
Political Amateurs	About Common Core,	NancyPelosiRocks,
	Lynne Taylor, Enraged NY Mom	BlueWave2018VoteDems, 3ChicsPolitico
Media Elites	thetechedvocate	philip lewis, Johnetta Elzie
	achievethecore.org, Matthew Lynch	YourAnonNews,
Pros	Elle Moxley, Education Post	David Dennis Jr., Bassem Masri,
	Stephanie Simon	George M Johnson
Citizen Journalists/Allies	Lynne M Taylor	ChuckModi,
	1lady4liberty	Brother Abdul Qiyam Muhammad
Reactors	Geoff Diehl for MAGOP	Sha’Naye Shakir-Muhammad
	Mercy	M Dyke Shyamalan, Mark Ferguson

Note: This tables shows Twitter handles and usernames for top-influential users in each account type

Table 10. Top-influential users in engagement level

Engagement level	Users	
	CCSS	BLM
Number of tweets (1)	Josh Dawsey, Betsy DeVos,	Gillian Anderson,
	Very Lonely Luke	michael clifford, Camelia Juarez
Number of tweets (2-10)	The Rino Report, James Woods,	Bill Clinton,
	Danielle Butcher	Norman Lear, Joe Biden
Number of tweets (11-100)	FoxNews, Donald J. Trump	Chance The Rapper,
	Dan Scavino	Candace Owens
Number of tweets (>100)	Lynne Taylor, Diane Ravitch	zellie,
	achievethecore.org, Matthew Lynch	deray, Shaun King

Note: This tables shows Twitter handles and usernames for top-influential users in each account type

Table 11. Influence of account types on each other in CCSS

Account type A	Account type B	$I_{A \to B}$
Political Elites	Reactors	0.33
Media Elites	Reactors	0.32
Political Elites	Political Amateurs	0.27
Citizen Journalists/Allies	Reactors	0.20
Political Elites	Political Pros	0.09
Political Amateurs	Political Elites	0.09
Political Amateurs	Reactors	0.08
Political Elites	Citizen Journalists/Allies	0.08
Political Elites	Media Elites	0.08
Political Elites	Pros	0.08
Media Elites	Citizen Journalists/Allies	0.06
Citizen Journalists/Allies	Media Elites	0.06

Table 13. Influence of users with different engagement levels on each other in CCSS

Engagement Level A	Engagement Level B	$I_{A \to B}$
Elites(>100)	Reactors(11-100)	0.53
Elites(>100)	Reactors(>100)	0.53
Elites(>100)	Reactors(2-10)	0.42
Amateurs(>100)	Reactors(>100)	0.30
Elites(>100)	Reactors(1)	0.25
Elites(11-100)	Reactors(2-10)	0.24
Elites(>100)	Elites(11-100)	0.21
Elites(11-100)	Reactors(1)	0.21
Elites(11-100)	Reactors(11-100)	0.19
Elites(>100)	Amateurs(11-100)	0.19
Elites(2-10)	Reactors(1)	0.17
Elites(>100)	Amateurs(>100)	0.16

Table 12. Influence of account types on each other in BLM

Account type A	Account type B	$I_{A \to B}$
Political Elites	Reactors	0.33
Political Elites	Political Amateurs	0.30
Political Elites	Citizen Journalists/Allies	0.19
Media Elites	Reactors	0.19
Political Elites	Pros	0.17
Political Elites	Political Pros	0.16
Media Elites	Citizen Journalists/Allies	0.11
Political Elites	Media Elites	0.10
Citizen Journalists/Allies	Reactors	0.09
Media Elites	Pros	0.08
Political Amateurs	Political Elites	0.06
Media Elites	Political Amateurs	0.06

Table 14. Influence of users with different engagement levels on each other (BLM)

Engagement Level A	Engagement Level B	$I_{A \to B}$
Elites(>100)	Reactors(>100)	0.76
Elites(>100)	Reactors(11-100)	0.65
Elites(>100)	Reactors(2-10)	0.52
Elites(>100)	Amateurs(>100)	0.50
Elites(>100)	Reactors(1)	0.42
Elites(>100)	Amateurs(11-100)	0.41
Elites(>100)	Pros(>100)	0.41
Elites(>100)	Elites(11-100)	0.36
Elites(>100)	Pros(11-100)	0.36
Elites(>100)	Pros(2-10)	0.28
Elites(>100)	Elites(2-10)	0.24
Elites(>100)	Amateurs(2-10)	0.24

5.1 Changes over Time

In this section, we look at the changes in the influence of account types over time. First, we look at the distribution of users per group (Figure 3 and Figure 5) and then per account type within the groups (Figure 4 and Figure 6).

For both CCSS and BLM online conversations, *apolitical* users have been dominating the conversation during the entire time period of 2011-2018: they make up over 50% of users in every year. Their proportion has been decreasing over time with *political* users reaching their peak and accounting for 47% of users in the discussion in 2016 in case of CCSS and over 25% in 2017 in case of BLM. In the CCSS online discussion, this trend can potentially be explained by the fact that the Common Core standards remained a salient controversy in the 2016 presidential election (especially among Republican presidential candidates) and, to a lesser extent, after the 2016 general election. In both cases, as can be seen from Figure 4 and Figure 6, among *atopical* users, it is *citizen journalists* who have driven the conversation, which was then picked up by *reactors* and *political amateurs*.

We observe a similar pattern when we look at the users with different engagement levels (Figure 7 and Figure 8) with *amateurs* (the category that includes *citizen journalists*) dominating both conversations at the early stages and *reactors* getting more engaged over time.

In order to see changes in the influence of these groups, we look at the changes in production (i.e., the proportion of tweets in period t sent by group g, Figure 9) and reach of the account types over time (Figure 11). For both the CCSS and BLM discussions, we see that *citizen journalists* have decreased both their production and reach over time in each discussion. In the early parts of these discussions they accounted for almost 100% of tweets, but as the discussions matured by 2016 their share of online tweets went down to below 20% . As production and reach of *citizen journalists* was going down, production and reach of *political amateurs* and reach of *political elites* have expanded. For example, production of *political amateurs* reached about 50% in 2017 in both CCSS and BLM online discussions. As regards the influence, the reach of *political elites* in BLM conversation has been higher than the reach of any other account types by 2015. Finally, the analysis of changes in production and reach account types over time suggests that *media elites* played an important role in the BLM online discussion with the spike in both production and reach in 2012. Figure 10 and Figure 12 show that this spike is driven by highly engaged in BLM topic users with large audience.

6. Conclusion

In this Data Report, we identify the most influential users in the online conversations of two contentious topics, using the examples of Black Lives Matter movement and Common Core State Standards policy debate. We find that while both discussions are dominated by *apolitical* social media users, for both issues it is *politically motivated* users who drive the conversation. *Politically motivated* users both produce the largest number of tweets and get retweeted more than any other group. Finally, we find that *political elites*, *media elites*, and *citizen journalists* are more likely to influence other types of users. If we look at the changes in the population of online participants in the conversation across time, we see that it is *political amateurs* who were the most consistently active in CCSS and BLM discussions during the time period of 2010-2018 years. Perhaps our starkest finding, though, is from Tables 2 and 3. While *apolitical* users make up 73% of the users who tweeted about CCSS, they account for just 43% of tweets about the topic. They were thus effectively being drowned out by *politically motivated* users, who made up just 27% of users, but accounted for over half (57%) of all tweets. Since there is no reason to believe that these *politically motivated* users were bringing domain-specific expertise to the subject, what may have been a discussion among concerned parties about an issue became a discussion among persons who did *not* have particular concerns about the issue, but were simply online users with a proclivity for tweeting about politics.

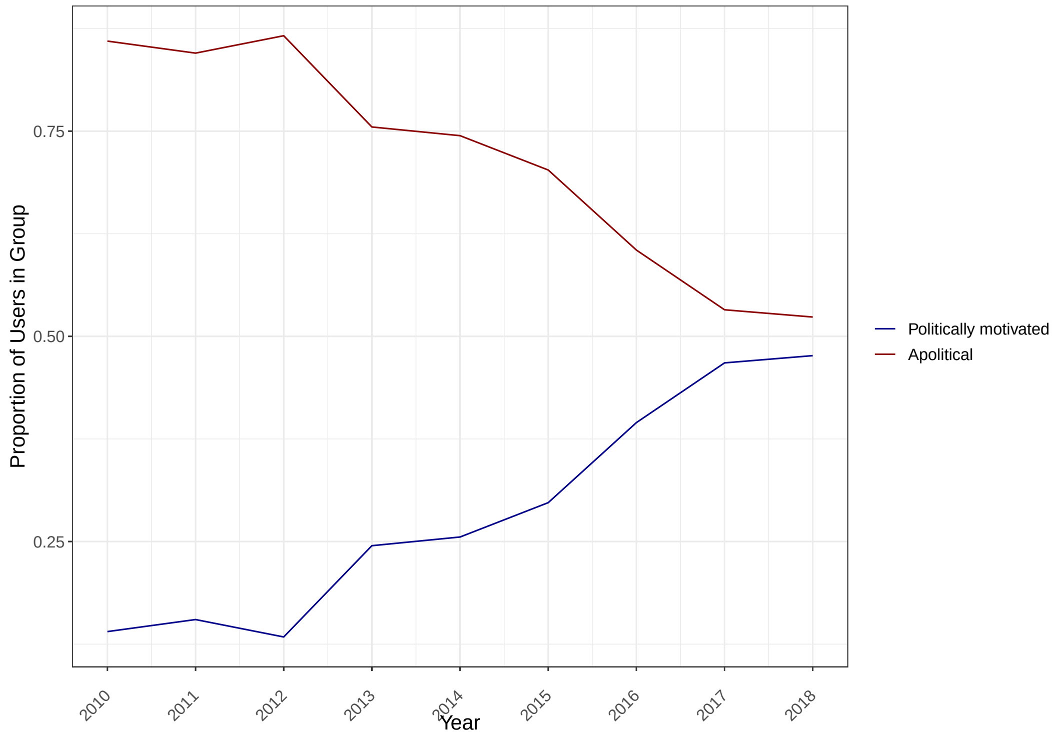


Figure 3. Proportion of users per group by year (CCSS)

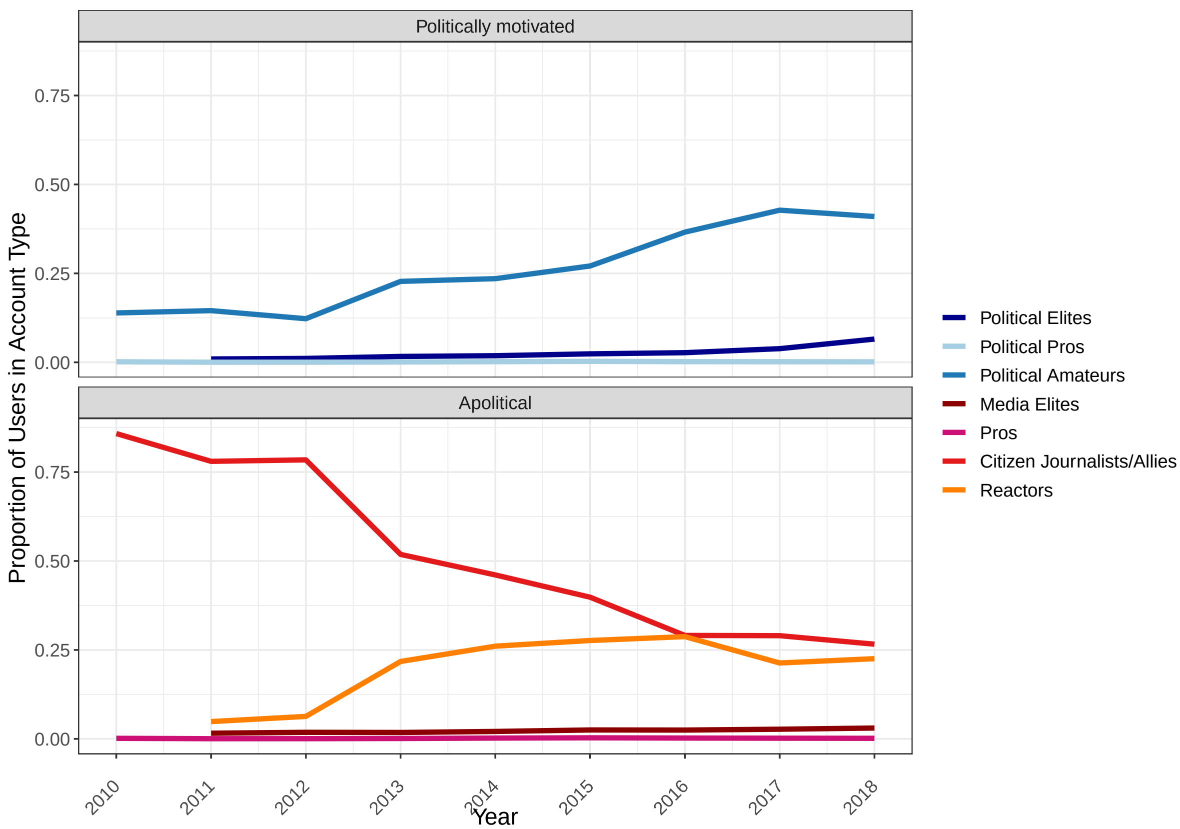


Figure 4. Proportion of users per account type by year (CCSS)

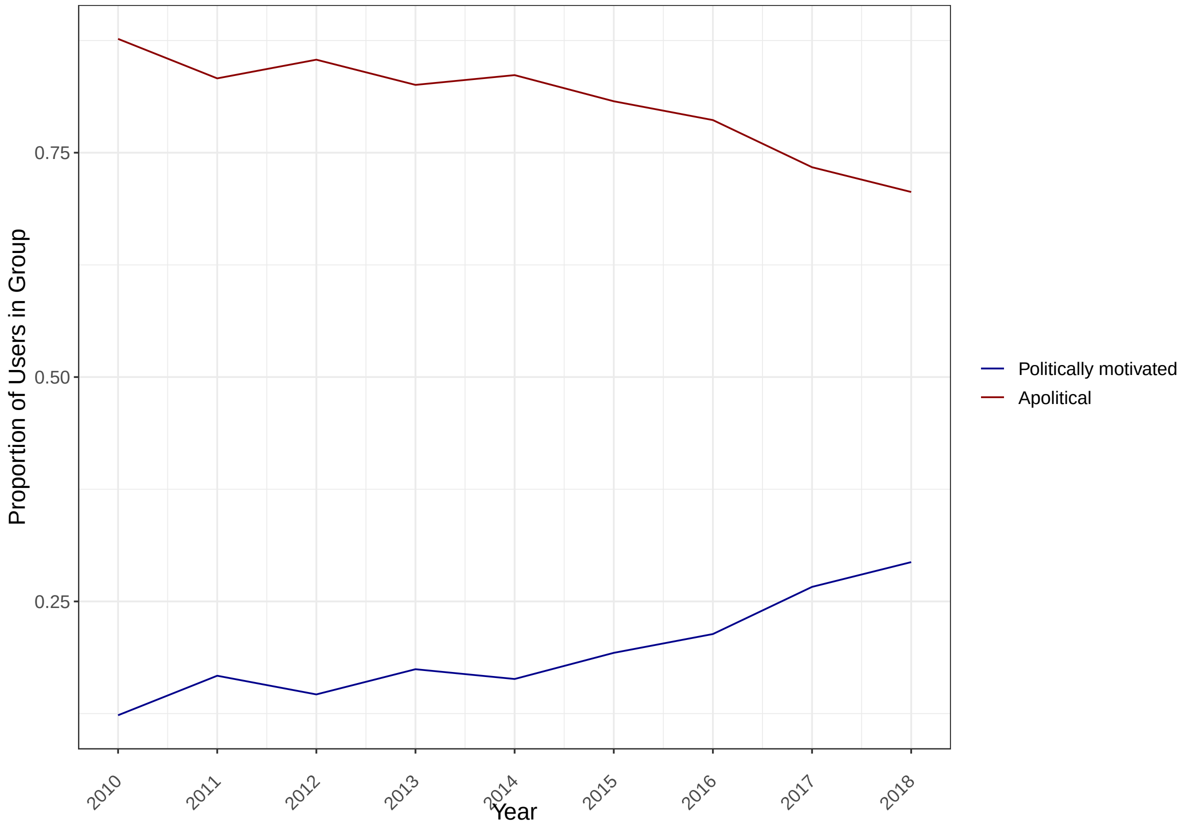


Figure 5. Proportion of users per group by year (BLM)

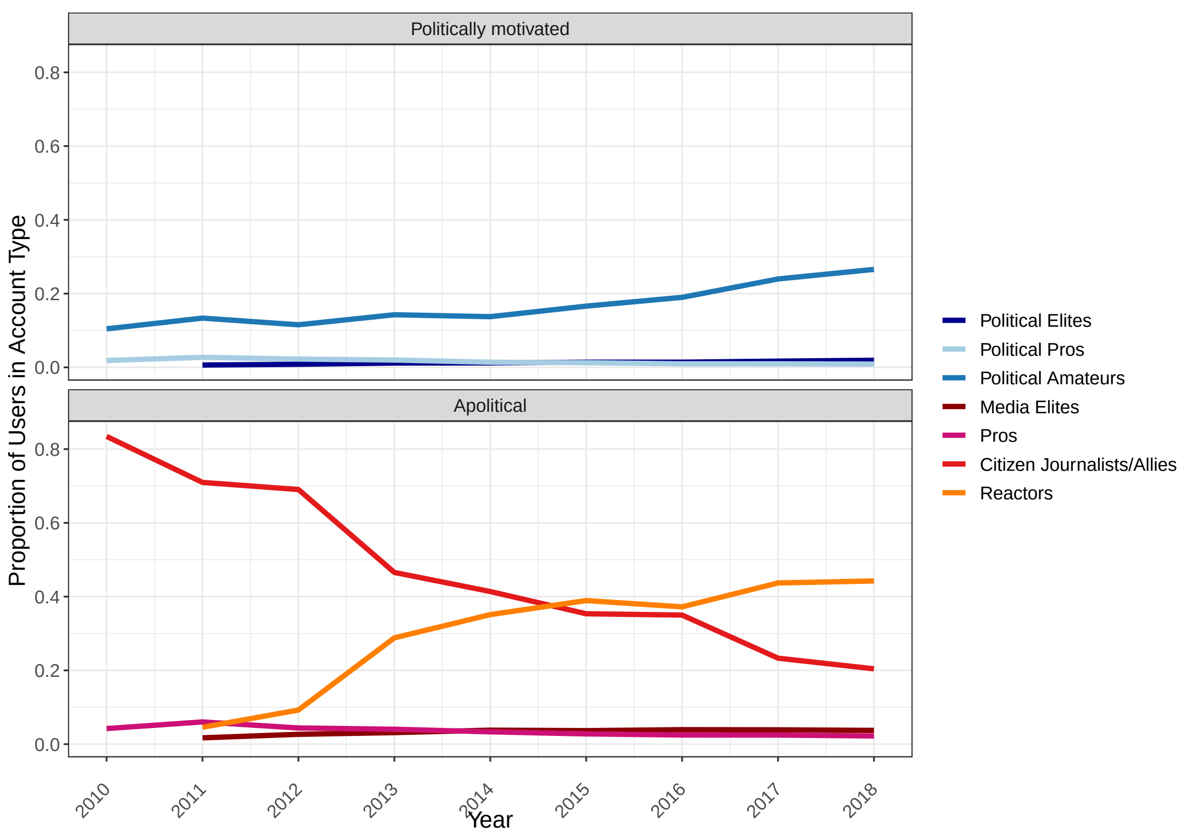


Figure 6. Proportion of users per account type by year (BLM)

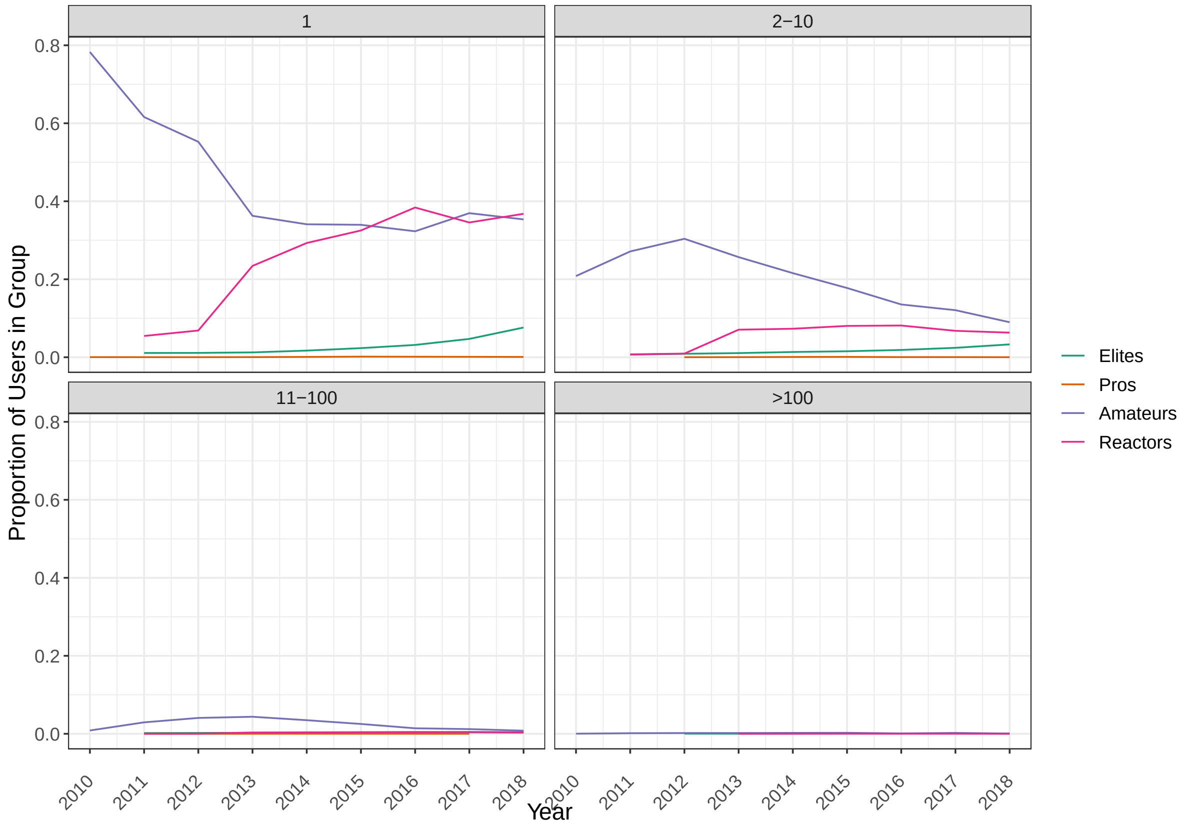


Figure 7. Proportion of users per group by year (CCSS)

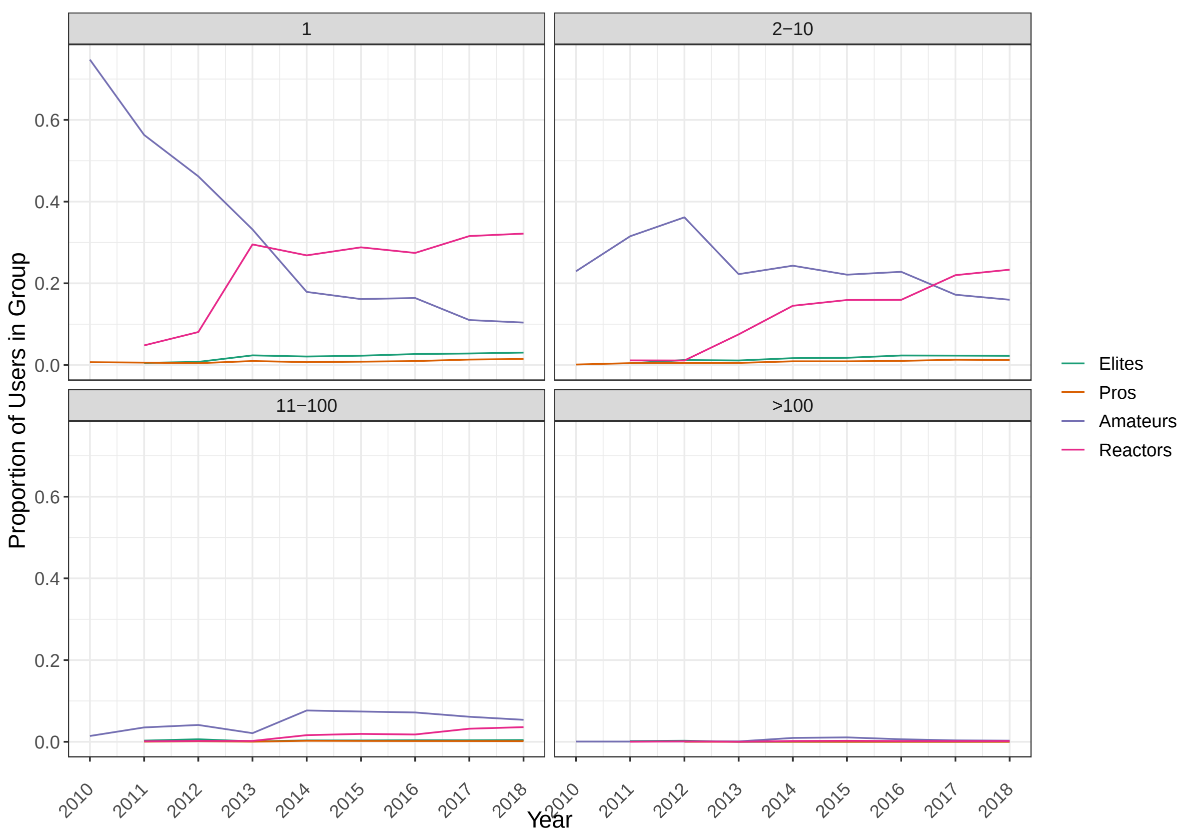
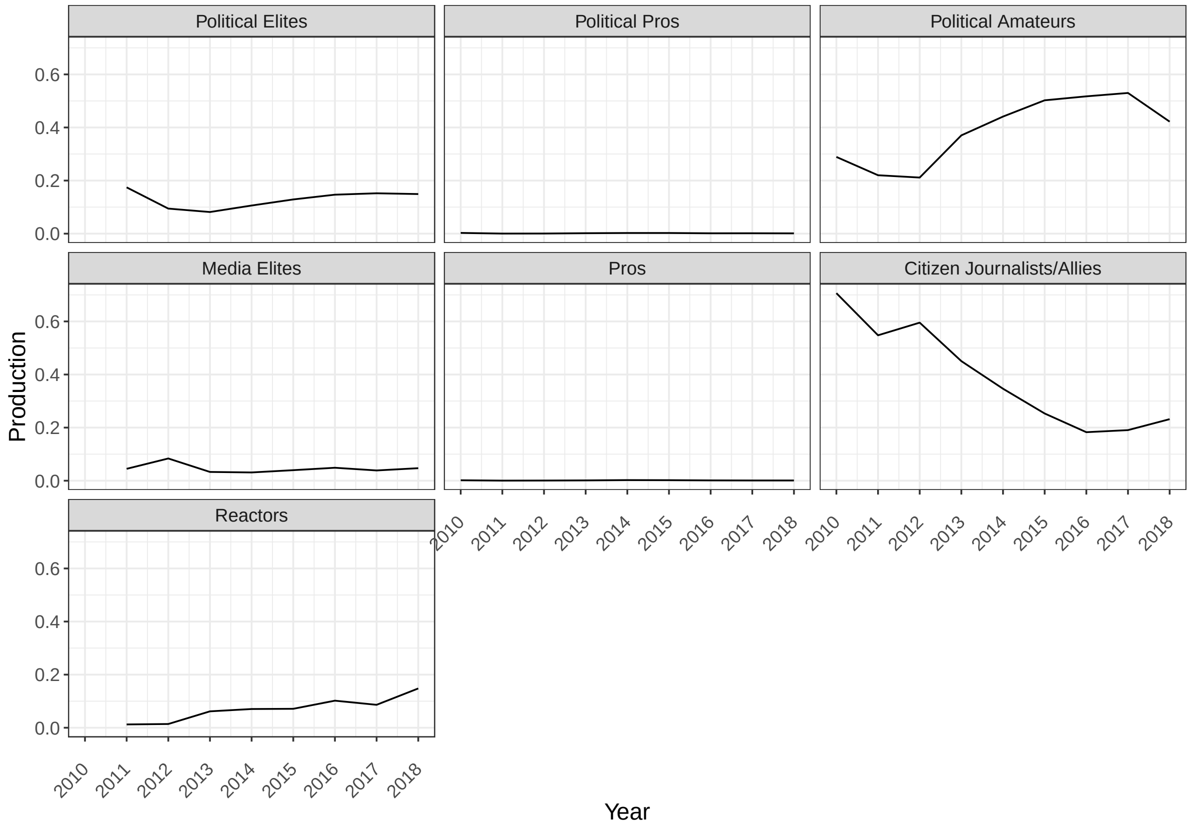
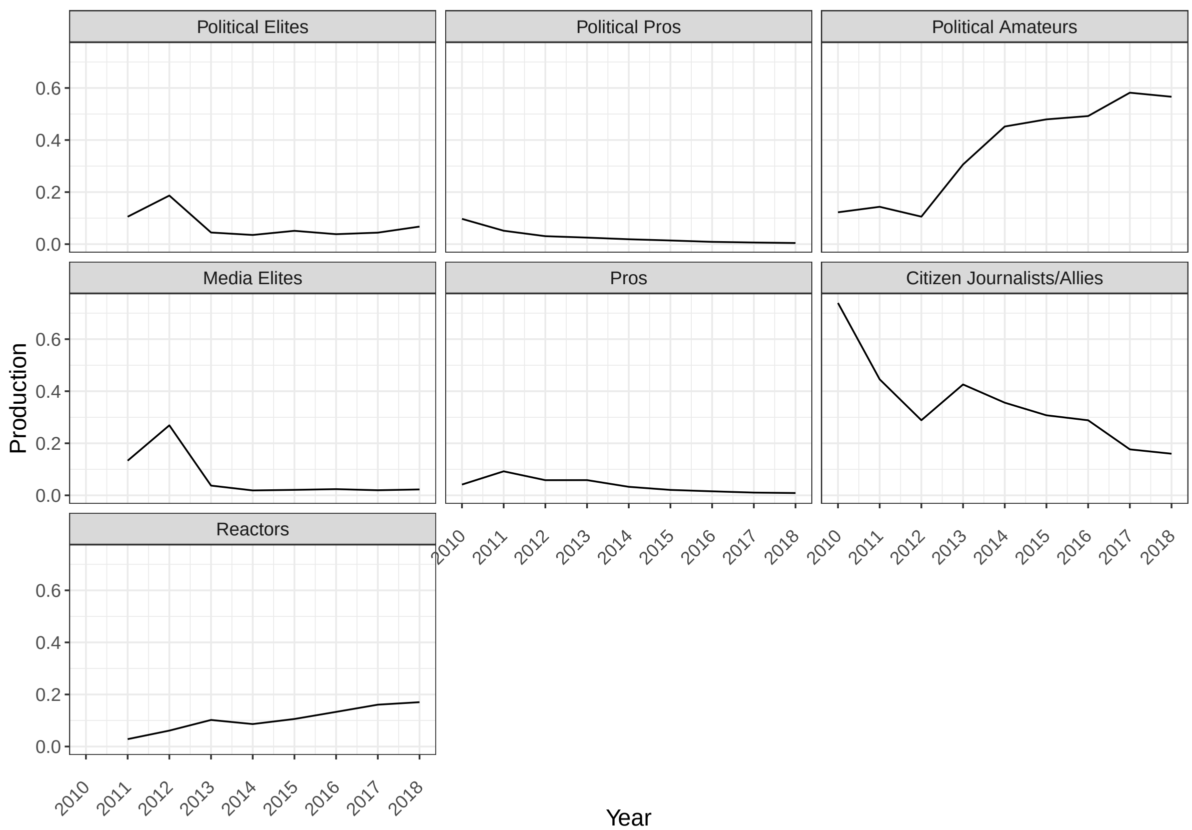


Figure 8. Proportion of users per group by year (BLM)

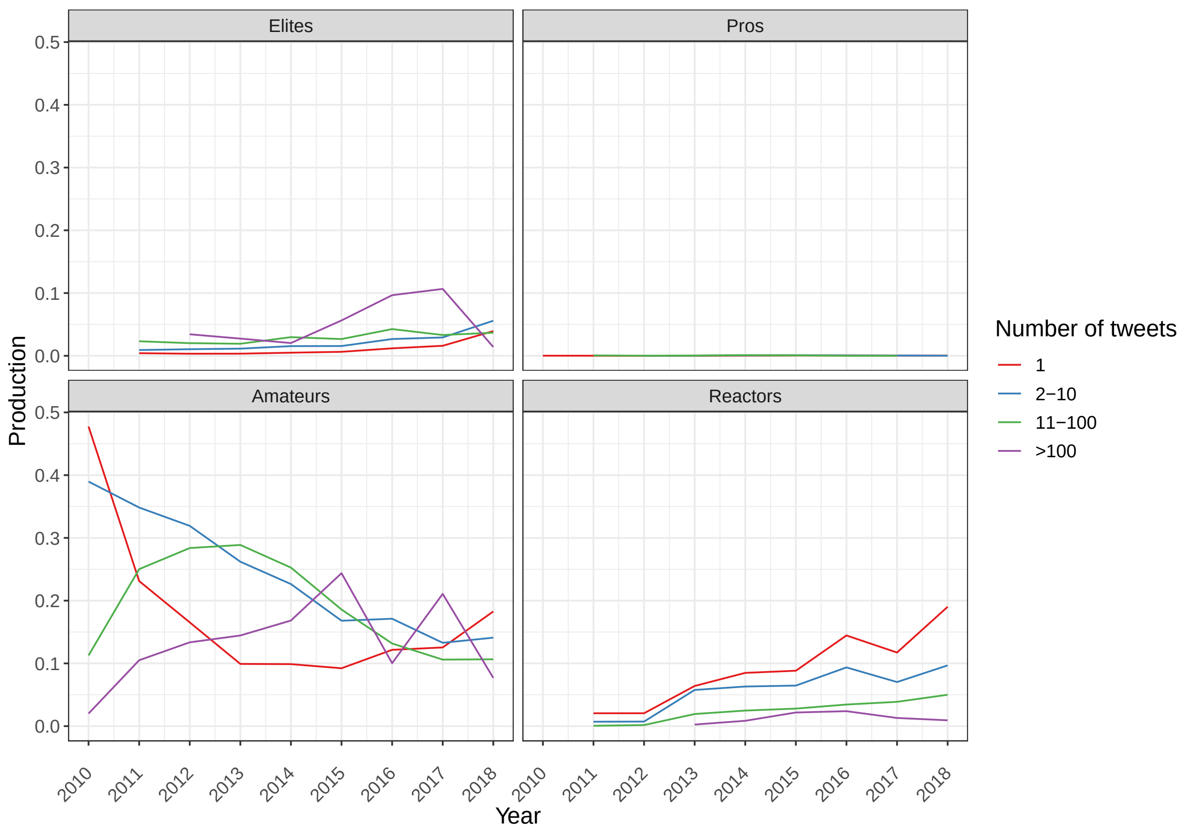


[a]

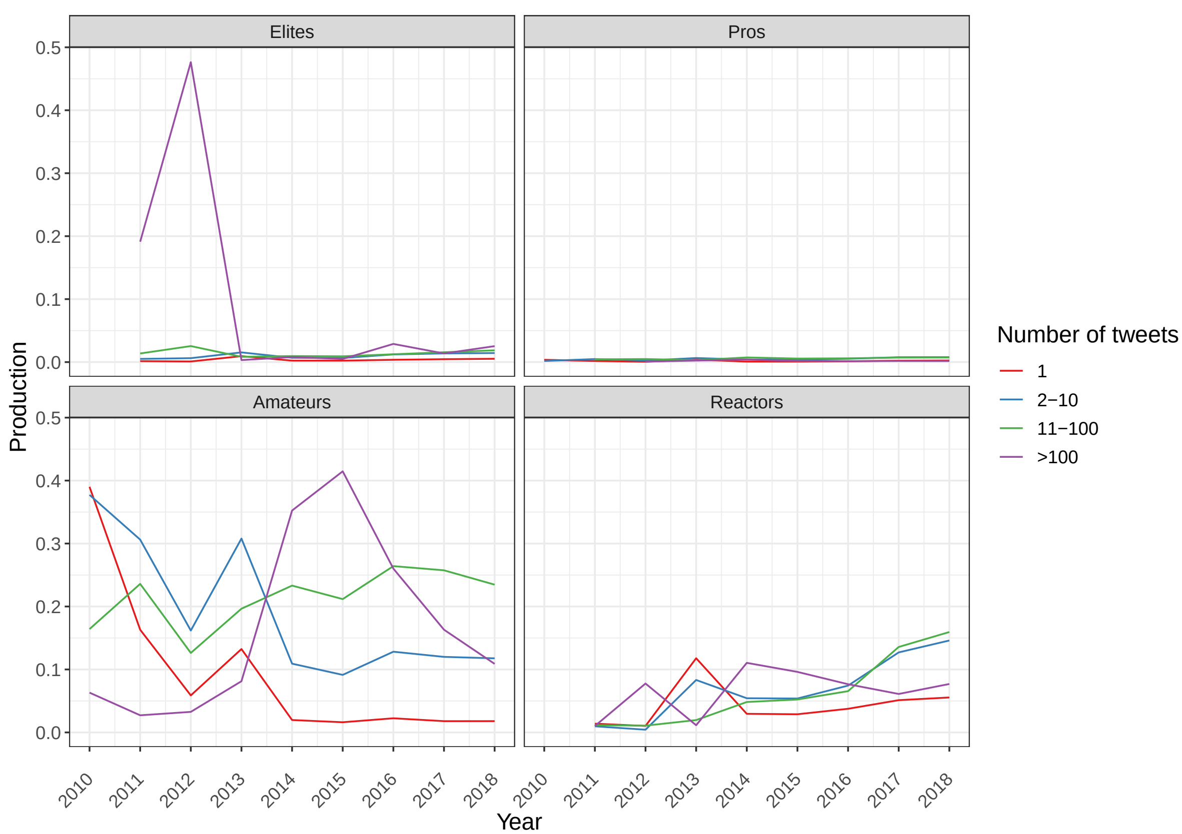


[b]

Figure 9. Changes in production for each account type over time in CCSS (a) and BLM (b) conversations

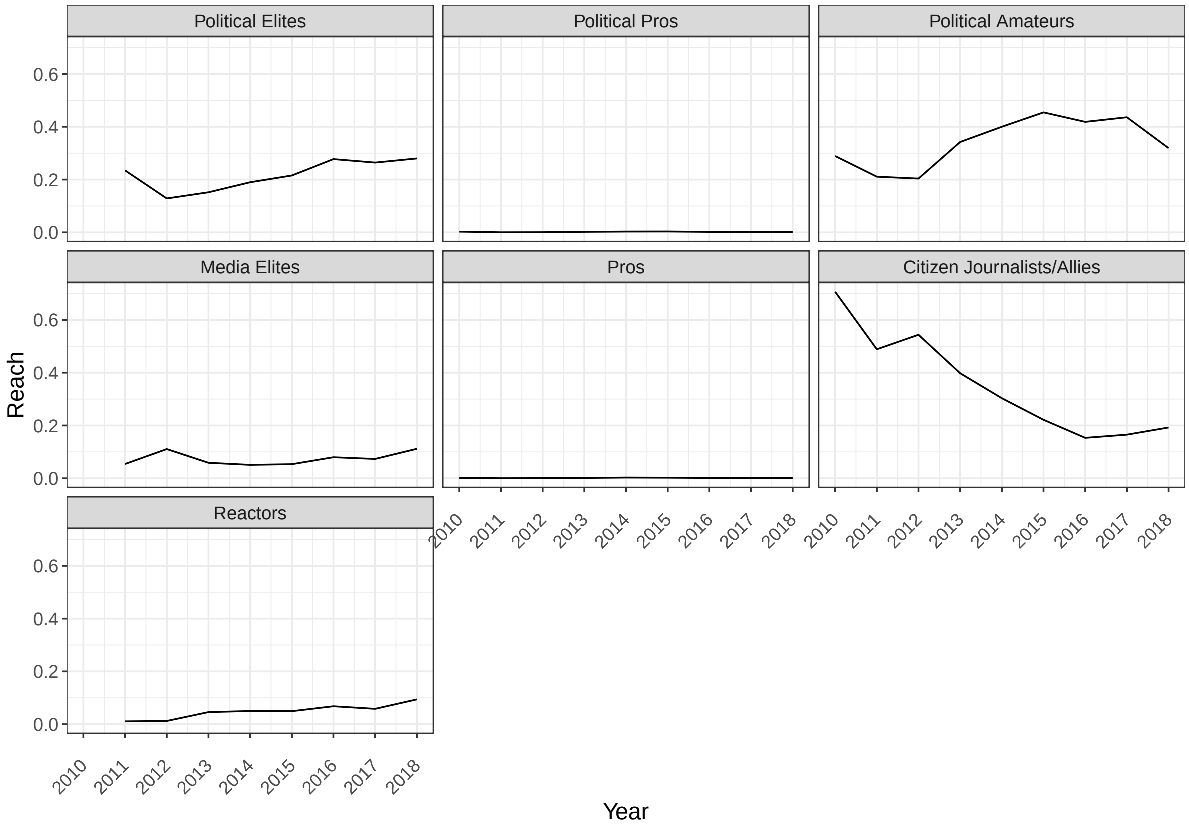


[a]

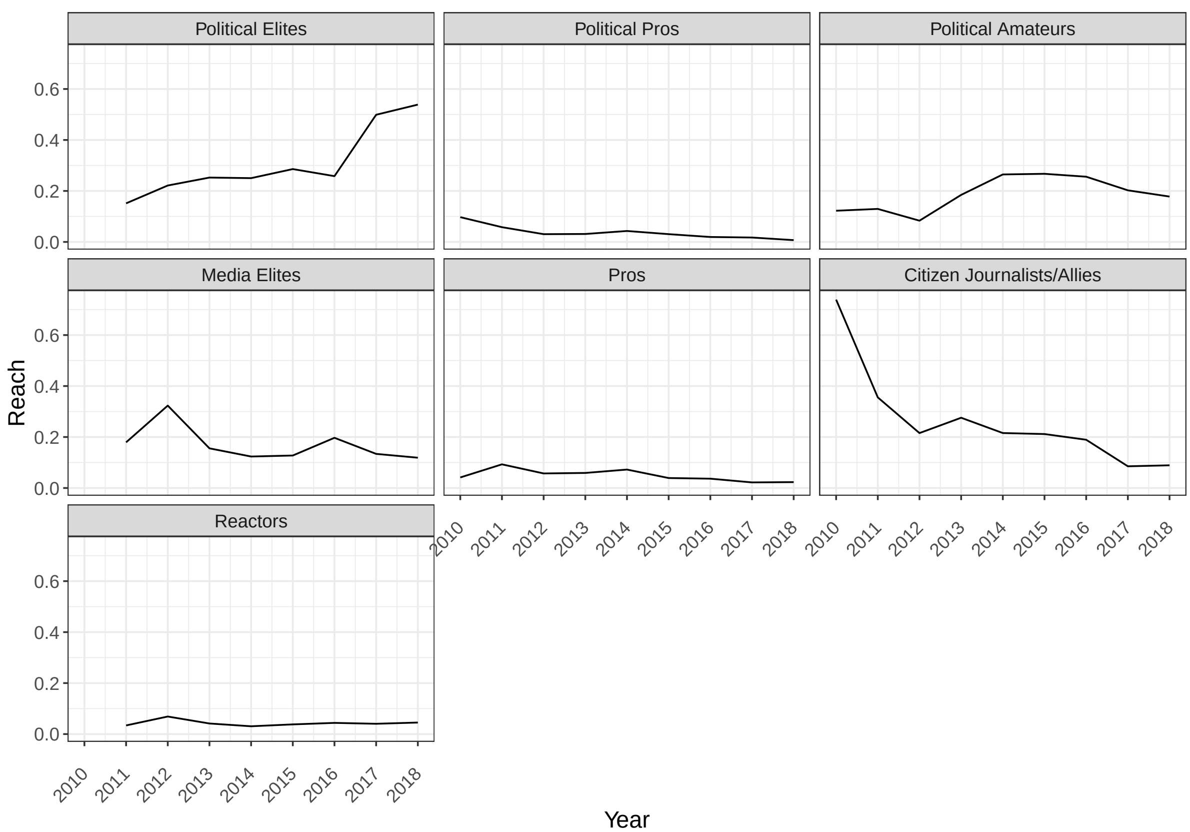


[b]

Figure 10. Changes in production for each account type over time in CCSS (a) and BLM (b) conversations

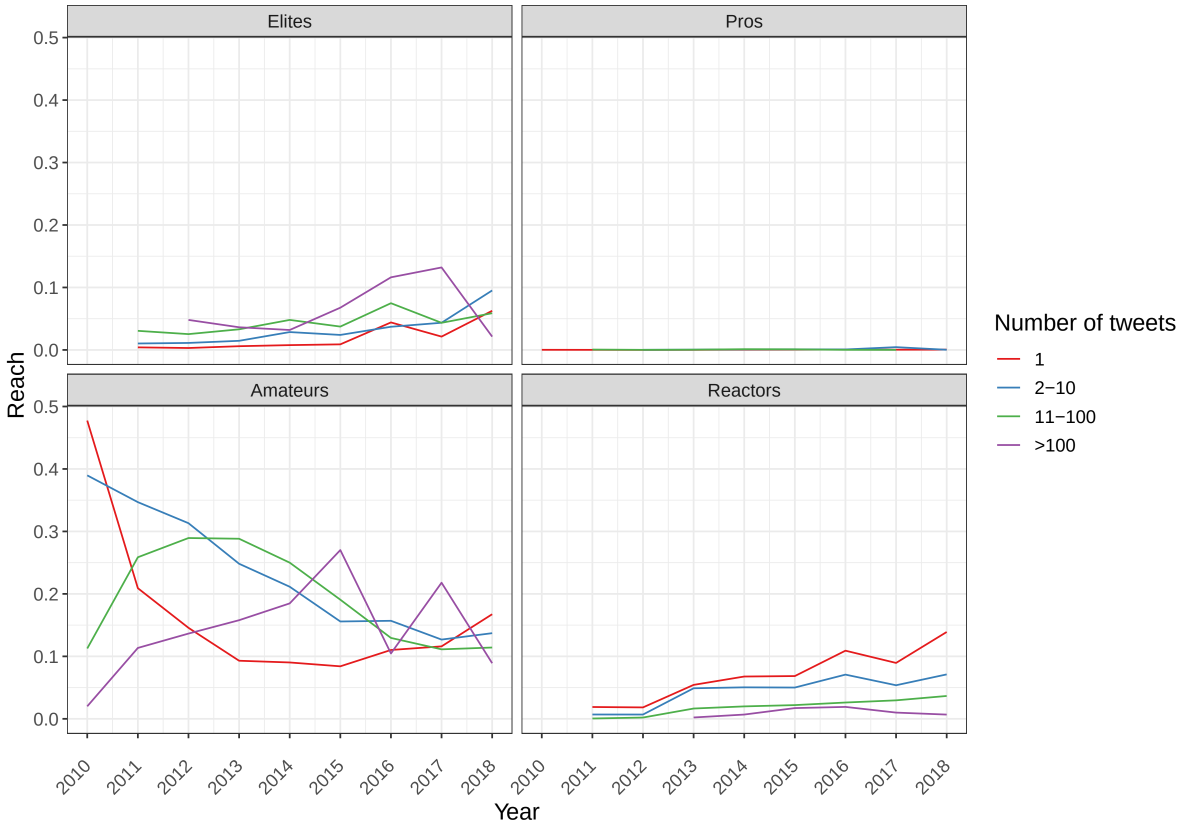


[a]

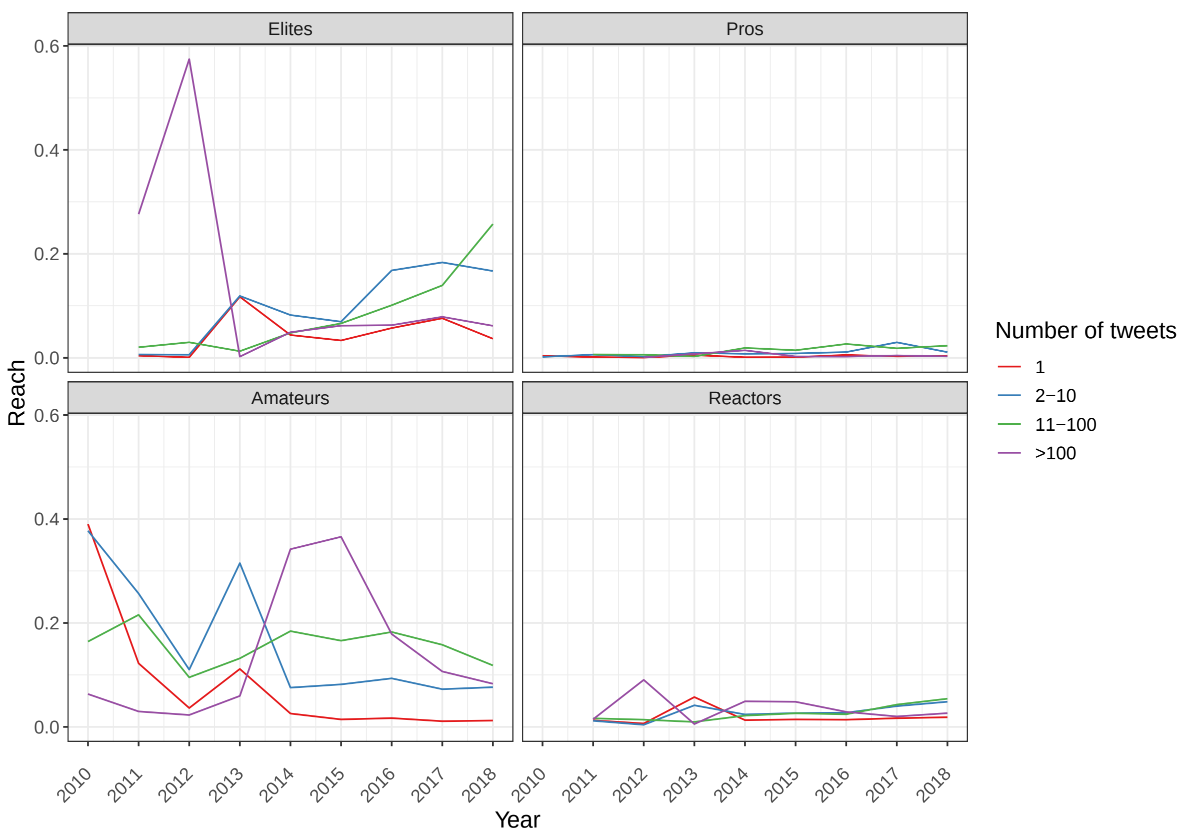


[b]

Figure 11. Changes in reach for each account type over time in CCSS (a) and BLM (b) conversations



[a]



[b]

Figure 12. Changes in reach for each account type over time in CCSS (a) and BLM (b) conversations

Acknowledgments

We thank Jen Rosiere Reynolds, the Center's lab manager, for her helpful comments and suggestions, Megan A. Brown, research engineer and data scientist at the Center, for her assistance in data collection and data analysis, Cody Buntain, assistant professor in Informatics at New Jersey Institute of Technology, for his extensive support in data processing and measures, as well as the Bill and Melinda Gates Foundation for supporting this project. We also gratefully acknowledge that the Center for Social Media and Politics at New York University is supported by funding from the John S. and James L. Knight Foundation, the Charles Koch Foundation, Craig Newmark Philanthropies, the William and Flora Hewlett Foundation, the Siegel Family Endowment, the Bill and Melinda Gates Foundation, and the National Science Foundation.

References

[1] About the Standards | Common Core State Standards Initiative.

[2] Development Process | Common Core State Standards Initiative.

[3] Adopting Agency, March 2017.

[4] U.S. Secretary of Education Duncan Announces Winners of Competition to Improve Student Assessments | U.S. Department of Education.

[5] Catherine Gewertz. In National First, Kentucky Adopts Common Standards - Education Week. *Education Week*, February 2010.

[6] Education Next. Ednext Poll Interactive Ten Year Trends Public Opinion, August 2016.

[7] Anthony Cody, Network for Public Education co founder, and Former Teacher. Political Rivals Find Common Ground Over Common Core.

[8] Joseph P Williams. Who is fighting against common core. *US News & World Report*, 2014.

[9] David Freedl and er On 09/28/15 at 10:54 AM EDT. How the GOP Turned on Common Core, September 2015.

[10] Standards in Your State | Common Core State Standards Initiative.

[11] Which States Are Using PARCC or Smarter Balanced? - Education Week. *Education Week*, February 2017.

[12] Marija Anna Bekafigo and Allan McBride. Who tweets about politics? political participation of twitter users during the 2011gubernatorial elections. *Social Science Computer Review*, 31(5):625–643, 2013.

[13] Yeojin Kim and Wilson Lowrey. Who are citizen journalists in the social media environment? personal and social determinants of citizen journalism activities. *Digital Journalism*, 3(2):298–314, 2015.

[14] Jessica T Feezell. Agenda setting through social media: The importance of incidental news exposure and social filtering in the digital era. *Political Research Quarterly*, 71(2):482–494, 2018.

[15] Andrew Guess, Kevin Munger, Jonathan Nagler, and Joshua Tucker. How accurate are survey responses on social media and politics? *Political Communication*, 36(2):241–258, 2019.

Appendix

Appendix A: Relevance Classifier

In order to identify the tweets relevant to CCSS or BLM, we constructed a relevance classifier. We used a sample of 2,000 tweets for each CCSS and BLM from the filtered public sample stream data. Each tweet was hand coded as 'relevant' or 'not relevant' to CCSS/BLM. We used Random Forest with character n-grams and achieve the accuracy score of 0.88 and F1 score of 0.90 for CCSS and accuracy score of 0.86 and F1 score of 0.88 for BLM tweets.

Appendix B: Political classifier

Our political classifier was trained on 3,433 Reddit and Facebook comments and tweets collected by Andy Guess and Magdalena Wojcieszak. Each comment/tweet was hand coded as 'political' or 'non-political'. We classified tweets as political if they are about politics, including 'politicized issues', such as vaccination, sexual harassment, or global warming. Using Logistic regression with elastic net regularization and character n-grams, we achieved the accuracy and F1 scores of 0.92.

Appendix C: Influence of account types on each other

Table 15. Influence of account types on each other in CCSS

Account type A	Account type B	$I_{A \to B}$
Political Elites	Reactors	0.33
Media Elites	Reactors	0.32
Political Elites	Political Amateurs	0.27
Citizen Journalists/Allies	Reactors	0.20
Political Elites	Political Pros	0.09
Political Amateurs	Political Elites	0.09
Political Amateurs	Reactors	0.08
Political Elites	Citizen Journalists/Allies	0.08
Political Elites	Media Elites	0.08
Political Elites	Pros	0.08
Media Elites	Citizen Journalists/Allies	0.06
Citizen Journalists/Allies	Media Elites	0.06
Citizen Journalists/Allies	Pros	0.04
Political Amateurs	Media Elites	0.04
Citizen Journalists/Allies	Political Amateurs	0.04
Political Amateurs	Citizen Journalists/Allies	0.04
Media Elites	Pros	0.04
Political Amateurs	Political Pros	0.03
Political Amateurs	Pros	0.03
Media Elites	Political Amateurs	0.03
Citizen Journalists/Allies	Political Elites	0.03
Citizen Journalists/Allies	Political Pros	0.02
Media Elites	Political Pros	0.02
Political Pros	Pros	0.02
Media Elites	Political Elites	0.02
Pros	Political Pros	0.01

Note: This table shows accounts with the influence score higher than 0.00 and does not include the information on influence between the same account types

Table 16. Influence of users with different engagement levels on each other in CCSS

Account type A	Account type B	$I_{A\rightarrow B}$
Elites(>100)	Reactors(11-100)	0.53
Elites(>100)	Reactors(>100)	0.53
Elites(>100)	Reactors(2-10)	0.42
Amateurs(>100)	Reactors(>100)	0.30
Elites(>100)	Reactors(1)	0.25
Elites(11-100)	Reactors(2-10)	0.24
Elites(>100)	Elites(11-100)	0.21
Elites(11-100)	Reactors(1)	0.21
Elites(11-100)	Reactors(11-100)	0.19
Elites(>100)	Amateurs(11-100)	0.19
Elites(2-10)	Reactors(1)	0.17
Elites(>100)	Amateurs(>100)	0.16
Elites(>100)	Elites(2-10)	0.15
Elites(11-100)	Elites(2-10)	0.12
Amateurs(>100)	Reactors(11-100)	0.12
Elites(>100)	Amateurs(2-10)	0.11
Amateurs(2-10)	Reactors(1)	0.10
Amateurs(1)	Reactors(1)	0.09
Elites(>100)	Pros(>100)	0.09
Elites(2-10)	Elites(1)	0.09
Elites(11-100)	Pros(1)	0.09
Elites(2-10)	Reactors(2-10)	0.09
Elites(11-100)	Elites(1)	0.08
Elites(>100)	Pros(11-100)	0.08
Amateurs(>100)	Elites(>100)	0.08
Amateurs(11-100)	Reactors(2-10)	0.07
Amateurs(>100)	Reactors(2-10)	0.07
Elites(>100)	Elites(1)	0.07
Amateurs(11-100)	Reactors(11-100)	0.07
Elites(11-100)	Reactors(>100)	0.07
Elites(1)	Reactors(1)	0.07
Elites(11-100)	Pros(2-10)	0.07
Elites(2-10)	Pros(1)	0.06
Amateurs(2-10)	Reactors(2-10)	0.06
Amateurs(>100)	Amateurs(11-100)	0.06
Elites(>100)	Pros(2-10)	0.06
Amateurs(11-100)	Reactors(1)	0.06
Elites(11-100)	Amateurs(11-100)	0.06
Elites(11-100)	Amateurs(2-10)	0.05
Amateurs(1)	Elites(1)	0.05
Amateurs(11-100)	Reactors(>100)	0.05
Amateurs(2-10)	Elites(1)	0.04
Elites(11-100)	Pros(11-100)	0.04
Amateurs(>100)	Elites(11-100)	0.04
Amateurs(11-100)	Elites(11-100)	0.04
Amateurs(>100)	Reactors(1)	0.04
Amateurs(2-10)	Elites(2-10)	0.04
Amateurs(2-10)	Pros(1)	0.04
Elites(2-10)	Reactors(11-100)	0.04
Amateurs(11-100)	Pros(2-10)	0.03
Amateurs(11-100)	Pros(11-100)	0.03
Amateurs(>100)	Pros(>100)	0.03
Amateurs(2-10)	Pros(2-10)	0.03
⋮	⋮	⋮

Table 17. Influence of users with different engagement levels on each other in BLM

⋮	⋮	⋮
Elites(11-100)	Elites(>100)	0.03
Elites(>100)	Pros(1)	0.03
Amateurs(11-100)	Elites(2-10)	0.03
Amateurs(1)	Reactors(2-10)	0.03
Elites(2-10)	Elites(11-100)	0.03
Pros(11-100)	Pros(1)	0.03
Amateurs(11-100)	Amateurs(2-10)	0.03
Amateurs(2-10)	Reactors(11-100)	0.03
Elites(1)	Pros(1)	0.03
Pros(11-100)	Pros(2-10)	0.03
Amateurs(11-100)	Elites(>100)	0.03
Amateurs(11-100)	Amateurs(>100)	0.02
Amateurs(>100)	Amateurs(2-10)	0.02
Amateurs(>100)	Pros(11-100)	0.02
Amateurs(2-10)	Elites(11-100)	0.02
Amateurs(11-100)	Elites(1)	0.02
Elites(2-10)	Pros(2-10)	0.02
Amateurs(>100)	Elites(2-10)	0.02
Amateurs(1)	Elites(2-10)	0.02
Elites(2-10)	Amateurs(2-10)	0.02
Pros(>100)	Pros(11-100)	0.02
Elites(11-100)	Amateurs(>100)	0.02
Amateurs(1)	Pros(1)	0.02
Pros(2-10)	Pros(1)	0.02
Amateurs(11-100)	Pros(>100)	0.02
Amateurs(11-100)	Pros(1)	0.02
Amateurs(2-10)	Pros(11-100)	0.02
Amateurs(2-10)	Reactors(>100)	0.02
Elites(11-100)	Pros(>100)	0.01
Amateurs(2-10)	Amateurs(11-100)	0.01
Elites(1)	Reactors(2-10)	0.01
Pros(>100)	Pros(2-10)	0.01
Amateurs(>100)	Elites(1)	0.01
Amateurs(1)	Pros(2-10)	0.01
Elites(2-10)	Amateurs(11-100)	0.01
Elites(1)	Elites(2-10)	0.01
Elites(2-10)	Reactors(>100)	0.01
Amateurs(>100)	Pros(2-10)	0.01
Amateurs(1)	Amateurs(2-10)	0.01
Amateurs(1)	Reactors(11-100)	0.01
Amateurs(1)	Elites(11-100)	0.01
Amateurs(2-10)	Elites(>100)	0.01
Pros(11-100)	Pros(>100)	0.01
Amateurs(>100)	Pros(1)	0.01
Pros(2-10)	Reactors(1)	0.01
Elites(2-10)	Pros(11-100)	0.01
Amateurs(2-10)	Pros(>100)	0.01
Amateurs(2-10)	Amateurs(>100)	0.01
Pros(>100)	Pros(1)	0.01
Elites(2-10)	Elites(>100)	0.01

Note: This table shows accounts with the influence score higher than 0.00 and does not include the information on influence between the same account types

Table 18. Influence of account types on each other in BLM

Account type A	Account type B	$I_{A\to B}$
Political Elites	Reactors	0.33
Political Elites	Political Amateurs	0.30
Political Elites	Citizen Journalists/Allies	0.19
Media Elites	Reactors	0.19
Political Elites	Pros	0.17
Political Elites	Political Pros	0.16
Media Elites	Citizen Journalists/Allies	0.11
Political Elites	Media Elites	0.10
Citizen Journalists/Allies	Reactors	0.09
Media Elites	Pros	0.08
Political Amateurs	Political Elites	0.06
Media Elites	Political Amateurs	0.06
Political Amateurs	Reactors	0.05
Political Amateurs	Citizen Journalists/Allies	0.05
Political Amateurs	Political Pros	0.04
Citizen Journalists/Allies	Pros	0.04
Media Elites	Political Pros	0.04
Citizen Journalists/Allies	Political Amateurs	0.04
Political Amateurs	Pros	0.04
Citizen Journalists/Allies	Media Elites	0.03
Media Elites	Political Elites	0.03
Pros	Reactors	0.02
Political Amateurs	Media Elites	0.02
Pros	Political Pros	0.02
Citizen Journalists/Allies	Political Pros	0.02
Pros	Citizen Journalists/Allies	0.02
Citizen Journalists/Allies	Political Elites	0.02
Political Pros	Pros	0.01
Pros	Media Elites	0.01
Pros	Political Amateurs	0.01
Pros	Political Elites	0.01
Political Pros	Political Elites	0.01
Political Pros	Reactors	0.01
Political Pros	Political Amateurs	0.01
Political Pros	Citizen Journalists/Allies	0.01
Political Pros	Media Elites	0.01

Note: This table shows accounts with the influence score higher than 0.00 and does not include the information on influence between the same account types

Table 19. Influence of account types on each other in BLM

Account type A	Account type B	$I_{A\to B}$
Elites(>100)	Reactors(>100)	0.76
Elites(>100)	Reactors(11-100)	0.65
Elites(>100)	Reactors(2-10)	0.52
Elites(>100)	Amateurs(>100)	0.50
Elites(>100)	Reactors(1)	0.42
Elites(>100)	Amateurs(11-100)	0.41
Elites(>100)	Pros(>100)	0.41
Elites(>100)	Elites(11-100)	0.36
Elites(>100)	Pros(11-100)	0.36
Elites(>100)	Pros(2-10)	0.28
Elites(>100)	Elites(2-10)	0.24
Elites(>100)	Amateurs(2-10)	0.24
Elites(11-100)	Reactors(1)	0.20
Elites(>100)	Pros(1)	0.20
Elites(11-100)	Reactors(2-10)	0.19
Elites(>100)	Elites(1)	0.18
Elites(11-100)	Reactors(11-100)	0.15
Elites(11-100)	Elites(2-10)	0.14
Elites(2-10)	Reactors(1)	0.13
Elites(11-100)	Elites(1)	0.13
Elites(11-100)	Pros(1)	0.12
Elites(11-100)	Pros(2-10)	0.11
Elites(2-10)	Elites(1)	0.10
Elites(2-10)	Reactors(2-10)	0.10
Elites(11-100)	Amateurs(11-100)	0.09
Elites(11-100)	Pros(11-100)	0.08
Elites(2-10)	Pros(1)	0.08
Elites(11-100)	Amateurs(2-10)	0.08
Elites(11-100)	Reactors(>100)	0.08
Amateurs(11-100)	Reactors(2-10)	0.07
Amateurs(2-10)	Reactors(1)	0.07
Amateurs(11-100)	Reactors(1)	0.06
Amateurs(>100)	Reactors(>100)	0.06
Amateurs(11-100)	Reactors(11-100)	0.06
Amateurs(>100)	Elites(>100)	0.06
Elites(11-100)	Elites(>100)	0.05
Elites(2-10)	Reactors(11-100)	0.05
Elites(11-100)	Amateurs(>100)	0.05
Amateurs(2-10)	Reactors(2-10)	0.04
Elites(11-100)	Pros(>100)	0.04
Elites(1)	Reactors(1)	0.04
Amateurs(11-100)	Elites(11-100)	0.04
Elites(2-10)	Pros(2-10)	0.04
Amateurs(2-10)	Elites(1)	0.04
Amateurs(>100)	Reactors(11-100)	0.04
Amateurs(11-100)	Elites(2-10)	0.04
Amateurs(11-100)	Reactors(>100)	0.04
Elites(2-10)	Amateurs(2-10)	0.03
Amateurs(>100)	Amateurs(11-100)	0.03
Amateurs(11-100)	Amateurs(2-10)	0.03
Amateurs(2-10)	Pros(1)	0.03
Elites(2-10)	Elites(11-100)	0.03
Amateurs(2-10)	Elites(2-10)	0.03
Amateurs(11-100)	Elites(1)	0.03
Amateurs(>100)	Reactors(2-10)	0.03
Amateurs(1)	Reactors(1)	0.03
⋮	⋮	⋮

⋮	⋮	⋮
Amateurs(>100)	Pros(>100)	0.03
Amateurs(11-100)	Elites(>100)	0.03
Amateurs(11-100)	Amateurs(>100)	0.03
Amateurs(11-100)	Pros(2-10)	0.03
Amateurs(>100)	Elites(11-100)	0.03
Elites(2-10)	Amateurs(11-100)	0.03
Amateurs(11-100)	Pros(11-100)	0.03
Amateurs(11-100)	Pros(1)	0.02
Amateurs(1)	Elites(1)	0.02
Amateurs(>100)	Reactors(1)	0.02
Amateurs(2-10)	Pros(2-10)	0.02
Amateurs(2-10)	Reactors(11-100)	0.02
Elites(1)	Pros(1)	0.02
Amateurs(11-100)	Pros(>100)	0.02
Amateurs(2-10)	Elites(11-100)	0.02
Amateurs(>100)	Elites(2-10)	0.02
Elites(1)	Elites(2-10)	0.02
Amateurs(>100)	Amateurs(2-10)	0.02
Elites(2-10)	Reactors(>100)	0.02
Elites(2-10)	Pros(11-100)	0.02
Amateurs(>100)	Pros(11-100)	0.02
Elites(1)	Reactors(2-10)	0.02
Amateurs(2-10)	Amateurs(11-100)	0.02
Amateurs(1)	Pros(1)	0.02
Pros(11-100)	Pros(2-10)	0.01
Amateurs(>100)	Elites(1)	0.01
Amateurs(1)	Reactors(2-10)	0.01
Amateurs(>100)	Pros(2-10)	0.01
Amateurs(1)	Elites(2-10)	0.01
Amateurs(2-10)	Pros(11-100)	0.01
Amateurs(2-10)	Reactors(>100)	0.01
Pros(11-100)	Pros(1)	0.01
Elites(2-10)	Elites(>100)	0.01
Elites(2-10)	Amateurs(>100)	0.01
Pros(2-10)	Pros(1)	0.01
Pros(11-100)	Pros(>100)	0.01
Amateurs(2-10)	Elites(>100)	0.01
Amateurs(2-10)	Amateurs(>100)	0.01
Amateurs(>100)	Pros(1)	0.01
Pros(>100)	Pros(11-100)	0.01
Elites(2-10)	Pros(>100)	0.01
Elites(1)	Pros(2-10)	0.01
Elites(1)	Amateurs(2-10)	0.01
Amateurs(1)	Amateurs(2-10)	0.01
Elites(1)	Reactors(11-100)	0.01

Note: This table shows accounts with the influence score higher than 0.00 and does not include the information on influence between the same account types