Spreading Like Wildfire: The Securitization of the Amazon Rainforest Fires on Twitter (Supporting Information)

A. Query terms

Table A.1 displays the full list of 28 query terms that were employed in the data collection.

Table A.1: Twitter Queries

Query
amazon forest, amazon rainforest, amazon is burning, amazonwatch, the planets lungs, amazon rain forest, planets oxygen, the amazon basin, fires in the amazon, the amazon burning, amazon fire, lungs of the planet, lungs of our planet, pray for the amazon, actforamazon, prayforamazonas, sosamazonia, savetheamazon, amazonasenllamas, lamazonie, amazonia, stopbolsonaro, worlds oxygen, amazonrainforest, amazonfires, sosamazonas, actfortheamazon, salvemoselamazonas

A.2 Dataset

The final dataset developed and employed in tthis study consists of 3,806,624 tweets posted by 3,800,777 unique users. The frequency distribution of tweets collected from each query can be found in Figure A.1.

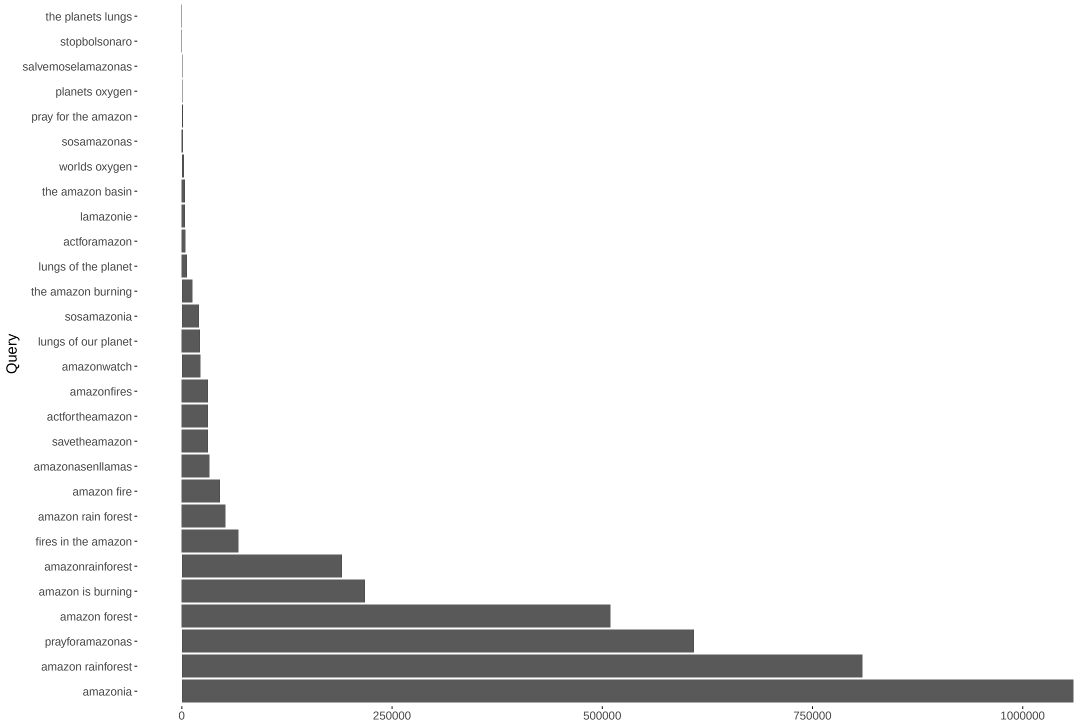

Figure A.1: Frequency of query terms

B. Stopwords

Seeking to remove all tweets that were not related to the Amazon fires from the dataset, the study develops a list of stopwords, in most cases related to Amazon.com. The full list is displayed in Table A.2.

Table A.2: Stopwords

Stopwords
stick, fire tv, amazoniancos, amazonhelp, warehouse, go store, marketplace, ny, amazon deal, new york, firestick, fba, echo, alexa, gift card, primeday, google, hq, package, delivery, mail, item, amazonstrike, uber, nyc, sellout, jeff bozo, workingbackwards, jeff bezos, order via, customer, prime video, board of directors, working conditions, amazonberkshirejpmorgan, chevron, ai and bias, worldwaterdaywater, netflix, retail, guyana, photodujour, leave a review, amazonwearenotrobots, amazonkindle, workers, amazonmusicuk, amazonuk, amazon prime, amazonprime, amazon machine learning, hbo, fcfanclub, vatican, cowrywise, amazonbasics, priest, echo, amazonianpixel

C. User Classification

Building on the dataset developed by Umansky (2022), which includes tweets discussing the Amazon rainforest fires and manual annotations classifying users into five actor groups (politicians, the media, advocates, politician's Twitter friends, and citizens on Twitter), I test the typology and the classification developed in this study by exploring the correlations among groups. Particularly, I expect influentials and broadcasters to correlate highly with politicians, the media, advocates, and politician's Twitter friends (prominent personalities with large audiences), while hidden influentials and common users are expected to correlate with the citizens on Twitter group. The results of this analysis are displayed in Figure A.2.

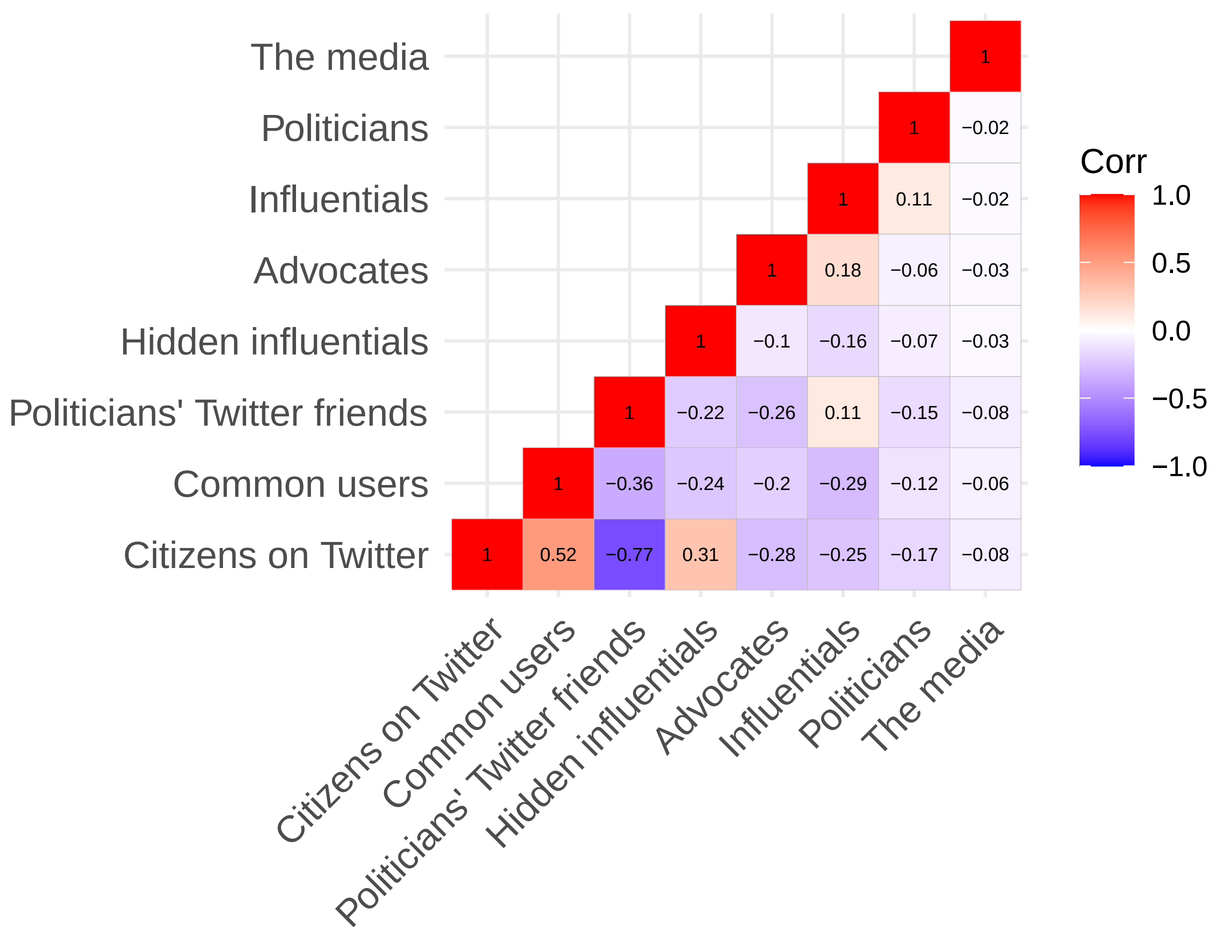

Figure A.2: Correlation between groups and types of users

As shown in Figure A.2, the results align with the expectations, displaying higher positive correlations between common users and citizens on Twitter, hidden influentials and citizens on Twitter, influentials and advocates, and, at a lower rate but significant, between politicians and influentials.

Thus, these results strengthen the typology developed in this study.