SUPPLEMENTARY MATERIAL

TWEETING BEYOND TAHRIR
Ideological Diversity and Political Intolerance
in Egyptian Twitter Networks

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Supplementary Materials

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Training a Classifier Using Human Coded Data

We initially developed a 6 category coding scheme for relevant tweets. Tweets were first coded as relevant or irrelevant to civil liberties in Egypt and then classified as follows: **1**= Tweets that promote civil liberties and rights for Islamists **2**= Tweets that promote civil liberties and rights for Secularists (non-Islamists) **3**= Tweets that promote civil liberties and rights in general (for all Egyptians or groups of Egyptians that may include both Islamists and non-Islamists) **4**= Tweets that support restricting the civil liberties and rights of Islamists **5**= Tweets that support restricting the civil liberties and rights of Secularists (non-Islamists) **6**= Tweets that support restricting civil liberties and rights of groups that include both Islamists and non-Islamists.

Under this coding scheme, tweets that promote civil liberties include those that oppose: unfair trials, unlawful detentions, arbitrary arrests, death sentences, torture, censorship, limitations on free speech or assembly, excluding any group from participating in government, electoral fraud, police or military violence against civilians, and banning political parties, NGOs, or other civil society organizations. Tweets that promote civil liberties also include those that call for freedom, democracy, human rights, and an end to discriminatory or exclusionary policies. By contrast, as mentioned in Section 4 of the paper, tweets that support restricting civil liberties include those that favor civilian arrests, death sentences, or torture; those limiting the right to free speech, protest, or assembly; and tweets advocating banning political parties or excluding certain groups from formal or informal political participation.

In order to assess the reliability of our coding scheme, we began by training four undergraduate native-Arabic speaking volunteers to code a small sample of 300 tweets containing keywords relevant to civil liberties in Egypt. A complete list of these keywords are in Figure A2 below.[34]

Reliability among the coders was fairly high, with average agreement at 88%.[35] Having established that these tweets could be consistently coded by native Arabic-speaking college students, we then determined that these tweets could also be reliably classified using crowd-sourced coding. Using Figure8, a data enrichment platform that allows a researcher to launch microtasks to a "crowd" of over five million contributors, we launched the same 300 tweets that we had given to the volunteers to be coded by the Arabic-speaking "crowd."[36] Each of the 300 tweets was coded by three Figure8 users, and the average sentiment confidence was 84%.[37] This gave us confidence that while perhaps not quite as reliable as elite native Arabic speaking college students, members of the "crowd" could still code tweets quite consistently.

[34] Tweets were filtered as a random sample from a collection of tweets geolocated in Egypt collected between January 2014 and April 2015.

[35] Sentiment confidence was measured as the number of coders choosing the dominant sentiment category divided by the total number of coders.

[36] Using test questions for quality control, we ensured that the contributors were coding tweets accurately and conscientiously. If a contributor answered a certain percentage of test questions incorrectly, that contributor was removed from the job and their data was erased. This enabled us to ensure that the members of the "crowd" coding my tweets were fluent in Arabic and understood the task at hand.

[37] Here sentiment confidence was measured as above, but also weighted contributor responses by how "trusted" users were given their percentage of correct answers to test questions, according to Figure8's algorithm.

Figure A1: **Arabic civil liberties keywords**

قبض	arrest
حظر	ban
مراقبة	censorship
مواطن	citizen
دستور	constitution
انقلاب	coup
محكمة	court
جريمة	crime
ديمقراطية	democracy
كرامة	dignity
تمييز	discrimination
منشق	dissident
انتخابات	elections
اعدام	execution
فاشية	fascism
منع	forbid
ممنوع	forbidden
تزوير	fraud
حرية	freedom
حكومة	government
حبس	imprisonment
ظلم	injustice
القاضي	judge
القضاء	judiciary
عدالة	justice
قانون	law
قوانين	law
حكم العسكر	military rule
اضطهاد	persecution
سياسة	policy
سجن	prison
تظاهر	protest
عقوبة	punishment
عنصرية	racism
حقوق	rights
حكم	rule
سلامة	safety
طائفية	sectarianism
امن	security
الشريعة	Sharia
الأعتصام	sit in
الاستبداد	tyranny
انتهاك	violation

The English version of the coding instructions provided to the Figure8 coders is as follows:

Overview: Tweets will be coded according to whether or not they advocate protecting civil liberties and the extension of political freedoms to Islamists, Secularists (non-Islamists), or Egyptian citizens in general.

Process: 1) Read the tweet. 2) Determine if the tweet is relevant to civil liberties in Egypt. 3) Determine if the tweet supports extending civil liberties to Egyptian citizens or not and to which political groups in Egypt (Islamists, Secularists or Non-Islamists, or citizens in general)

Tweets can be classified as: 1) Tweets that promote civil liberties and rights for Islamists. 2) Tweets that promote civil liberties and rights for Secularists (non-Islamists). 3) Tweets that promote civil liberties and rights in general (for all Egyptians or groups of Egyptians that may include both Islamists and non-Islamists) 4) Tweets that support restricting the civil liberties and rights of Islamists. 5) Tweets that support restricting the civil liberties and rights of Secularists (non-Islamists) Tweets that support restricting civil liberties and rights in general (for groups that include both Islamists and non-Islamists).

Tweets that promote civil liberties and rights include those that: Oppose censorship or the arrests of journalists; Oppose unfair trials/ unlawful detentions/ arbitrary arrests /death sentences/ torture; Oppose the protest law or other limitations on free speech, the right to protest or assemble etc.; Oppose excluding any groups of Egyptians from participating in government. Oppose banning political parties, NGO's, or other organizations; Oppose corruption; Oppose labeling all Islamists as terrorists or all Secularists as infidels (kafir) or other terms that suggest that these groups should be excluded from politics; Oppose discriminatory election laws or electoral fraud; Call for an end to sectarianism/discrimination/inequality; Call for the release of activists/journalists/political prisoners; Call for participatory democracy, freedom, and rights; Call for an end to authoritarian rule/policies; Oppose state violence.

Tweets that support restricting civil liberties or rights include those that: Support civilian arrests, death sentences, torture etc; Support limiting the right to protest, free speech etc; Call for banning political parties or excluding groups from politics or elections; Call for violence/undemocratic policies or state actions; Promote sectarianism, discrimination or unequal policies; Label all members of a political group as terrorists or infidels or any label which indicates that they should not be allowed to participate in politics.

After coding about five thousand additional tweets on Figure8 to create a set, we then trained a classifier to predict whether or not a tweet was relevant.[38] Assessing the classifier's performance using 5-fold cross validation, the classifier obtained 74% average precision and 76% average recall.[39] Because intolerant and tolerant tweets are relatively rare, we needed to collect more data to train our classifier to accurately identify intolerant tweets. We therefore collected up to 50 tweets that the classifier identified as relevant from 837 Egyptian Twitter users that had tweeted keywords relevant to civil liberties in Egypt. This produced a training dataset of over 50,000 tweets classified along the six category coding scheme outlined above. 81% of the tweets in this dataset were relevant, suggesting that the relevance classifier was in fact performing better than expected. Using this training data, we trained a second classifier to classify intolerance. Relevant tweets in categories 4-6 (tweets that support restricting civil liberties and rights for Islamists, Secular Egyptians, or Egyptians in general) were classified as intolerant. The intolerance classifier performed well, with five-fold cross validation yielding average precision of 80% and average recall of 87%, levels of accuracy that were comparable to our levels of intercoder reliability in the human coded data. After testing the performance of several classifiers, we chose to use an AdaBoosted Multinomial Naive Bayes classifier. We chose this classifier because it maximized precision. This means that the tweets that are classified as intolerant are very likely to be intolerant, even if we lose a bit of recall, or fail to classify some tweets that were in fact intolerant. While we might be concerned that selecting a training data set based on keywords could bias our results, because these terms occur commonly in online Egyptian discourse, a training set of tweets containing these terms can be effectively used to characterize Egyptian online discourse as relevant to civil liberties or not. If we had instead used a random sample of our dataset as training data, we would have

[38]We first cleaned the text of punctuation and other symbols, and then converted words in the tweets to their roots using the ISRI Arabic Stemming Without a Root Dictionary stemmer Then, using word count vectors from the training dataset, we trained a Naive Bayes classifier to predict whether or not a tweet was relevant.

[39]Precision is a measure of True Positives/(True Positives + False Positives) while Recall is a measure of True Positives/(True Positives + False Negatives).

needed a prohibitively expensive number of human-coded tweets to have sufficient balance in our training data.

Identifying Egyptian Elites on Twitter:

Elites were identified using Twitter Counter, a site that tracks statistics for over 94 million Twitter users worldwide, to rank Egyptian Twitter users by their follower numbers. This allowed us to compile a list of all Egyptian politicians and political movements that have over 10,000 followers on Twitter and well-known political affiliations, resulting in a list of 85 Egyptian political elite users. A list and description of these users is displayed in Table A2.

Locating Twitter Users in Egypt

Geolocation data is determined by the latitude and longitude coordinates detected by those Twitter users that enable geolocation services. Less than 1 percent of tweets in the global Twittersphere contain geolcoation metadata, and this finding is reflected in our sample as well. However, location can also be determined using a user's location field in the metadata of their Twitter account. Here Twitter users write in location information. Any user listing Arabic or English words for Egypt or a city in Egypt were classified as Egyptian Twitter users. As demonstrates, a user's country and state can be determined with decent accuracy using self-reported Twitter data, and users often reveal location information with or without realizing it. As argues, because large numbers of users report their location in the "location" field and in aggregate these reports are quite accurate, this seems a reasonable (and commonly used) way to determine a user's location. This is especially true given that we are more interested in obtaining a high degree of precision (ensuring that the users are actually Egyptian) than recall (obtaining the entire population of tweets sent by politically engaged Egyptians).

Figure A2: **Summary of Data Collection Process**

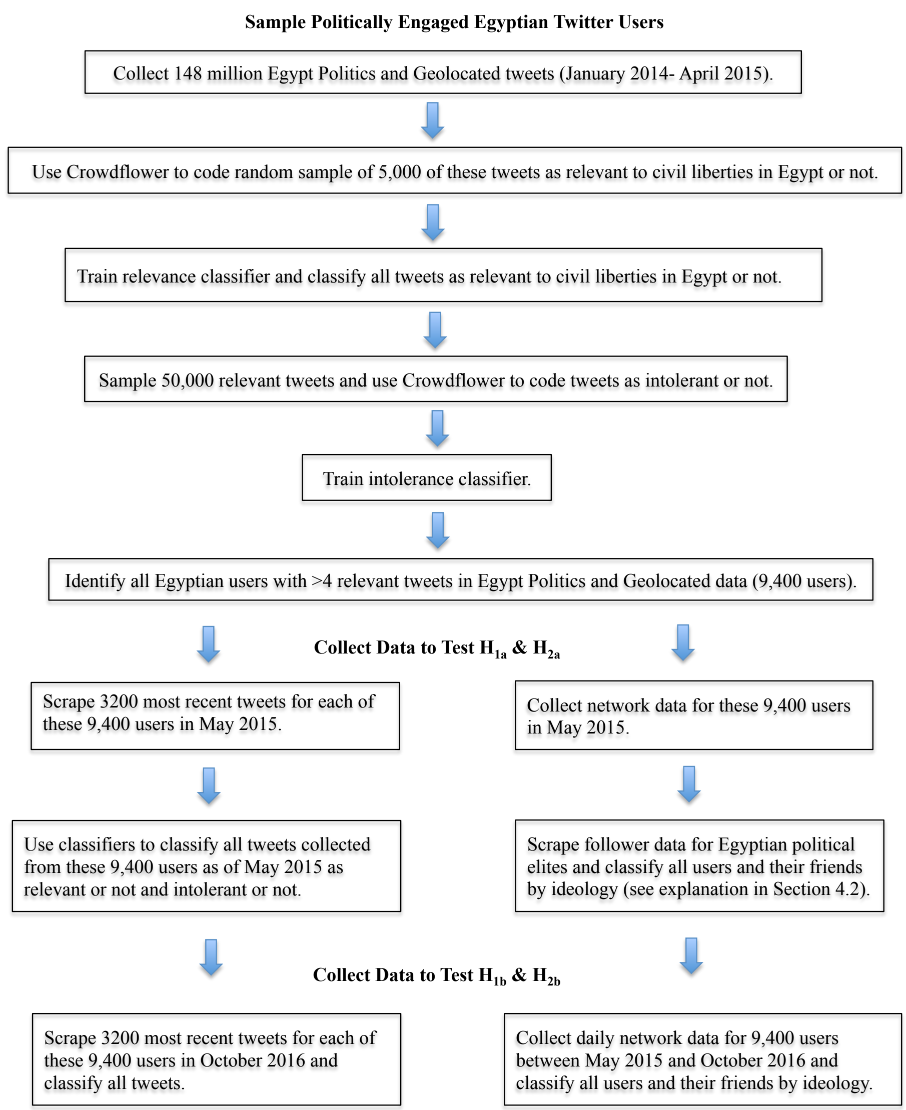


Table A1: **Randomly Selected Relevant and Intolerant Tweets (English Translations)**

	Randomly Sampled Relevant Tweets	Randomly Sampled Intolerant Tweets
1	There are many innocent prisoners #freedom	RT @khaledmontaser: The Brotherhood with their stupidity and their terrorism and their torture, their Fairmont elite have put a ceiling on our ambitions and they have fallen completely after the days of bread freedom and social justice
2	Who are the people you donkey. Egypt is a people ruled by the people. Egypt recognizes and condemns any dog but it shakes things up a little bit. Legitimacy, democracy, liberalism, military, so what.	Twitter and facebook activists begin using the hashtag #congratulations on executing the leader [of the Muslim Brotherhood]
3	Free Mansoura from prisons of the coup #pray _for_them http://t.co/EKP2fVOQw5	Yes, to excluding the Brotherhood from any political activity ... They do not deserve to threaten the security of Egypt and kill its soldiers and justify their killing ... they do not deserve to participate in any electoral or political process.
4	@KhoKhaZ @ANAS_ELSHAER The constitution of the cross will not rule the Muslims. #Our_date_is_January _25	The Muslim Brotherhood are fascist dictators like the old ones. Either they rule us or there is violence.
5	Alexandria: The revolutionaries shout down down with military rule in the Asawi region during the night march #Rabawi [Muslim Brotherhood supporters after the Rabaa al-Adawiya massacre]	RT @ DR_Amr_K_Imam1: Badi will be the leader of the terrorist Muslim Brotherhood tomorrow, God willing, after the second execution in the enemy trial and the execution of 682 others Congratulations Congratulations
6	The revolutionaries of the village of flags of the Fayoum Center continued their activities against the bloody bloody coup by holding a mass march in solidarity ... http://t.co/70BSnw7xyc	I believe the security forces should massacre the Muslim Brotherhood so there will be blame and punishment and the same crime will not be committed twice
7	Follow up on the march of the Pyramid revolutionaries. The national alliance for support of legitimacy and the rejection of the military coup will hold a march at 9pm. http://t.co/b66J50o4sy	The death certificate for Sharia is being written. #Muslim Brotherhood #Yes to the constitution
8	People formed a human chain in Damietta this morning to reject the coup #Egypt is Islamic	RT @Almogaz: The Muslim Brotherhood continues to exploit #children. Al-Jazeera showed a video called "Children Against the Coup" in #Port Said. #The Muslim Brotherhood is a Terrorist Organization #Egypt
9	RT @MuhammadMorsi: # President Mohamed Morsi confirms his adherence to constitutional legitimacy and rejects any attempt to get out of it and calls on the armed forces to withdraw their warning	If the government is serious about considering the Muslim Brotherhood as a terrorist organization, then why shouldn't heir leaders be arrested from their homes? #Complete cleansing of Egypt of the sheep
10	The funny thing is that after the disappointments of January 25 and June 30, the army and the intelligence services decided to rule Egypt with ordinary legitimacy in July. What revolution boys and girls?	@SnDrellaSky @ mgabr2004 @eahram Where are the days of security and safety, without any Muslim Brotherhood dogs running or walking in the street. http://t.co/XCfZXkhZBL
11	Talking again about reviving Toshka's failed project confirms the vacuum of the Republic of July and its representative Sisi. Soon we will have a choice, either democracy or chaos.	The problem with releasing and giving amnesty to some of the activists is that the first thing they will do is demonstrate in front of the union to insult President Sisi
12	There is nothing worse than the activist who speaks to you about freedom, democracy, justice and rights, but at the same time he rejects peace ...who is he and where does he come from?	@Amanyel_khayat what I was saying before is not spin but I acknowledge the reality and hope we can discuss the subject of imprisoning Abdel Fattah al-Sisi
13	This fascism is what the intellectuals want and they are manufacturing a professional state. We are dealing with fascist tendencies in an authoritarian era.	The left-wing nationalist gang that controls the human rights field in Egypt gets all riled up when one of them is attacked
14	That's what the military rulers want, military democracy so that they can steal the country and take all of it's resources	RT @ essami55: Wael Abbas and Wael Ghoneim ..the state security bees and their snakes must stop you from committing terrorism .... Oh sons of dogs traitors
15	#Against the protest law #Worker Mohamad Jabar	The death penalty for terrorists is not a surprise in my opinion. The punishment of murderers is right and just #Egypt
16	Freedom for the Mansura Girls Freedom for Almansoura Girls, Disgrace to Egypt's great army imprisoned Girls #FreeMansouraGirls	The corrupt people who wanted to escape from prison need to have death sentances or military trials. The terrorist dogs want to flee.
17	RT @ titotarek8: In Maspero the blood flowed, do not forget Meena Daniel and Imad Effat, Sheikh of Al-Azhar died by the bullets of treason Down down with military rule	Breaking: The militias of the coup attacked the march that left from the al-Rayyan mosque in Maadi with tear gas Egypt is an Islamic country
18	RT @benaatanmia: Former detainee: There are executions of detainees in military camps in Sinai. Haitham Ghneim, a human rights activist, spoke about one of them ... http://t.co/...	Any terrorist dog objecting or commenting on the verdicts of the judiciary, must face trial immediately ,,, when we remove the dirt from this country
19	RT @ajmmisr: URGENT The Presidential Election Commission officially announces the extension of the third-day voting period due to the severe heat wave #ajmmisr http://t.co/kSPCSSDi...	The security solution is required but it is not the only solution. All of our problems over past years have reduced security and that's it.
20	RT @gamaleid Unjust and unfair #down_with_protest_law	@RT @Biso_Sharm: Immediate arrest of all treasonous activists and immediate death penalty for the leaders of the Muslim Brotherhood. Lock up any media that incites

Table A2: **Top Egyptian Politicians and Political Movements by Twitter Followers**

Handle	Name	Followers	Political Orientation	Biography
@amrkhaled	Amr Khaled	2667999	Islamist	Former head of the Egypt Party, Preacher
@ElBaradei	Mohamed El Baredei	2435248	Secular	Former VP, Constitution Party Head
@MuhammadMorsi	Muhammad Morsi	2026386	Islamist	Former President of Egypt
@HamdeenSabahy	Hamdeen Sabahy	1954326	Secular	Head of Popular Current Party
@HamzawyAmr	Amr Hamzawy	1838439	Secular	Head of Masr Al-Huriya Party
@DrAbolfotoh	Abdel Moneim Aboul Fotouh	1545437	Islamist	Former Pres. Candidate, Strong Egypt Party
@NaguibSawiris	Naguib Sawiris	1445649	Secular	Head of Free Egyptians Party
@AymanNour	Ayman Nour	1217582	Secular	Head of Al-Gahad Party, Former Pres. Candidate
@GameelaIsmail	Gameela Ismail	1126805	Secular	Constitution Party Former Presidential Candidate
@amremoussa	Amre Moussa	1112843	Secular	Former Head of Conference Party
@naderbakkar	Nader Bakkar	863505	Islamist	Al Nour Party Spokesperson
@shabab6april	April 6th Youth	806764	Secular	April 6th Youth Movement Official Twitter
@Essam_Elerian	Essam Elarian	689893	Islamist	Vice Chairman of the Freedom and Justice Party
@FJparty	Freedom and Justice Party	633982	Islamist	Freedom and Justice Party Official Twitter
@Saad _Elkatatny	Saad Elkatatny	623642	Islamist	Freedom and Justice Party Chairman
@bothainakamel1	Bothaina Kamel	568562	Secular	Independent Presidential Candidate
@HazemSalahTW	Hazem Abu Ismail	553096	Islamist	Former Salafi Presidential Candidate
@AhmedShafikEG	Ahmed Shafik	474945	Secular	Former PM and Head of the Egyptian Patriotic Mov.
@AsmaaMahfouz	Asmaa Mahfouz	421758	Secular	Founder of April 6th Movement
@lassecgen	Nabil Elaraby	393189	Secular	Former member of Mubarak Gov't
@almorshid	Mohammed Badie	390546	Islamist	Supreme Guide of the Muslim Brotherhood
@GameelaElex2014	Gameela Ismail's Election Campaign	380975	Secular	Gameela Ismail's Election Campaign Official Account
@DrEssamSharaf	Essam Sharaf	357727	Secular	Former Prime Minister, Former NDP
@khairatAlshater	Khairat Al-Shater	341298	Islamist	First Deputy Chairman of the Muslim Brotherhood
@DrHaniSarieldin	Hani Sarieldin	334355	Secular	Founder of Free Egyptians Party
@MohamedElgawady	Mohamed El-Gawady	307958	Islamist	Brotherhood Activist
@M6april	April 6th News	305240	Secular	April 6th Movement Official News Portal
@ElBaradeiOffice	Mohamed El-Baradei's Office	288314	Secular	El-Baradei's Office Official Account
@Alwasatpartyeg	Al-Wasat Party	279991	Islamist	Al- Wasat Party
@wael	Wael Khalil	269138	Secular	Former prominent member of the Revolutionary Socialists
@a_sayyad	Ayman Sayyad	262415	Islamist	Former member of Morsi's advisory board
@HatemAzzam	Hatem Azzam	255592	Secular	Former MP, Civilization Party
@DoctorMahsoob	Mohamed Mahsoob	222381	Islamist	Former Islamist MP
@3arabawy	Hossam El-Hamalawy	208453	Secular	Prominent Member of the Revolutionary Socialists
@GhostyMaher	Ahmed Maher	195243	Secular	Founder of the April 6th Movement
@AlsisiOfficial	Abdel Fatah El-Sisi	194612	Secular	El-Sisi's Official Twitter
@AlDostourP	Constitution Party	194217	Secular	Constitution Party Official Twitter
@MisrAlQawia	Strong Egypt Party	186447	Islamist	Strong Egypt Party Official Twitter
@ma7mod_badr	Mahmoud Badr	177167	Secular	Founder of Tamarod Movement
@RevSocMe	Revolutionary Socialists Party	159835	Secular	Revolutionary Socialists Party Official Twitter
@DrHigazy	Mostafa Higazy	145727	Secular	Sisi Advisor, NASAQ Foundation for Strategic and Humanis
@TayarSha3by	Popular Current	132848	Secular	Popular Current Party Official Site
@Ikhwanweb	Ikhwan Web	126472	Islamist	Official Account of the Muslim Brotherhood
@ikhwantawasol	Ikhwan Online	112472	Islamist	Official Muslim Brotherhood News Portal
@DrMohamadYousri	Mohamad YousriIbrahim	109186	Islamist	Salafi Politician
@DrMorsiNews	Morsi News	100879	Islamist	Morsi News Official Twitter
@almogheer	Ahmed Al-Mogheer	98146	Islamist	Prominent Brotherhood Member
@Dr_pakinam	Pakinam El-Sharkawy	96348	Islamist	Morsi Aid
@bkhafagy	Bassem Khafagy	92880	Islamist	Former Islamist Presidential Candidate
@tamarrod	Tamarod Movement	91801	Secular	Tamarod Official Twitter
@alwafdwebsite	Al-Wafd Party	91234	Secular	Al-Wafd Party
@mrmeit	Mohammed Adel	85473	Secular	Founder of April 6th Movement
@abkamal	Abdullah Kamal	83529	Secular	Former MP National Democratic Party
@hossam_moanis	Hossam Moanis	83263	Secular	Popular Current Party Spokesperson
@gelhaddad	Gehad el-Haddad	72067	Islamist	Media Spokesperson for the Muslim Brotherhood
@Elsisi_General	President Sisi	65614	Secular	President of Egypt
@basemkamel	Basem Kamel	56292	Secular	MP and member of the Social Democratic Party
@amr _darrag	Amr Darrag	51291	Islamist	Former Secretary General of the Egyptian Constituent Asse
@MasreyeenAhrrar	Free Egyptians Party	48460	Secular	Free Egyptians Party Official Twitter
@salafynews	Salafi News	41217	Islamist	Pro-Salafi News Twitter
@tamroud	Tamarod Account	40130	Secular	Tamarod Account
@RabaaHeros	Rabaa Heros	36782	Islamist	Rabaa al-Adawiya Twitter Account
@FJPartyAlex1	Alexandria FJP	35945	Islamist	Alexandria Official FJP Twitter
@MasrAlhureyya	Masr Al-Huriya Party	34243	Secular	Egypt Freedom Party Official Twitter
@drtarekelzomor	Tarek El-Zomor	33548	Islamist	Head of Building and Devleopment Party
@A_khaleel_kh	Ahmed Khalil Khairallah	32622	Islamist	Former Salafi MP
@anasalafy1	I am Salafi	30663	Islamist	Pro-Salafi Twitter
@AZELHARIRY	Abu Azel Hariry	30625	Secular	Former MP and member of the Popular Socialist Alliance P
@EladlParty	Justice Party	30519	Secular	Justice Party Official Twitter
@dryasserborhamy	Yasser Borhamy	27409	Islamist	VP of the Salafi Call, founder of Al-Nour Party
@6AprilYouth	April 6th Youth	20116	Secular	April 6th Movement Official Twitter
@NabdRab3a	Rabaa al-Adawiya	19842	Islamist	Rabaa al-Adawiya Twitter Account
@DrSayedElbadawy	Sayed El-Badawy	19251	Secular	Head of al-Wafd Party
@FjpartyOrg	FJP English Official	18100	Islamist	The official English Twitter of the Freedom and Justice Par
@HalaShuk	Hala Shukralla	16446	Secular	Head of Egyptian Constitution Party
@ch4hazim	Hazem Abu Ismail Support Page	14816	Islamist	Hazem Abu Ismail Suport Twitter
@elnourpartynews	Al-Nour Party News	13675	Islamist	Al-Nour Party Official News Portal
@alwafdportal	al-Wafd Party News	13365	Secular	Al-Wafd Party News Portal
@yonosmakhyoun	Yunos Makhyoun	13093	Islamist	Prominent Salafi
@DrAbdelhafeez	Mohamed Abdelhafeez	12389	Islamist	Prominent Freedom and Justice Party Member
@ashoukry	Ahmed Shoukry	11595	Islamist	Strong Egypt Party Prominent Member
@abd _mon_sh	Abdel Moneim El-Shahat	11581	Islamist	Leader of Salafi Call, Islamist Preacher

Descriptive Statistics

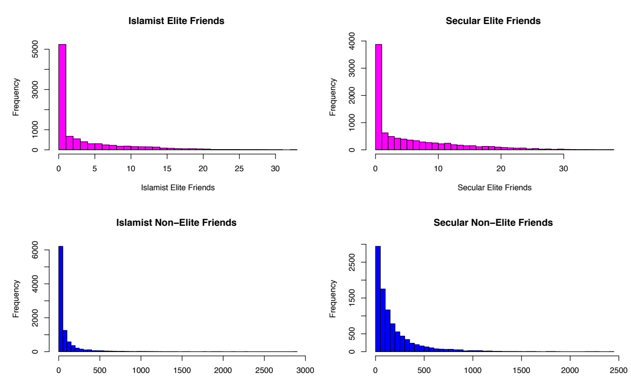
Table A3: **Descriptive Statistics (Full Sample)**

Statistic	N	Mean	St. Dev.	Min	Max
Elite Diversity	9,400	0.575	0.388	0	1
Non-Elite Diversity	9,400	0.434	0.305	0	1
Elite Friends	9,400	9.365	11.022	0	62
Non-Elite Friends	9,400	751.514	1,267.665	0	48,800
Intolerant Tweet Count	9,400	0.885	2.218	0	40
Days on Twitter	9,400	1,848.189	436.857	1,107	3,725
Relevant Tweet Count	9,400	2,071.186	920.251	1	3,206

Table A4: **Descriptive Statistics by Political Orientation**

	Political Orientation	N	Mean	St. Dev.	Median	Min	Max
Elite Diversity	Islamist	1341	0.31	0.29	0.29	0	0.79
	Moderate	3748	0.97	0.06	1.00	0.80	1
	Secular	4311	0.32	0.27	0.33	0.00	0.79
Non-Elite Diversity	Islamist	1341	0.62	0.24	0.65	0.00	1
	Moderate	3748	0.56	0.30	0.60	0	1
	Secular	4311	0.27	0.24	0.18	0	1
Elite Total Friends	Islamist	1341	10.14	9.47	7	1	47
	Moderate	3748	5.83	10.94	0	0	62
	Secular	4311	12.20	10.67	9	1	61
Non-Elite Total Friends	Islamist	1341	791.16	1032.79	430	1	11526
	Moderate	3748	687.99	1379.41	306	0	27156
	Secular	4311	794.41	1229.93	494	0	48800
Intolerant Tweet Count	Islamist	1341	0.85	1.63	0	0	14
	Moderate	3748	0.56	1.71	0	0	33
	Secular	4311	1.18	2.68	0	0	40
Days on Twitter	Islamist	1341	1794.06	412.60	1788	1107	3589
	Moderate	3748	1750.42	411.81	1709.50	1107	3440
	Secular	4311	1950.03	442.97	1974	1107	3725
Relevant Tweet Count	Islamist	1341	1801.51	891.96	2030	0	3157
	Moderate	3748	2178.03	882.57	2608	0	3196
	Secular	4311	2062.18	943.20	2528	0	3206

Figure A3: **Histograms of Twitter Friend Counts**



This Figure shows variation in the counts of Secular and Islamist elites and non-elites followed by the users in our study.

Appendix B: Regression Tables

Table B1: **Network Diversity and Intolerance: Quasi-Poisson and OLS Models Excluding Moderates in Non-Elite Diversity Measure**

	Quasi-Poisson	Quasi-Poisson	OLS	OLS
(Intercept)	0.4246^{***}	-2.5587^{**}	0.0008^{***}	0.0035^{***}
	(0.0459)	(0.8608)	(0.0000)	(0.0006)
Elite Diversity	-0.4273^{***}	-0.4143^{***}	-0.0002^{***}	-0.0002^{**}
	(0.0676)	(0.0766)	(0.0000)	(0.0001)
Non-Elite Diversity	-0.8253^{***}	-0.3995^{***}	-0.0004^{***}	-0.0002^{*}
	(0.0924)	(0.1057)	(0.0001)	(0.0001)
Log Non-Elite Friends		-0.1881^{***}		-0.0001^{***}
		(0.0245)		(0.0000)
Log Elite Friends		0.5333^{***}		0.0002^{***}
		(0.0265)		(0.0000)
Log Relevant Tweets		0.7553^{***}		-0.0001^{***}
		(0.0493)		(0.0000)
Log Days on Twitter		-0.3765^{***}		-0.0002^{**}
		(0.1079)		(0.0001)
Islamist		-0.0253		-0.0001^{*}
		(0.0789)		(0.0001)
N	9400	9400	9396	9396
R^2			0.0079	0.0336
adj. R^2			0.0076	0.0329
Resid. sd			0.0018	0.0017

Standard errors in parentheses

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

This Table displays the results of quasi-Poisson models (with and without controls) evaluating the relationship between network diversity and users' number of intolerant tweets as well as the results of OLS regressions evaluating the relationship between network diversity and the proportion of users' intolerant tweets.

Table B2: **Network Diversity and Intolerance: Quasi-Poisson and OLS Models Including Moderates in Non-Elite Diversity Measure**

	Quasi-Poisson	Quasi-Poisson	OLS	OLS
(Intercept)	1.0253^{***}	-1.0061	0.0011^{***}	0.0040^{***}
	(0.0617)	(0.8596)	(0.0001)	(0.0006)
Elite Diversity	-0.2473^{***}	-0.2373^{**}	-0.0001^{**}	$-0.0001^{\dagger}$
	(0.0687)	(0.0755)	(0.0001)	(0.0001)
Non-Elite Diversity w Moderates	-2.1920^{***}	-1.5000^{***}	-0.0009^{***}	-0.0006^{***}
	(0.1384)	(0.1615)	(0.0001)	(0.0001)
Log Non-Elite Friends		-0.1401^{***}		-0.0001^{***}
		(0.0249)		(0.0000)
Log Elite Friends		0.4564^{***}		0.0002^{***}
		(0.0271)		(0.0000)
Log Relevant Tweets		0.7199^{***}		-0.0001^{***}
		(0.0482)		(0.0000)
Log Days on Twitter		-0.5083^{***}		-0.0003^{**}
		(0.1070)		(0.0001)
Islamist		0.1190		-0.0001
		(0.0759)		(0.0001)
N	9336	9336	9332	9332
R^2			0.0143	0.0358
adj. R^2			0.0140	0.0350
Resid. sd			0.0018	0.0018

Standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

This Table displays the results of quasi-Poisson models (with and without controls) evaluating the relationship between network diversity and users' number of intolerant tweets as well as the results of OLS regressions evaluating the relationship between network diversity and the proportion of users' intolerant tweets. These regressions measure non-elite network diversity including moderates.

Table B3: **Network Diversity and Intolerance Quasi-Poisson and OLS Models Human Coded Data**

	OLS Model	Quasi-Poisson Model
(Intercept)	0.667*	2.914
	(0.120)	(1.539)
Elite Diversity	−0.041*	−0.468*
	(0.017)	(0.192)
Non-Elite Diversity	−0.072*	−0.614*
	(0.026)	(0.283)
Log Non-Elite Friends	0.005	0.078
	(0.003)	(0.044)
Log Elite Friends	−0.007	−0.099
	(0.005)	(0.067)
Islamist	−0.061*	−0.833*
	(0.011)	(0.147)
Log Days on Twitter	−0.070*	−0.605*
	(0.016)	(0.216)
N	837	837
R^2	0.091	
adj. R^2	0.085	
Resid. sd	0.136	

Standard errors in parentheses
* indicates significance at $p < 0.05$

This table includes the results of an OLS and quasi-Poisson model of the relationship between network diversity and intolerance using only human-coded (rather than machine-coded) measures of intolerance.

Table B4: **Network Diversity and Tolerance: Quasi-Poisson and OLS Models**

	Quasi-Poisson	Quasi-Poisson	OLS	OLS
(Intercept)	7.6130***	−0.0141***	0.9992***	0.9970***
	(0.0095)	(0.0006)	(0.0000)	(0.0006)
Elite Diversity	0.0420***	0.0001*	0.0002***	0.0001**
	(0.0125)	(0.0000)	(0.0000)	(0.0001)
Non-Elite Diversity	−0.0042	0.0002***	0.0004***	0.0002*
	(0.0158)	(0.0001)	(0.0001)	(0.0001)
Log Non-Elite Friends		0.0000**		0.0001***
		(0.0000)		(0.0000)
Log Elite Friends		−0.0001***		−0.0002***
		(0.0000)		(0.0000)
Log Relevant Tweets		1.0016***		
		(0.0000)		
Log Days on Twitter		0.0001†		0.0003***
		(0.0001)		(0.0001)
Islamist		0.0001*		0.0001†
		(0.0000)		(0.0001)
N	9400	9400	9396	9396
AIC				
BIC				
$\log L$				
R^2			0.0079	0.0287
adj. R^2			0.0076	0.0280
Resid. sd			0.0018	0.0018

Standard errors in parentheses
† significant at $p < .10$; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

This Table replicates the analysis provided in Table B1 using tolerant tweets rather than intolerant tweets as the outcome variable.

Table B5: **Network Diversity and Irrelevant Tweets: Quasi-Poisson and OLS Models**

	Quasi-Poisson	Quasi-Poisson	OLS	OLS
(Intercept)	5.9243***	4.1476***	0.1475***	0.2531***
	(0.0213)	(0.3541)	(0.0029)	(0.0468)
Elite Diversity	−0.0638*	0.1310***	−0.0139***	0.0206***
	(0.0270)	(0.0312)	(0.0038)	(0.0041)
Non-Elite Diversity	0.4642***	0.2616***	0.0743***	0.0497***
	(0.0339)	(0.0402)	(0.0049)	(0.0055)
Log Non-Elite Friends		0.0710***		0.0019
		(0.0097)		(0.0012)
Log Elite Friends		0.0400***		0.0152***
		(0.0095)		(0.0013)
Log Relevant Tweets		−0.0484		−0.0215***
		(0.0458)		(0.0062)
Log Days on Twitter		0.2093***		
		(0.0145)		
Islamist		0.3850***		0.0688***
		(0.0299)		(0.0045)
N	9400	9400	9400	9400
AIC	NA	NA		
BIC	NA	NA		
$\log L$	NA	NA		
R^2			0.0243	0.0709
adj. R^2			0.0241	0.0703
Resid. sd			0.1373	0.1340

Standard errors in parentheses
† significant at $p < .10$; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

This table replicates the analysis provided in Table B1 using irrelevant tweets rather than intolerant tweets as the outcome variable.

Table B6: **Network Diversity and Intolerant Tweets: Negative Binomial Model**

	Negative Binomial Model
Elite Network Diversity	-0.4184^{***}
	(0.0646)
Non-Elite Network Diversity	-0.5195^{***}
	(0.0885)
Log Non-Elite Friends	-0.1557^{***}
	(0.0210)
Log Elite Friends	0.5077^{***}
	(0.0215)
Log Relevant Tweets	0.7352^{***}
	(0.0338)
Log Days on Twitter	-0.2575^{**}
	(0.0977)
Islamist	-0.0309
	(0.0691)
Constant	-3.3922^{***}
	(0.7530)
N	9400
AIC	21297.1079
BIC	21554.4527
$\log L$	-10612.5540

Standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

This table replicates the analysis provided in table B1 using a negative binomial model instead of a quasi-Poisson model to evaluate the relationship between network diversity and users' number of intolerant tweets.

Table B7: **Network Diversity and Intolerant Tweets: Quasi-Poisson Models Thresholds for Classifying Users as Islamist or Secular Range from .55 to .85**

	Model 55	**Model 60**	Model 65	Model 70	Model 75	Model 80	Model 85
Elite Network Diversity 55	−0.4034***						
	(0.0724)						
Non-Elite Network Diversity 55	−0.4582***						
	(0.1066)						
Islamist 55	0.0476						
	(0.0753)						
Elite Network Diversity		−0.4143***					
		(0.0766)					
Non-Elite Network Diversity 60		−0.3995***					
		(0.1057)					
Islamist 60		−0.0253					
		(0.0789)					
Elite Network Diversity 65			−0.4303***				
			(0.0737)				
Non-Elite Network Diversity 65			−0.4036***				
			(0.0997)				
Islamist 65			−0.0540				
			(0.0830)				
Elite Network Diversity 70				−0.4517***			
				(0.0744)			
Non-Elite Network Diversity 70				−0.3747***			
				(0.0963)			
Islamist 70				−0.1343			
				(0.0904)			
Elite Network Diversity 75					−0.4771***		
					(0.0745)		
Non-Elite Network Diversity 75					−0.3606***		
					(0.0943)		
Islamist 75					−0.2399*		
					(0.1015)		
Elite Network Diversity 80						−0.4858***	
						(0.0741)	
Non-Elite Network Diversity 80						−0.3710***	
						(0.0919)	
Islamist 80						−0.3071**	
						(0.1113)	
Elite Network Diversity 85							−0.4860***
							(0.0737)
Non-Elite Network Diversity 85							−0.3716***
							(0.0903)
Islamist 85							−0.3061**
							(0.1176)
Log Non-Elite Friends	−0.1863***	−0.1881***	−0.1866***	−0.1879***	−0.1877***	−0.1870***	−0.1879***
	(0.0244)	(0.0245)	(0.0243)	(0.0243)	(0.0243)	(0.0242)	(0.0242)
Log Elite Friends	0.5272***	0.5333***	0.5278***	0.5263***	0.5243***	0.5209***	0.5204***
	(0.0262)	(0.0265)	(0.0260)	(0.0261)	(0.0260)	(0.0260)	(0.0260)
Log Relevant Tweets	0.7549***	0.7553***	0.7503***	0.7493***	0.7465***	0.7454***	0.7473***
	(0.0494)	(0.0493)	(0.0491)	(0.0489)	(0.0488)	(0.0487)	(0.0487)
Log Days on Twitter	−0.3802***	−0.3765***	−0.3884***	−0.3910***	−0.3996***	−0.4083***	−0.4077***
	(0.1077)	(0.1079)	(0.1077)	(0.1076)	(0.1074)	(0.1074)	(0.1074)
Constant	−2.5113**	−2.5587**	−2.4108**	−2.3674**	−2.2626**	−2.1714*	−2.1816*
	(0.8603)	(0.8608)	(0.8603)	(0.8592)	(0.8580)	(0.8577)	(0.8583)
N	9400	9400	9400	9400	9400	9400	9400

Standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

This table replicates the analysis in table B1 using quasi-Poisson models to evaluate the relationship between network diversity and user's number of intolerant tweets. Each model uses a different threshold to classify users as Secular or Islamist ranging from .55 to .85. The threshold used in the other analyses in the paper is .6, bolded in the table.

Table B8: **Network Diversity and Intolerance Over Time (Quasi-Poisson Models)**

Elite Network Diversity	-0.6876^{***}	-0.5485^{***}	-0.5580^{***}	-0.4118^{***}
	(0.1361)	(0.1214)	(0.1392)	(0.1229)
Non-Elite Network Diversity	-0.7864^{***}	-0.5980^{***}		
(No Moderates)	(0.1877)	(0.1812)		
Non-Elite Network Diversity			-1.9172^{***}	-1.7351^{***}
(Including Moderates)			(0.2791)	(0.2724)
Log Non-Elite Friends		0.0677		0.1236^{**}
		(0.0448)		(0.0455)
Log Elite Friends		0.3590^{***}		0.2847^{***}
		(0.0434)		(0.0448)
Log Days on Twitter		-0.1046		-0.2749
		(0.1888)		(0.1906)
Log Islamist		-0.0196		0.0835
		(0.1345)		(0.1320)
Δ Relevant Tweets		0.0009^{***}		0.0009^{***}
		(0.0000)		(0.0000)
Intolerant Tweet Count Pre-May 2015	0.0315	0.2168^{***}	0.0130	0.2122^{***}
	(0.0623)	(0.0325)	(0.0653)	(0.0329)
(Intercept)	-1.5798^{***}	-2.9253^{*}	-1.0563^{***}	-1.3479
	(0.0908)	(1.4416)	(0.1257)	(1.4717)
N	7843	7843	7802	7802

Standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

This table displays the results of quasi-Poisson lagged dependent variable models evaluating the association between network diversity (with and without moderates) and the change in a user's intolerant tweet count after spending one additional year in a network. Users in our sample who do not have relevant tweets both before May 2015 and after May 2016 were excluded from the analysis.

Table B9: **Network Diversity and Intolerance Over Time (OLS Models)**

Elite Network Diversity	-0.0755^{***}	-0.0670^{***}	-0.0595^{***}	-0.0514^{**}
	(0.0151)	(0.0160)	(0.0153)	(0.0165)
Non-Elite Network Diversity	-0.0767^{***}	-0.0614^{**}		
(No Moderates)	(0.0194)	(0.0215)		
Non-Elite Network Diversity			-0.1958^{***}	-0.2387^{***}
(Including Moderates)			(0.0295)	(0.0350)
Log Non-Elite Friends		0.0102^{*}		0.0346^{***}
		(0.0051)		(0.0053)
Log Elite Friends		0.0284^{***}		-0.0054
		(0.0051)		(0.0054)
Log Days on Twitter		-0.0108		-0.0137
		(0.0245)		(0.0254)
Islamist		-0.0159		-0.0018
		(0.0176)		(0.0179)
Δ Relevant Tweets		0.0001^{***}		
		(0.0000)		
Intolerant Tweet Count Pre-May 2015	0.0043	0.0332^{***}	0.0018	0.0009
	(0.0083)	(0.0082)	(0.0083)	(0.0083)
(Intercept)	0.1839^{***}	0.0939	0.2416^{***}	0.1635
	(0.0116)	(0.1865)	(0.0158)	(0.1948)
N	7843	7843	7802	7802
R^2	0.0076	0.0683	0.0112	0.0169
adj. R^2	0.0072	0.0674	0.0108	0.0160
Resid. sd	0.4934	0.4782	0.4932	0.4919

Standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

This table displays the results of OLS lagged dependent variable models evaluating the association between network diversity (with and without moderates) and the change in a user's intolerant tweet count after spending one additional year in a network. Users in our sample who do not have relevant tweets both before May 2015 and after May 2016 were excluded from the analysis.

Table B10: **Network Diversity and Intolerance Over Time: Lagged Dependent Variable Models With Fixed Effect**

	Intolerant Tweet Count post-May 2016	Intolerant Tweet Count post-May 2016	Intolerant Proportion post-May 2016	Intolerant Proportion post-May 2016
Elite Network Diversity	-0.0670^{***}	-0.0566	-0.0005^{**}	-0.0005^{**}
	(0.0160)	(0.0345)	(0.0002)	(0.0002)
Non-Elite Network Diversity	-0.0614^{**}	-0.0615	0.0002	0.0001
	(0.0215)	(0.0405)	(0.0002)	(0.0002)
Log Elite Friends	0.0284^{***}	0.0291^{***}	0.0001^{**}	0.0001^{**}
	(0.0051)	(0.0052)	(0.0000)	(0.0000)
Log Non-Elite Friends	0.0102^{*}	0.0101^{*}	-0.0000	-0.0000
	(0.0051)	(0.0051)	(0.0000)	(0.0000)
Log Days on Twitter	-0.0108	-0.0095	-0.0002	-0.0002
	(0.0245)	(0.0246)	(0.0001)	(0.0001)
Islamist	-0.0159	-0.0171	-0.0002^{*}	-0.0002^{*}
	(0.0176)	(0.0177)	(0.0001)	(0.0001)
Δ Relevant Tweets	0.0001^{***}	0.0001^{***}		
	(0.0000)	(0.0000)		
Δ Elite Network Diversity		0.0340		-0.0000
		(0.0229)		(0.0001)
Δ Non-Elite Network Diversity		0.0155		-0.0001
		(0.0421)		(0.0002)
Diverse Elite Network Dummy		-0.0029	0.0003^{*}	0.0003^{*}
		(0.0257)	(0.0001)	(0.0001)
Diverse Non-Elite Network Dummy		-0.0001	-0.0001	-0.0001
		(0.0233)	(0.0001)	(0.0001)
Prop Intolerant Tweets pre-May 2015			$0.0170^{\dagger}$	$0.0171^{\dagger}$
			(0.0092)	(0.0092)
Intolerant Tweet Count pre-May 2015	0.0332^{***}	0.0334^{***}		
	(0.0082)	(0.0082)		
Constant	0.0939	0.0793	$0.0016^{\dagger}$	$0.0017^{\dagger}$
	(0.1865)	(0.1870)	(0.0009)	(0.0009)
N	7843	7843	7843	7843
R^2	0.0683	0.0686	0.0048	0.0048
adj. R^2	0.0674	0.0672	0.0037	0.0034
Resid. sd	0.4782	0.4782	0.0023	0.0023

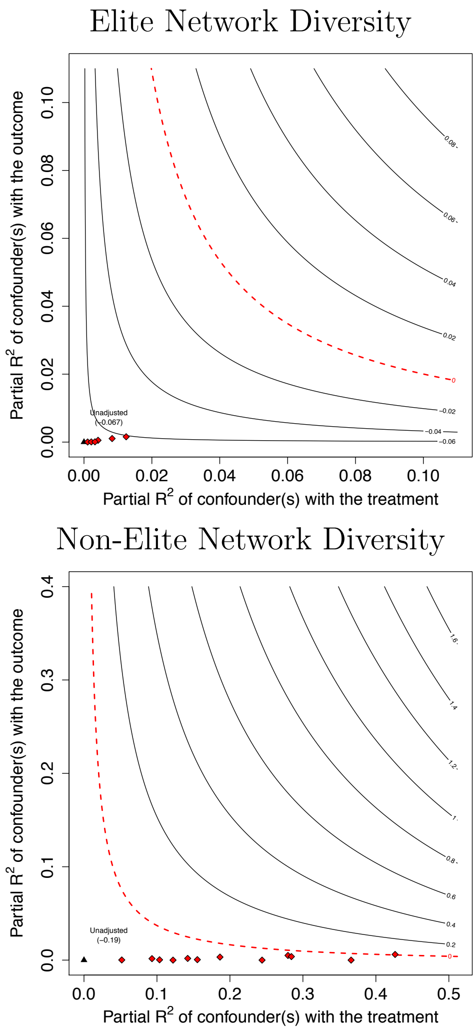
Standard errors in parentheses
† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table includes results of lagged dependent variable models evaluating the relationship between network diversity and the change in users' intolerant tweet counts and proportion of intolerant tweets after spending an additional year in their respective networks. This replicates the over time analysis adding fixed effects or dummy variables for high (greater than .5) elite and non-elite network diversity at time t_1 (May 2015).

Appendix C: Sensitivity Analysis

In an attempt to address the possibility of unobserved confounders driving our results, we conduct sensitivity analysis using the sensmakr R package. Figure A4 demonstrates that the negative coefficient estimates on elite network diversity and non-elite network diversity are robust to hypothetical unobserved confounders that are between one and three times as large as any of the covariates included in our models. The horizontal axis shows the hypothetical residual share of variation of the treatment that unobserved confounding explains. The vertical axis shows the hypothetical partial $R2$ of unobserved confounding with the outcome. The contours show what would be the estimate for change in intolerance that we would have obtained in the full regression model including unobserved confounders with such hypothetical strengths. The plots are parameterized in way that hurts our hypothesis, by pulling the estimates towards zero. The bounds on the strength of confounding are also shown in the plots.

Figure C1: **Sensitivity Analysis**



These results are also displayed numerically in the tables below:

Table C1: **Elite Network Diversity Sensitivity Analysis**

	bound_label	r2dz.x	r2yz.dx	treatment	adjusted_estimate	adjusted_se	adjusted_t	adjusted_lower_CI	adjusted_upper_CI
1	1x Islamist	0.1441	0.0001	Elite Diversity	-0.0602	0.0173	-3.4678	-0.0942	-0.0262
2	2x Islamist	0.2882	0.0003	Elite Diversity	-0.0516	0.0190	-2.7123	-0.0889	-0.0143
3	3x Islamist	0.4322	0.0005	Elite Diversity	-0.0402	0.0213	-1.8880	-0.0820	0.0015
4	1x Log Non-Elite Friends	0.0041	0.0005	Elite Diversity	-0.0649	0.0161	-4.0385	-0.0965	-0.0334
5	2x Log Non-Elite Friends	0.0083	0.0010	Elite Diversity	-0.0628	0.0161	-3.9009	-0.0944	-0.0313
6	3x Log Non-Elite Friends	0.0124	0.0016	Elite Diversity	-0.0607	0.0161	-3.7631	-0.0924	-0.0291
7	1x Log Days on Twitter	0.0011	0.0000	Elite Diversity	-0.0668	0.0161	-4.1594	-0.0983	-0.0353
8	2x Log Days on Twitter	0.0022	0.0000	Elite Diversity	-0.0666	0.0161	-4.1428	-0.0981	-0.0351
9	3x Log Days on Twitter	0.0032	0.0001	Elite Diversity	-0.0663	0.0161	-4.1262	-0.0978	-0.0348
10	1x Non-Elite Diversity	0.1457	0.0014	Elite Diversity	-0.0451	0.0174	-2.5997	-0.0791	-0.0111
11	2x Non-Elite Diversity	0.2914	0.0029	Elite Diversity	-0.0177	0.0190	-0.9286	-0.0550	0.0196
12	3x Non-Elite Diversity	0.4371	0.0047	Elite Diversity	0.0190	0.0213	0.8889	-0.0229	0.0608

Table C2: **Non-Elite Network Diversity Sensitivity Analysis (Including Moderates)**

	bound_label	r2dz.x	r2yz.dx	treatment	adjusted_estimate	adjusted_se	adjusted_t	adjusted_lower_CI	adjusted_upper_CI
1	1x Islamist	0.1220	0.0000	Non-Elite Diversity	-0.1919	0.0364	-5.2732	-0.2633	-0.1206
2	2x Islamist	0.2440	0.0000	Non-Elite Diversity	-0.1906	0.0392	-4.8584	-0.2675	-0.1137
3	3x Islamist	0.3660	0.0000	Non-Elite Diversity	-0.1889	0.0428	-4.4097	-0.2728	-0.1049
4	1x Log Non-Elite Friends	0.0932	0.0016	Non-Elite Diversity	-0.1546	0.0358	-4.3199	-0.2247	-0.0844
5	2x Log Non-Elite Friends	0.1864	0.0032	Non-Elite Diversity	-0.1110	0.0377	-2.9416	-0.1850	-0.0370
6	3x Log Non-Elite Friends	0.2795	0.0050	Non-Elite Diversity	-0.0608	0.0401	-1.5166	-0.1393	0.0178
7	1x Log Days on Twitter	0.0518	0.0002	Non-Elite Diversity	-0.1841	0.0350	-5.2558	-0.2527	-0.1154
8	2x Log Days on Twitter	0.1036	0.0003	Non-Elite Diversity	-0.1745	0.0360	-4.8449	-0.2451	-0.1039
9	3x Log Days on Twitter	0.1553	0.0005	Non-Elite Diversity	-0.1643	0.0371	-4.4277	-0.2370	-0.0915
10	1x Elite Diversity	0.1421	0.0018	Non-Elite Diversity	-0.1410	0.0368	-3.8325	-0.2131	-0.0689
11	2x Elite Diversity	0.2842	0.0038	Non-Elite Diversity	-0.0763	0.0402	-1.8963	-0.1552	0.0026
12	3x Elite Diversity	0.4263	0.0061	Non-Elite Diversity	0.0091	0.0449	0.2023	-0.0789	0.0971