Building Bridges or Digging the Trench? International Organizations, Social Media, and Polarized Fragmentation

- Online Appendix –

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A1 Selection of tweets

Corpus 1 contains GCM-related tweets of the following 23 UN accounts directly run by the Department of Global Communication of the UN Secretariat (UNDGC):[1]

@UN
@_UNChronicle
@africarenewal
@antonioguterres
@GlobalGoalsUN
@UN_Careers
@UN_Disarmament
@UN_DPA
@UN_News_Centre
@UN_PGA
@UN_Photo
@UN_Spokesperson
@UNDESA
@UNDGACM_EN
@UNHumanRights
@UNlibrary
@UNMediaLiaison
@UNOCHA
@UNPeacebuilding
@UNPeacekeeping
@unpublications
@UNWebTV
@UNYearbook

All original tweets in English (excluding retweets) posted by these X/Twitter handles between October 2016 and the end of 2019 were retrieved if they contained the terms "pact," "compact," or "treaty" in combination with at least one of the terms "migrant," "migrants," "immigrants," "immigrant," "migration," and "immigration." After reading the results, N=270 tweets were identified as directly addressing the GCM.

For *Corpus 2,* I used purpose sampling of all tweets and retweets (from all handles) for six important days along the GCM process, for which a minimal relevance of the topic—and consequently high turnout—could be expected. While purpose sampling had important practical

[1] Identification of UNDGC handles relied on information provided by the department itself on a webpage, now archived on https://web.archive.org/web/20200920051411/https://www.un.org/en/sections/about-website/un-social-media/index.html (last access on 24 October 2023).

advantages, there are arguably two drawbacks: First, the degree to which results can be generalized across days remains unclear. Second, focusing on days with GCM-related events at the UN level might skew the picture toward content that addresses the UN. After a close inspection of UN communication online, the following six days were identified as most promising for analysis by maximizing (a) the number of tweets released per day and (b) a desirable spread throughout the GCM process:

- 12 October 2017, the final thematic session, "Irregular migration and regular pathways,"
- 4 December 2017, the first day of the stocktaking meeting,
- 13 July 2018, the release of the finalized draft of the GCM,
- 26 September 2018, the high-level event "Road to Marrakech" at the UN,
- 10 December 2018, states adopt the GCM at the international conference in Marrakesh,
- 19 December 2018, the UN General Assembly endorsed the GCM (A/RES/73/195).

Again, all English tweets (including retweets) sent on these days were collected if containing the terms "pact," "compact," or "treaty" in combination with at least one of the terms "migrant," "migrants," "immigrants," "immigrant," "immigration," and "migration." The retrieval provided a total of N=69,609 tweets fulfilling these criteria, of which 9,925 (14.3%) are original tweets and 59,684 (85.7%) retweets.

A2 Manual coding of tweets

Selection of tweets for manual coding

In the next step, Corpus 1 (N=270) of UNDGC tweets underwent a qualitative content analysis. Additionally, a stratified random sample of Corpus 2 was also drawn and coded. For this sample, all retweets of Corpus 2 were excluded to focus on non-redundant content, and each original tweet was defined as an individual stratum. Then, the number of retweets per original tweet (+1 to prevent tweets with no retweets from being dropped) was used as sampling weights to account for the occurrence of similar text content in Corpus 2. A random sample (2,000 picks with replacement) was drawn, resulting in a sample of N=768 tweets. Due to the use of sampling weights, this sample is equivalent to a 31,528 sample (45.3%) of all items of Corpus 2 (N=69,609).

Development of the codebook

The analysis of tweet content was performed using Atlas.ti, a qualitative text analysis software that allows the exporting of coded content for later use in other software. The lead authors and one research assistant repeatedly read and annotated smaller selections of about 100 tweets of both corpora of tweet selection. The lead author set up the first version of the coding scheme and revised it in close cooperation with the research assistant. From the beginning, coding was not aimed at uniquely classifying whole tweets but focused on specific phrases. So, multiple codings per tweet were deemed likely and valid indications of more complex content. At each round of explorative coding, differences among both coders were noted, jointly discussed, and used by the author to refine the coding scheme. After five revisions, no further improvement seemed likely, so the codebook was deemed final in capturing evaluative statements of one of four aspects of the GCM debate on X/Twitter: the GCM, migration/migrants, multilateralism, and the UN. The estimated values of Krippendorff's Alpha (Lombard *et al.,* 2002) for the last portion of tweets suggested a formidable level of inter-coder agreement ranging from .8 to 1.0 across categories (see Table A1). As a last step, the research assistant went through all the tweets

again to streamline the final coding according to the latest version of the codebook. Problematic cases were jointly resolved by the end. For each of these four "code families," a positive and a negative code was given whenever an evaluative statement was found.

Table A1: Distribution of codings by corpus

Code Family	Code	Alpha		Corpus 1	Corpus 2	Total
#1 Global Compact	positive	.91	N	246	258	504
			%	91.11	33.59	48.55
	negative	.90	N	1	350	351
			%	0.37	45.57	33.82
#2 UN	positive	.80	N	18	40	58
			%	6.67	5.21	5.59
	negative	1.00	N	0	45	45
			%	0.00	5.86	4.34
#3 Multilateralism	positive	.88	N	32	49	81
			%	11.85	6.38	7.80
	negative	1.00	N	0	96	96
			%	0.00	12.50	9.25
#4 Migration	positive	.85	N	141	113	254
			%	52.22	14.71	24.47
	negative	1.00	N	0	58	58
			%	0.00	7.55	5.59
Tweets w/ no coding			N	13	145	158
			%	4.81	18.88	15.22
Total (codings)			N	451	1154	1605
			%	167.04	150.26	154.62
Total (tweets)			N	270	768	1,038

Note: Percentages are based on the total N of tweets (not codings) and reflect the share of tweets containing the respective kind of content. As multiple codings were possible per tweet, the total percent add up to more than 100. Krippendorff's Alpha (evaluating inter-coder agreement) is given for a sample of 100 tweets from Corpus 2.

Code Family 1: Evaluative statements explicitly referring to the Compact

#1.1 Positive reference to the GCM

Definition: Any positive reference to the GCM—explicitly mentioned by name or addressed as a comprehensive UN agreement on international migration.

Examples:

"Historic moment for @UN as an agreement was reached on the Global Compact #ForMigration."
(@UN_News_Centre, 2018-07-13, 1017890484793020416)

"#MigrationCompact in #Marrakech represents a 'cooperative approach that is grounded in principles of state sovereignty, responsibility-sharing, non-discrimination and human rights' - UN chief @antonioguterres"
(@UN_News_Centre, 2018-12-10, 1071953761365569538)

"Proud to have 1st called on the Gov to join the right side of history on this. Proud the Trump-ish' alternative fact' campaign by National died a quick death. This is a non-binding agreement to collaborate on a global issue. Perfectly Kiwi place to be https://t.co/IP0jC3VAGc"
(@golrizghahraman, 2018-12-19, 1075255193179025408)

#1.2 Negative reference to the GCM

Definition: Any negative reference to the GCM—explicitly mentioned by name or addressed as a comprehensive UN agreement on international migration.

Examples:

"New post: MEP Warns UN Pact Will Flood Europe With 59 Million Migrants By 2025 https://t.co/u2x76G1XGR #tcot"
(@American3rdP, 2018-12-10, 1072216386313830400)

"The UN Global Compact On Migration has all of a sudden went mainstream when it didn't two weeks ago ?? But don't sign it"
(@thecoolan, 2018-12-10, 1072260413025329153)

Code Family 2: Evaluative statements about or directed at the UN

#2.1 Positive reference to or directed at the UN

Definition: Any positive reference to the UN or its specific bodies, programs, or staff.

Examples:

"“#UNGA remains best place for states to address global issues & cross border challenges. This is not inconsistent w/ states determining their own migration policies. In fact, it strengthens our ability to protect migrants & also our citizens at home or abroad'-@ #GCM negotiations"
(@UN_PGA, 2018-06-04, 1003727213106290690).

"Today we are reminded why the [world] needs the UN. Arms embargo + targeted sanctions placed on #SouthSudan. Adoption of groundbreaking Global Compact on Migration. Election of robustly qualified member to UN Human Rights Council. Review of global progress on SDGs at #HLPF"
(@rykaminski, 2018-07-13, 1017796330255736833).

#2.2 Negative reference to or directed at the UN, including its specific bodies, programs, or personnel.

Definition: Any negative reference to the UN or its specific bodies, programs, or staff.

Examples:

"Elite Globalist, Louis Arbour, another one of our made in Canada traitors embedded into the UN' high commission', teams up with Justin Trudeau to push the migration compact that will flood the west with migrants. How did Canada go so wrong?"
(@gbobke, 2018-12-10, 1071982182929842176)

"“That is one reason the United States will not participate in the new Global Compact on Migration,' Trump said. 'Migration should not be governed by an international body, unaccountable to our own citizens.'"
(@ahomeaway1, 2018-09-26, 1045001797163782145)

Code Family 3: Evaluative statements about multilateralism in general

#3.1 Positive reference to multilateralism/international cooperation

Definition: Any positive reference to multilateralism or international cooperation in more general terms (that is, beyond the GCM and the UN).

Examples:

"“The Global Compact #ForMigration will be a product of our time - a time of consolidated respect for state sovereignty and enhanced interstate cooperation, pursuit of #GlobalGoals, conflict prevention and protection of human rights'.
https://t.co/xDdmT5uxci"
(@louise_arbour, 2017-12-06, 938530540243832832)

"'Everybody earns more and everybody benefits, including migrants, when you have more co-operation over things. And that's the basic gist of it,' said @UofT's @CraigDamian of the new migrant pact. #ctvpp #cdnpoli
More at https://t.co/uCQmGSpNgb. https://t.co/bWsclU0j2w"
(@CTV_PowerPlay, 2018-12-10, 1072258756103168000)

#3.2 Negative reference to multilateralism, international/global cooperation

Definition: Any negative reference to multilateralism or international cooperation in more general terms (that is, beyond the GCM and the UN).

Examples:

"The people of Belgium are now realizing that the Global Compact for Safe, Orderly and Regular Migration is a bad deal for their country. When will Canadians see the light and demand an end to the globalist agenda that has been imposed upon us, without our consent? https://t.co/lLnrYcIsAr"
(@Straighttalk02, 2018-12-19, 1075440495252258816)

"ANOTHER BLOW TO GLOBALIST ELITES! Belgian Prime Minister Offers Resignation Over Protests Against UN Migration Pact https://t.co/LWuB0Fhp4a"
(@WoMoAce, 2018-12-19, 1075277076532420609)

Code Family 4: Evaluative statements about migration or migrants

#4.1 Positive reference to migrants or migration

Definition: Any positive reference to migration or migrants.

Examples:

"Migrants are a remarkable engine for growth. The Global Compact for Safe, Orderly and Regular Migration will help the world harness the benefits of regular migration while safeguarding against the irregular movements that place people at risk - @antonioguterres https://t.co/4MfLYvb21q"
(@UN_Spokesperson, 2018-07-12, 1017439815745327106)

"This is great news. The Global Compact for Migration is a rare opportunity to develop a new approach to migration that is more effective and humane, protects dignity and saves lives. https://t.co/dKBpkeQjlv"
(@NZRedCross, 2018-12-19, 1075241798975418368)

#4.2 Negative reference to migrants or migration

Definition: Any negative reference to migration or migrants.

Examples:

"Wait until the UN Migration Pact hits UK. Thousands of LEGAL immigrants will be flooding into UK. Say thanks to May. https://t.co/DdcUkcc7kn" (@BeddoeRoger, 2018-12-19, 1075411542944956416)

"Wish send all illegal refugees to the house where the owner signed the UN' Immigration Pact which destroyed Canadian Sovereignty! No more hypocrites! #UNCompact #AntiUNCompactRally #UNGlobalistsThink #WhyImAgainstTheCompact #UNGlobalCompact #UNMigrationCompact https://t.co/Kvq6czz6rC" (@minminxie5656, 2018-12-10, 1072169246807908354)

Quoted Tweets

Note that 15 tweets (5.5%) in Corpus 1 and 769 tweets (7.7%) in Corpus 2 use X/Twitter's "quoted tweet" function to link another tweet as additional content.[2] Here, the main tweet text indeed "contextualizes" the quoted (secondary) tweet as suggested by the reviewer. That is why the analysis focuses on the text of the (quoting) tweet, but not what has been quoted, to capture the evaluative direction of the overall message correctly. 3,289 retweets (5.5%) in Corpus 2 also contain quotes because the shared tweet is a "quoted tweet."[3] In these cases, the analysis again focuses on the main text of the quoting tweet (that was retweeted) but not the quoted text for the same reason. A closer inspection of quotes reveals the following: While the observed number of "quotes" is marginal (N=15), the evaluative direction is in line with my overall argument, as UN-tweets that do quote are all advocative and quote advocative (or, in a single case, neutral) content (provided by other UN-accounts). While there are 769 "quoted tweets" in Corpus 2, only 40 are identified as UNDGC tweets, and 47 are authored by an account classified as "wider UN." From the 3,289 retweets that share a "quoted tweet," 47 share a tweet that quote an UNDGC-tweet plus another, and 123 share a tweet quoting a tweet sent by an account classified as "wider UN." With some rare exceptions, almost all quoting of UN tweets (as well as "wider-UN" tweets) by other users can be found in (a) tweets that are advocative and (b) have been sent by users classified as advocates. Thus, the results for quotes corroborate my overall conclusions of the empirical analysis.

A3 Checking for biases in the selection of tweets

As expected, the keyword search applied to identify GCM-related tweets could have been more effective. Regarding over-coverage of thematically irrelevant tweets, the manual coding of Corpus 2 yielded 10 "false positives" out of 768 randomly selected tweets—i.e., tweets unrelated to the GCM. This suggests a proportion of about 1.30% (with a standard error of .41 and a 95%-confidence interval of .50 to 2.10) in the overall corpus. The following tweet provides an example of how search terms failed to identify GCM-related content:

[2] For example: https://twitter.com/UNICEF/status/1017751992976969728 (last access on 4 February 2023).
[3] For example: https://twitter.com/Hoffmann1Brian/status/1017754149113376768 (last access on 4 February 2023).

> "First time a UN #HumanRights treaty body rules on a migrant with irregular legal status being denied access to #HealthCare necessary for them to live. It also affirmed that states must take actively protect the #RightToLife #HealthCareForAll https://t.co/iaBv1U4lee" (https://twitter.com/ESCRNet/status/1075239179070726144).

No large-N data of "false negatives" was gathered, i.e., thematically relevant tweets not found by the keyword search utilized. However, the keyword search excluded tweets sharing only visual content related to the GCM or more implicitly addressing the GCM, for example, by picking up on specific aspects of the GCM that the well-informed reader might interpret as part of a larger project. This suggests that the analysis underestimates the public resonance of UN tweets concerning both types of content and the number of users who sent it. While both might introduce some bias in principle, it seems rather unlikely that a more inclusive criterion would have yielded entirely different results. The same holds for the focus on days with GCM-related events at the UN level, which might have skewed the results towards content that addressed the UN or shared UN content to some extent.

A4 Automated coding of tweets

R was used to pre-process and automatically classify tweets not previously coded manually (see code in replication file "GCM.R"). Pre-processing of selected tweets included the removal of special characters (e.g., URLs, hashtags, and at-signs), the conversion to lowercase, the exclusion of stop words, and finally, the tokenization of all remaining text into bigrams (combinations of two words). Next, two Support Vector Machines (SVM) with a linear kernel (each with five times 5-fold cross-validation) were trained in R with *svmLinearWeights* (as included in the Caret package). "False positives" (see section A3) went into the training and testing of the two supervised machine learning algorithms to avoid biased results (as uncoded tweets to be automatically classified most likely also included such "false positives"). Input consisted of a rectangular data set with the single tweet as the main unit of analysis and the relative frequency information for each unigram and bigram (using Term Frequency Inverse Document Frequency, TD-IDF) as variables. Classifiers have been tuned with a split between 80% of training data and the remaining 20% of data for testing. The final specifications for both classifiers performed well (Table A2). However, according to standard metrics, the final classifier for positive content performs notably better than the one for negative content.

Table A2: Performance metrics for both classifiers of tweet content

	Positive content classifier	Negative content classifier
Accuracy	0.8889	0.8366
Kappa	0.7650	0.6761
Precision	0.8197	0.7674
Recall	0.8929	0.9296
F1	0.8547	0.8408
Balanced Accuracy	0.8897	0.8428

A5 Classification of users as "wider UN"

These are the X/Twitter handles (N=106) that have been identified as (a) not directly run by the UN Department of Global Communication but (b) belonging to other official branches or offices of the UN (classified as "Wider UN"):

@mbachelet
@louise_arbour
@UNICEF
@IOMatUN
@UNYouthEnvoy
@UNMGCY
@UN_Women
@UNGeneva
@KorieUNFPA
@UNRIC_Italia
@article19UN
@UNODC
@UNinBrussels
@UNICManama
@UN_Vienna
@UNAOC
@UN4Youth
@UNICEFInnocenti
@UNFPAasia
@Norimasa_UN
@PopDevUNFPA
@UNODC_HTMSS
@UNHCRWestAfrica
@UNESCO
@MaherNasserUN
@UNDevelopPolicy
@UNHCRDjibouti
@UNIDOAfg
@KenyaMUN19
@UNESCAP
@UNHCRSerbia
@HDRUNDP
@UNCityCPH
@UNESCO_Pacific
@UNODC_Brussels
@UNICBeirut
@UNandAgeing
@UNGuinea_Bissau
@UN_Lebanon
@UNODC_POSAL
@DUA_UNRWASyria
@Eritrea_UN
@UN_EWEC
@GlobalGoalsUN
@UNOGLibrary
@UNOHRLLS
@UNACNCR
@UN_Montenegro
@UN4ALL
@UNUCPR
@UNICEFGambia
@UN_ACT
@CarlaUNICEF
@UNICCairo
@UNOCHA
@UNICEFROSA
@UNhumansecurity
@Journal_UN_ONU
@UNDP_Danmark
@UNICEF_ECA
@Purna_UNW
@UNIraq
@UNHABITAT
@UNICEFCanada
@UNCTAD
@VisitUN
@UNCCD
@UNDP
@UN_Piper
@UNLibrary
@SayNO_UNiTE
@UNUniversity
@UNinGhana
@UNICLagos
@UNICEF_UA
@UNICEFAfrica
@UN_SPExperts
@UNICEFnl
@UNDESASocial
@UNODC_ROMENA
@UNODC_Nigeria
@UNICEFDjibouti
@UNHCRUK
@UNESCWA
@UNGamesAfrica
@UNDPUganda
@UNESCOdeBildung
@NLatUN
@UNICEF_uk
@UNCambodia
@UNmigration
@Radicetti_IOM
@IOMBurundi
@IOMFinland
@IOMROWCA
@IOM_Caribbean
@IOM_GMDAC
@IOM_MECC
@IOM_Uganda
@IOMatEU
@IOMchief
@Health_IOM
@unicefchief
@unhabitatyouth
@UnitedNationsTZ
@FAONewYork

A6 Classification of users by evaluative content

The results presented in Figure 3 of the main analysis draw on a categorization of users as "advocates," "critics," "ambivalent," or "neutral" to investigate audience resonance of UN tweets. This categorization of users is based on coded tweet content and, by implication, is possible only for those users who have tweeted on the GCM at least once. However, there are alternative specifications for how to use such information to categorize users, which allow to check the robustness of results presented in the main analysis:

First, the results of the main analysis draw on the classification of tweets based on supervised machine learning. Thus, the results' robustness is worth testing by comparing results with those based on manual coding alone. According to results presented in Table A3-A5, manual coding tends to increase (decrease) the proportion of advocates (critics) retweeting UNDGC content, mentioning UNDGC handles, or using #ForMigration. This hints at specific weaknesses of the two SVM algorithms with the correct detection of evaluative content. However, it also points to the robustness of my main (negative) conclusions because relying only on manually coded tweets suggests even stronger limitations of resonance beyond like-minded users.

Second, users who have consistently tweeted "advocative" ("critical," "mixed," "neutral") content are categorized as "advocate" ("critical," "ambivalent," "neutral") users in the main analysis. A "tie" —that is, an equal number of tweets recorded for multiple classes (e.g., four tweets overall, two "advocative," two "neutral")—is resolved according to the following rule:

- Equal numbers of "advocative" or "critical" tweets take precedence over equal numbers of "balanced" and "neutral" tweets.
- If there is an equal number of "advocative" and "critical" tweets, the user is coded as "ambivalent."
- If there is an equal number of "mixed" and "neutral" tweets," the user is coded as "ambivalent," too.

The following rule for resolving a "tie" is applied to check for the sensitivity of results:

- If observing a mix of "advocative," "critical," or "balanced" tweets, the user is always coded as "ambivalent."
- If observing only "advocative" and "neutral" tweets, the user is coded as "advocative."
- If observing only "critical" and "neutral" tweets, the user is coded as "critical."

According to results shown in Table A3-A5, such an alternative categorization of users (by handling "ties" differently) tends to slightly decrease (increase) the proportion of advocates (ambivalent users). This is to be expected, as it more inclusively defines "ambivalent users." However, it does not substantially affect the overall conclusions: UN communication on X/Twitter solely resonates with like-minded users but is by and large ignored by its critics.

Table A3: Retweeting of UNDGC-tweets based on alt. categorization of users and coding

Including ML-coding	Yes	Yes	No	No
User-Categorization	As Figure 3	Alternative	As Figure 3	Alternative
By advocates	82.55	79.50	91.92	91.92
By critics	6.93	6.65	1.01	1.01
By ambivalent users	4.43	8.59	5.05	5.05
By neutral users	6.09	5.26	2.02	2.02
Total	100.00	100.00	100.00	100.00
N	361	361	99	99

Table A4: Mentions of UNDGC-handles based on alt. categorization of users and coding

Including ML-coding	Yes	Yes	No	No
User-Categorization	As Figure 3	Alternative	As Figure 3	Alternative
By advocates	86.32	79.12	93.04	81.32
By critics	6.23	6.11	0.73	0.73
By ambivalent users	2.69	10.50	2.20	13.92
By neutral users	4.76	4.27	4.03	4.03
Total	100.00	100.00	100.00	100.00
N	819	819	273	273

Table A5: Use of UNDGC-Hashtag #ForMigration based on alt. categorization of users and coding

Including ML-coding	Yes	Yes	No	No
User-Categorization	As Figure 3	Alternative	As Figure 3	Alternative
By advocates	97.73	92.99	97.69	97.69
By critics	0.19	0.19	0.0	0.0
By ambivalent users	1.52	6.25	0.0	0.0
By neutral users	0.57	0.57	2.31	2.31
Total	100.00	100.00	100.00	100.00
N	528	528	130	130

A7 Classification of users by being more or less active on X/Twitter

Results presented in Figure 3 of the main analysis could also substantially differ across types of users being more or less active. Figures A6–8 compare the 10th percentile of most active users to the rest. While the results of both groups are in line with overall conclusions, results also suggest that differences between "advocates" and "critics" are more pronounced among those more active users.

Table A6: Retweeting of UNDGC tweets by user activity

	Less active	Most active	Total
By advocates	77.31	92.68	82.55
By critics	8.82	3.25	6.93
By ambivalent users	6.72	0.00	4.43
By neutral users	7.14	4.07	6.09
Total	100.00	100.00	100.00
N	238	123	361

Table A7: Mentioning UNDGC handles by user activity

	Less active	Most active	Total
By advocates	83.13	98.80	86.32
By critics	7.82	0.00	6.23
By ambivalent users	3.37	0.00	2.69
By neutral users	5.67	1.20	4.76
Total	100.00	100.00	100.00
N	652	167	819

Table A8: Use of #ForMigration by user activity

	Less active	Most active	Total
By advocates	98.03	100.00	98.18
By critics	0.16	0.00	0.15
By ambivalent users	1.31	0.00	1.21
By neutral users	0.49	0.00	0.46
Total	100.00	100.00	100.00
N	610	49	659

A8 Retweets, mentions, and hashtags

The following tables report the distribution of retweets, mentions, and hashtags in more detail.

Table A9: Retweets

Retweeted		Non-UN	Wider UN	UNDGC	Total
Retweeting user:					
Non-UN	N	42,784	3,014	3,274	49,072
	%	87.19	6.14	6.67	100.00
Wider UN	N	33	94	95	222
	%	14.86	42.34	42.79	100.00
UNDGC	N	0	10	14	24
	%	0.00	41.67	58.33	100.00
Total	N	42,817	3,118	3,383	49,318
	%	86.82	6.32	6.86	100.00

Note: Information on retweets of UNDGC-tweets is available only for those in Corpus 2

Table A10: Mentions

Mentioned		Non-UN	Wider UN	UNDGC	Total
Mentioning user:					
Non-UN	N	2,409	262	628	3,299
	%	73.02	7.94	19.04	100.00
Wider UN	N	26	42	71	139
	%	18.71	30.22	51.08	100.00
UNDGC	N	19	49	120	188
	%	10.11	26.06	63.83	100.00
Total	N	2,454	353	819	3,626
	%	67.68	9.74	22.59	100.00

Note: Information on UNDGC-tweets drawn from Corpus 1, all other tweets from Corpus 2

Table A11: Nine most often used hashtags by type of account

Non-UN		Wider UN		UNDGC	
#ForMigration	438	#ForMigration	78	#ForMigration	140
#GlobalCompactforMigration	267	#GCM	15	#migration	35
#UN	190	#AChildIsAChild	10	#forMigration	29
#migration	184	#ChildrenUprooted	9	#UNGA	21
#Migration	166	#UNGA	7	#SDGs	15
#GlobalCompactForMigration	118	#GlobalCompactforMigration	6	#Migration	13
#Marrakech	100	#migration	6	#UN4ALL	12
#GCM	97	#GlobalCompactForMigration	6	#UN4RefugeesMigrants	11
#GlobalCompact	65	#Migration	5	#GCM	11

Note: Information on UNDGC-tweets drawn from Corpus 1, all other tweets from Corpus 2

Table A12: Use of #ForMigration (including alternative spellings) by type of account

		Tweets without *#ForMigration*	Tweets including *#ForMigration*	Total
Tweeting user:				
Non-UN	N	9,225	528	9,753
	%	94.59	5.41	100.00
Wider UN	N	32	90	122
	%	26.23	73.77	100.00
UNDGC	N	97	173	270
	%	35.93	64.07	100.00
Total	N	9,354	791	10,145
	%	92.20	7.80	100.00

Note: Information on UNDGC-tweets drawn from Corpus 1, all other tweets from Corpus 2; Includes #forMigration, #ForMigration, #formigration, #Formigration.

A9 Visualization of the GCM network

Visualization of the GCM network on X/Twitter in Figure 4 of the main analysis is based on dyadic data of users combining information about retweets and mentions. It assumes X/Twitter communication to generate (or contribute to) a directed "edge" of a GCM network if a user (the "source") retweets or mentions another user (the "target"). An edge's ascribed relevance (or "weight") equals the sum of retweets and mentions per user dyad.

Similar to the classification of users in the main analysis (Figure 3), the classification of edges (Figure 4) was based on the mode of classified tweets being retweeted (the mode being defined as the most frequently occurring class). In the case of multiple modes per user dyad, a mode value indicating mostly "advocative" and "critical" tweets took precedence over modes of "ambivalent" and "neutral" tweets. Furthermore, dyads with an equal number of "advocative" and "critical" tweets were deemed "ambivalent." Dyads with an equal number of "balanced" and "neutral" tweets were classified as "ambivalent," too. About 72 percent of edges could thus be classified; for the rest (38 percent), no information was available.

The network data was imported in the most recent version of Gephi (0.9.4). Here, data was filtered to the largest connected ("giant") component of the network and users being mentioned or retweeted by at least one other user (indegree > 0). This applies to 1,695 nodes (4.4%) and 4,342 of the edges (7.6%).

Visualization used the following layout algorithms: First, the overall layout was generated with Force Atlas 2 with parameters set to Treads = 11, Tolerance = 1, and Approximate Repulsion = on. Approximation = 1.2, Scaling = 2, Gravity = 10, Edge Weight Influence = 1. Next, the graph was rotated to position the main clusters horizontally. Next, NoOverlap was applied to eliminate the overlap of nodes with parameters set to Speed = 5, Ration = 1.2, and Margin = 5. Finally, Label Adjust (Speed = 0.001) was used to enhance the readability of labels. To select and define the size of node labels, Eigenvector Centrality was calculated with 100 iterations.

An alternative classification of edges was used to check the robustness of the results. In line with the alternative classifications of users, it treats all dyads as "ambivalent" if observing a mix of "advocative," "critical," or "mixed" tweets (so that a mode of "advocative" or "critical" took only precedence over "neutral," but not otherwise). However, this alternative definition does not lead to observable differences in the visualized version of the network (see Figure A.1).

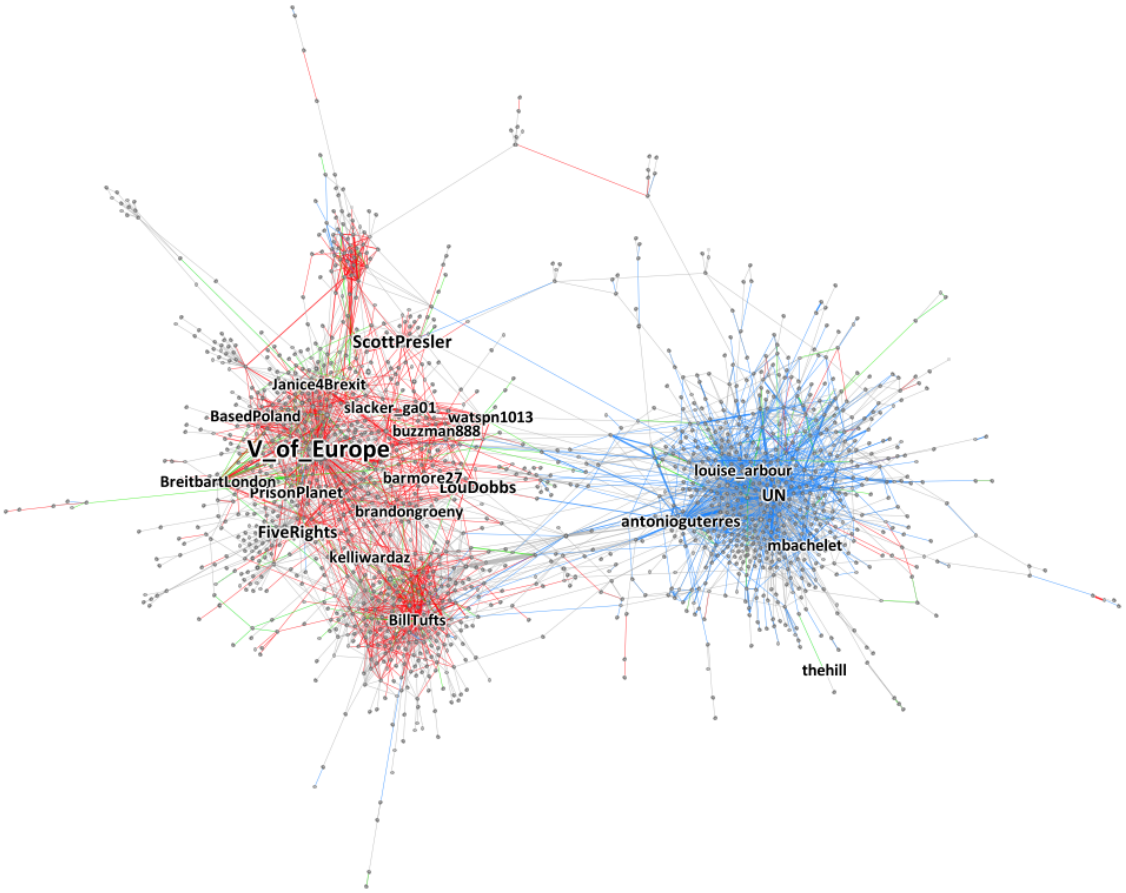

Figure A1: The GCM-network based on alternative classification of edges

Note: The network is based on weighted data of retweets and mentions from Corpus 2. Nodes are only shown for those users (N = 1,695) being mentioned or retweeted by at least one other user. Labels are given for the 20 most central accounts, with the size of labels and nodes reflecting the relative size of (eigenvector) centrality. The colors of edges are based on the alternative classification of the retweeted tweets, with blue indicating mostly advocative, red for mostly critical, green for mostly mixed or neutral (re)tweets, and grey for edges for which no information was available (about 38%). The size of the edges reflects the relative frequency of mentions and retweets for the respective pair of users.

Reference

Lombard, Matthew, Jennifer Snyder-Duch, and Cheryl Campanella Bracken (2002) 'Content analysis in mass communication: Assessment and reporting of intercoder reliability', *Human communication research* 28(4): 587–604.