Supplementary material: Exploring the limits of soft power – sentiments and narratives on China in Turkish social media and political speeches of elites

May 9, 2024

This document provides additional details on the methodology of the paper "Exploring the limits of soft power: sentiments and narratives on China in Turkish social media and political speeches of elites", as well as further analyses and visualizations that were not possible due to page limits.

Data and preprocessing

We use Twitter data collected using two separate approaches. The first approach relies on Twitter API for academic use, which permits querying historical tweets. The search API allows querying terms in a case-insensitive manner that also strips off all accents from the characters. We queried the *Çin* 'China' using this interface, which also retrieves all morphologically related forms, like *Çin'de* 'in China' and *Çinli* 'Chinese', as well as their forms without Turkish diacritics and non-standard, officially incorrect forms of these words (e.g., *Çinde*, *Cinde*, *cinli*). This is desirable as these non-standard writing practices are prevalent in social media. However, the query also brings other words such as *cin* 'genie', *çinko* 'zinc' and *Çine* (a town in south-western Turkey) as well as their derived/inflected forms. As a result, we first filter out tweets with words that only contain terms that match the query, but cannot be, or unlikely to be related to China (e.g., *çinko*, *cinlen* 'to be possessed by a genie/China').[1] However, this approach cannot distinguish many words that we want to keep in case it is related to China. For example *cini* 'genie-ACC' is a common way to spell the accusative form of *China*, and may also mean 'tile'. To disambiguate these forms, we use an off-the-shelf named entity recognizer (NER) especially trained on Twitter data (Çarık and Yeniterzi, 2022) to filter out the tweets that contain words that include non-standard forms (e.g., *cinde*) that are not recognized as location or organization by the NER system. We also eliminated all

[1] We keep the tweets if there are other words that match the query.

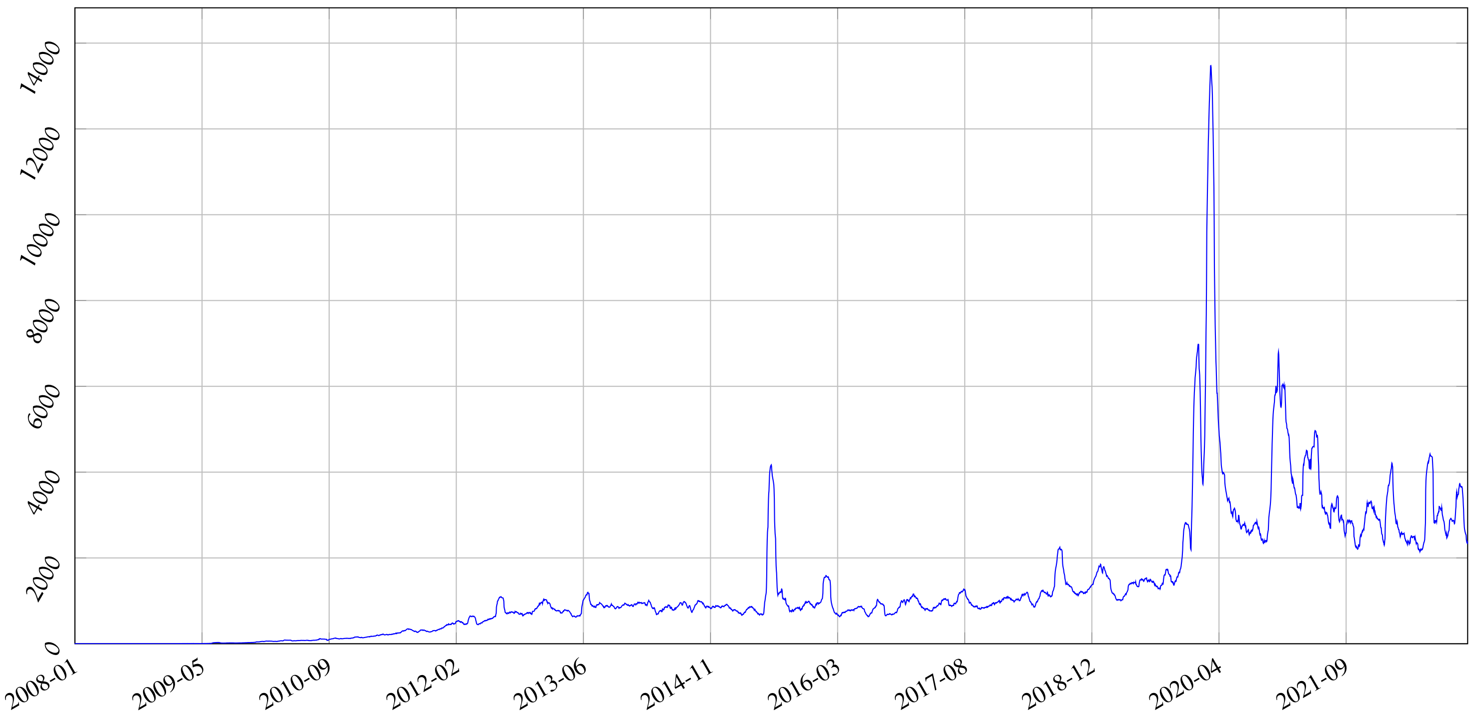

Figure 1: Number of daily tweets about China (30-day rolling average).

retweets, and all tweets with an identical text with an earlier tweet in the data set. The resulting data set contains 7 140 428 tweets. The daily volume of tweets throughout the whole period available in the data are presented in Figure 1.

The data goes back to the early days of Twitter (mid 2007). However, the popularity of twitter seems to have picked up after 2012 with over 1000 average daily tweets containing China by mid 2012. As a result we consider the data after 2012 for the rest of the visualizations and analyses. The effect of the COVID-19 pandemic is clear on the number of tweets including China. The number of tweets approximately doubles after early 2020. To allow inspecting more detail, Figures 2 and 3 presents the same data until and after late 2019 separately. With the split graphs, one can even see the effect of the Ürümchi riots in July 2009 even though the overall daily tweet volume was very low at the time. More salient bursts of tweets are observed after June 2012 Shanghai Cooperation Organisation (SCO) meeting including discussion about Turkey's partnership with the organization, July 2013 where there has been more violence in Xinjiang, July 2015 Erdoğan visits surrounding further crisis in Xinjiang, August 2018 UN report on Xinjiang and February 2019 Turkey's call to UN on 'human tragedy' in Xinjiang. Overall, except for the massive increase with COVID-19 pandemic, the main spikes of tweet volume are mainly related to Turkish support to Uyghurs in the Xinjiang province of China.

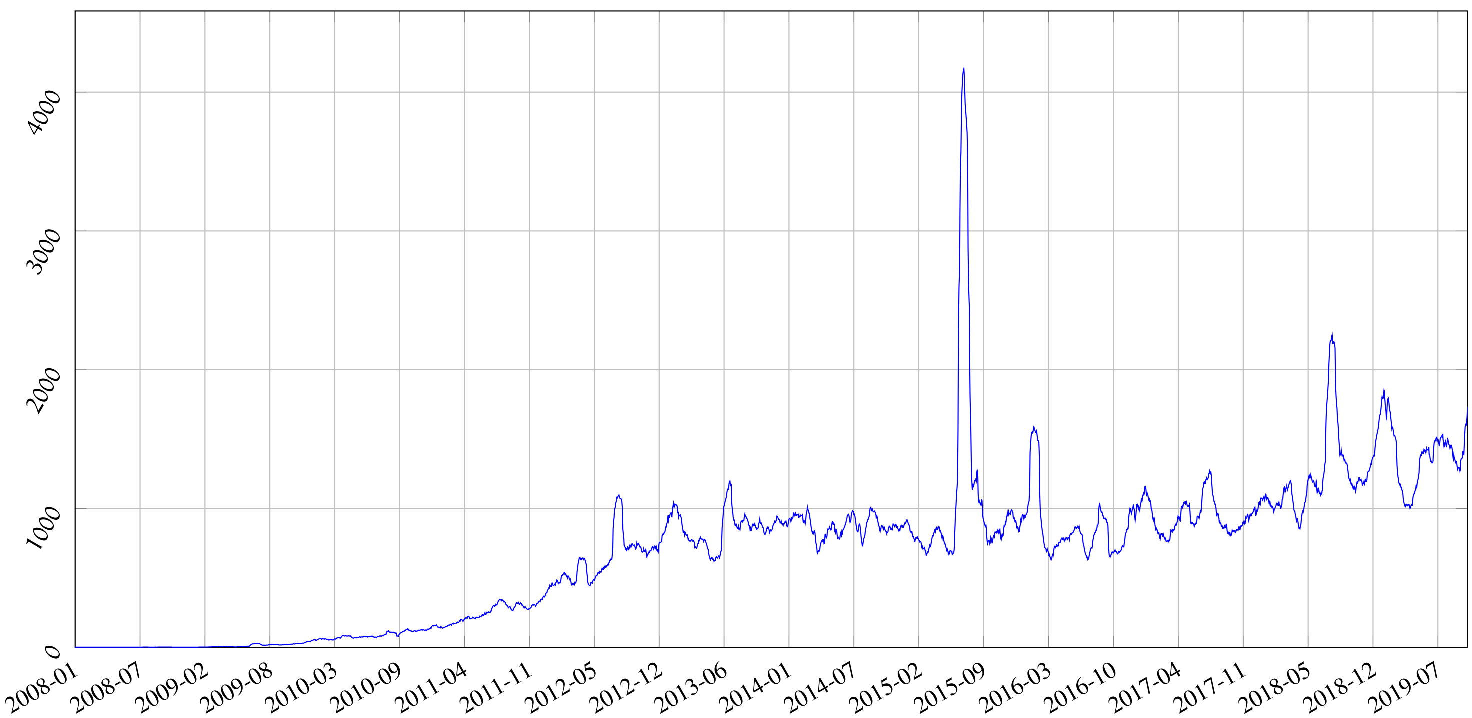

Figure 2: Number of daily tweets about China (30-day rolling average). Before the corona period.

Figure 3: Number of daily tweets about China (30-day rolling average). Covering the corona period.

Table 1: Distribution of the politician tweets in the data set to parties. The party assignment is made based on the last known party affiliation in the ParlaMint corpus. 'Other' includes all other past or present parties.

Party	Users	Tweets
AKP	716	6664
CHP	334	3120
MHP	158	1257
HDP	112	340
IYIP	38	1782
Other	196	1217

The dataset described above contains tweets from all Twitter users. To investigate potential differences between the general public and the politicians, we also extract the tweets by 1554 politicians whose twitter usernames are listed in the ParlaMint corpus (Erjavec, Ogrodniczuk, Osenova, Ljubešić, Simov, Pančur, Rudolf, Kopp, Barkarson, Steingrímsson, et al., 2022). The list contains Twitter usernames of politicians who served as parliament members and ministers between 2011 and 2022. The number of tweets in this data set is 14 380. We present the monthly tweet volume about China by politicians in Figure reffig:china-tweets-pm-counts. Not surprisingly, the COVID-19, and some of the events listed above also results in a higher volume of tweets by politicians.

We also collect the speeches in the Turkish section of the ParlaMint corpus that includes the word *Çin* 'China' (and its morphological alternations, but we do not include non-standard forms). The corpus contains transcripts of the main proceedings of the Turkish parliament between 2011 and 2022. The query returns 2022 speeches that mention China. Figure 6 presents the distribution of these speeches through time. Part of the periodicity in this graph is likely because of the fact that there are no meetings between July and September. Furthermore, there was a period during 2015 where the parliament was not fully functioning.

Comparing the emotions/sentiment towards China alone is not very informative. To provide comparisons with other countries, we also use tweets that mention Germany, Russia, United States and Mexico. Although the Twitter data collected using the Twitter search API for academic use allows older tweets to be retrieved, the limitations on the number of tweets, and non-flexible filtering makes it impractical to collect tweets using the Twitter search. For this purpose we use another data source, a large corpus of tweets from March 2018 that are collected through Twitter streaming API by querying for 400 Turkish words with high frequency. Although, this method allows collecting a rather large sample of the Turkish content on Twitter, it is necessarily incomplete. The data includes approximately 30 million tweets (after removing retweets). To obtain tweets mentioning these countries, we search for the names of countries and people, excluding false positives. For comparison, we also use the same method to obtain a second dataset for China. The total number of tweets obtained by this method for each country is

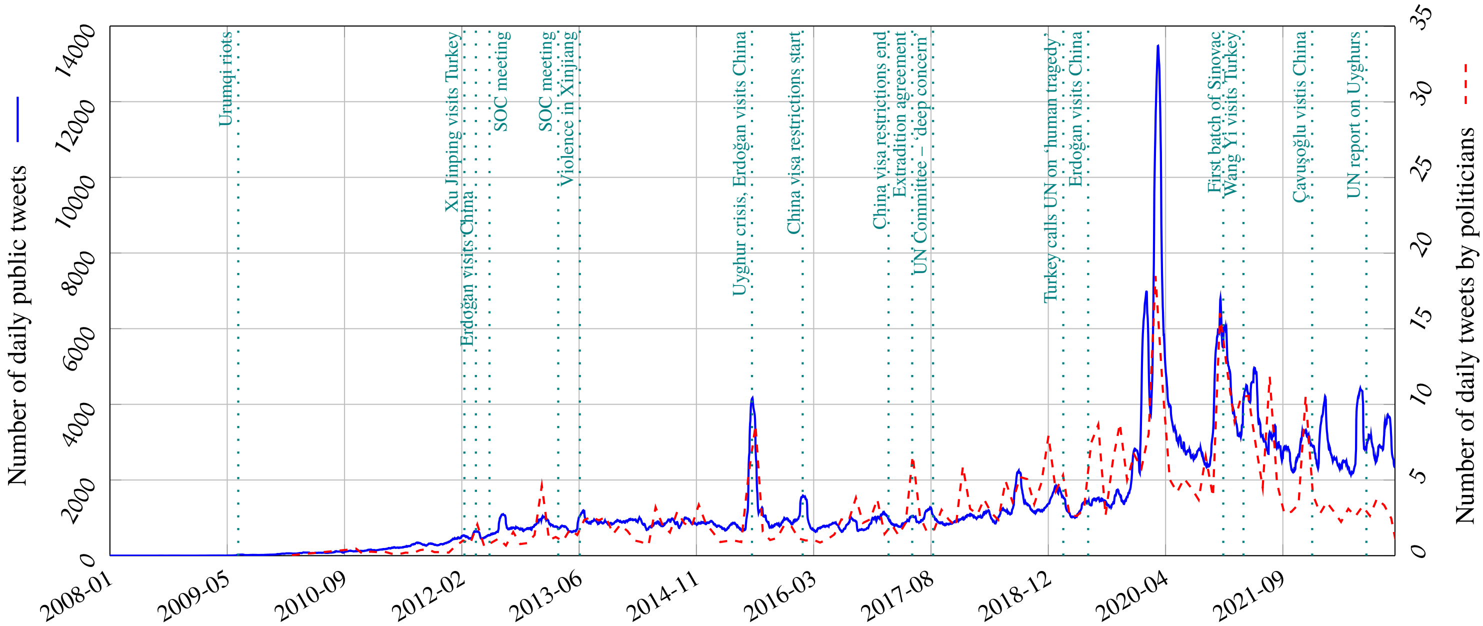

Figure 4: Number of daily tweets about China (30-day rolling average).

presented in Table 2. For completeness, the figures 7–11 present the daily distribution of these tweets.

Table 2: Number of tweets for each country obtained through the Twitter stream interface.

Country	Tweets
China	3 328 106
Germany	3 499 830
Mexico	200 238
Russia	4 664 779
United States	8 703 663

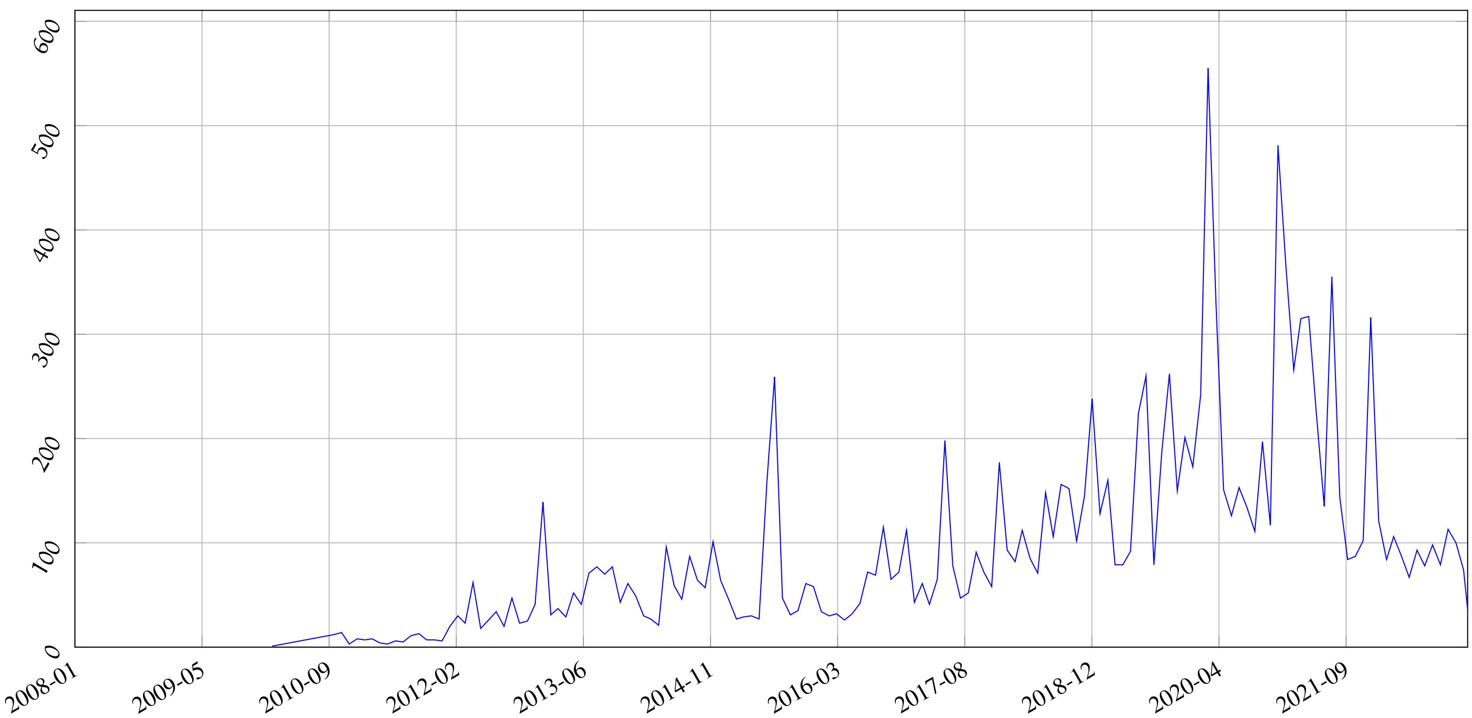

Figure 5: Number of monthly tweets about China by politicians.

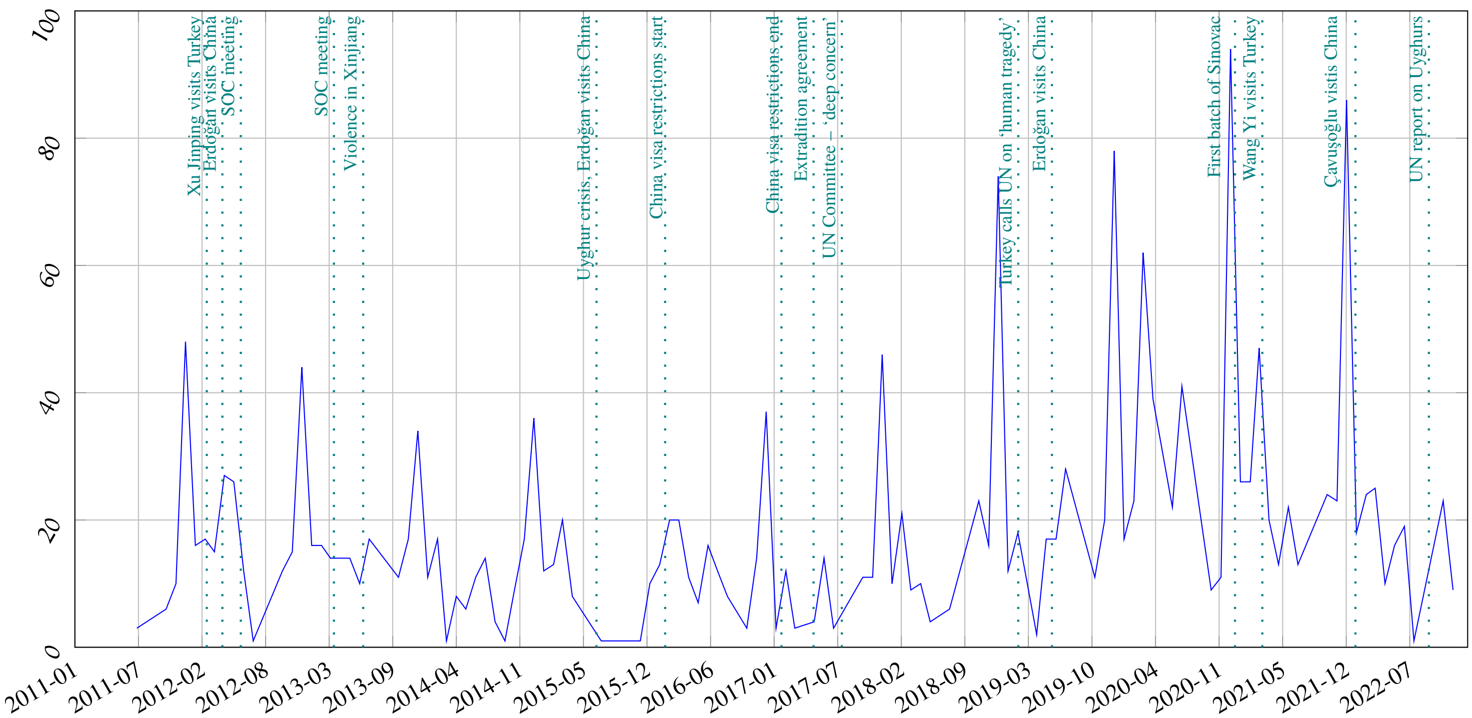

Figure 6: Number of monthly speeches in the Turkish parliament that mention China.

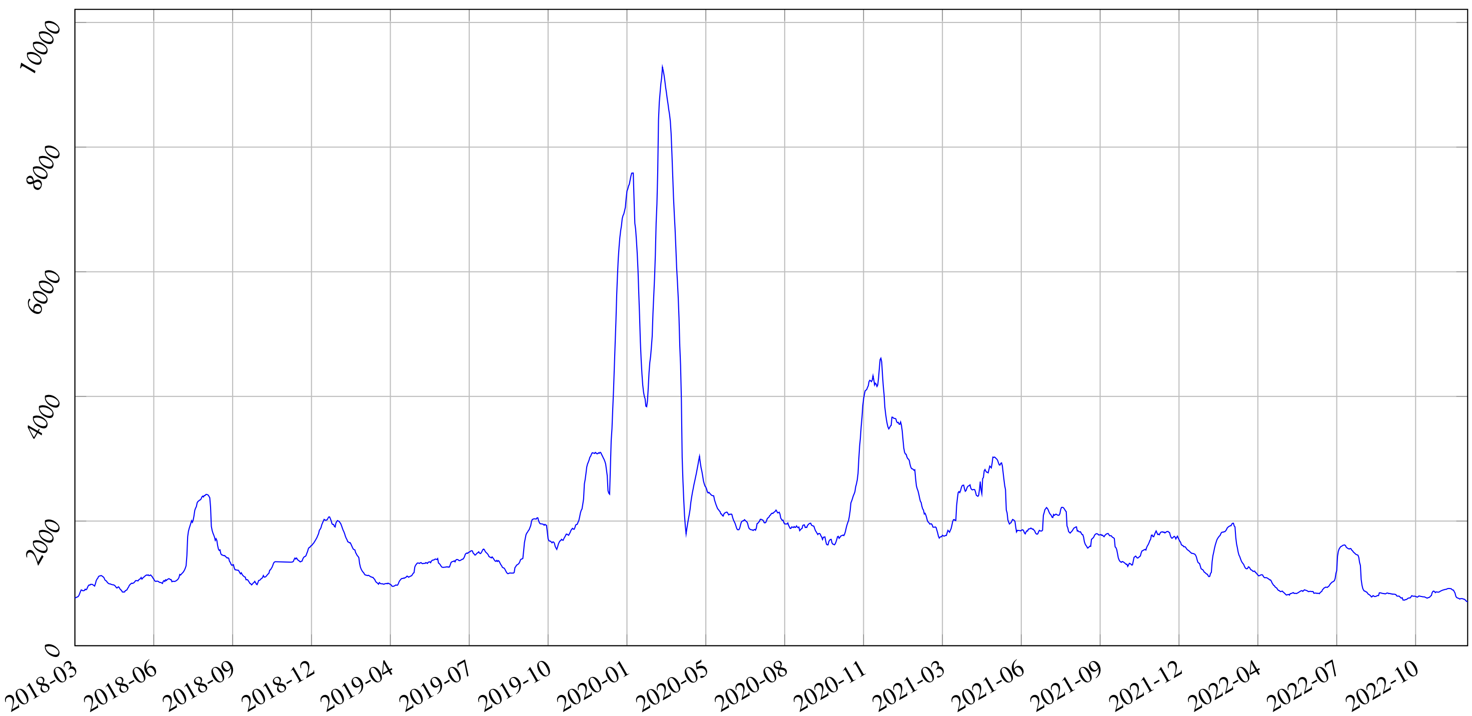

Figure 7: Number of daily tweets obtained through Twitter stream that mention China.

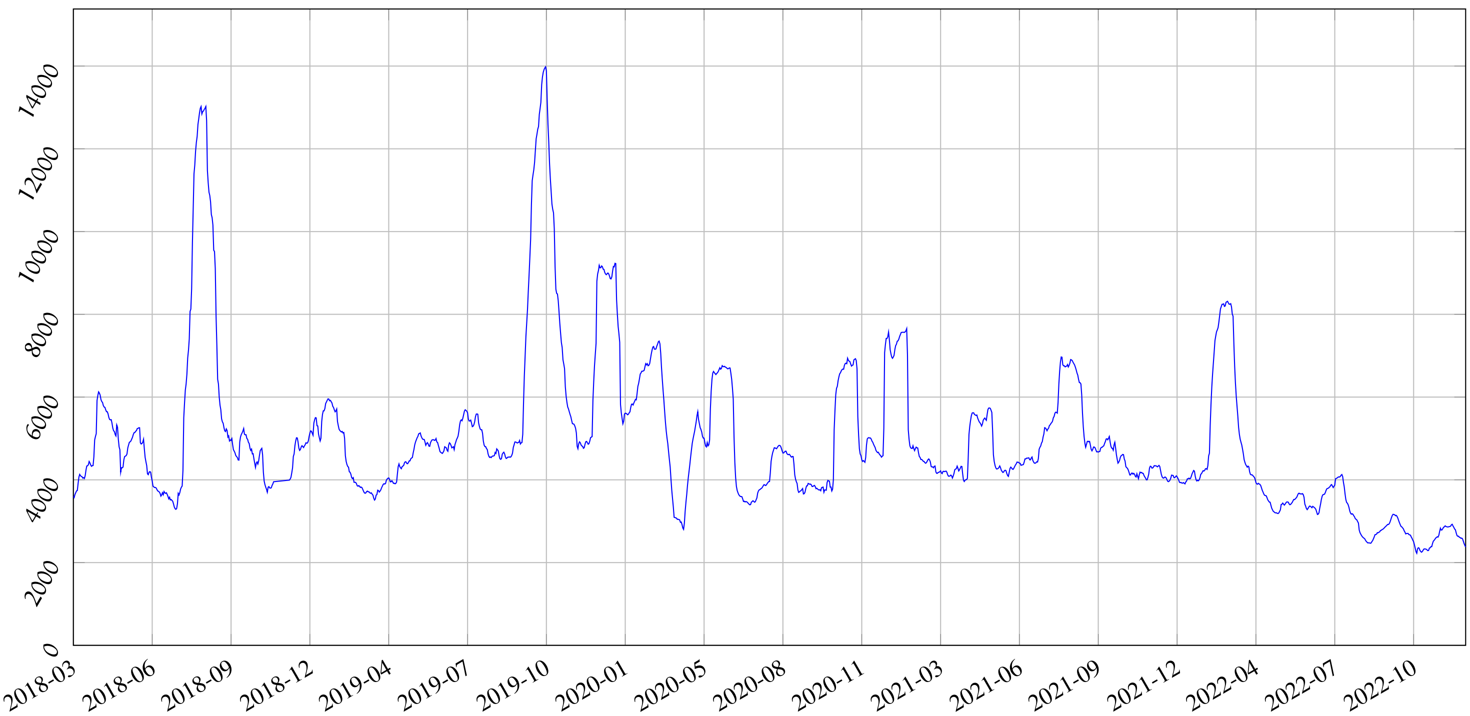

Figure 8: Number of daily tweets obtained through Twitter stream that mention United States.

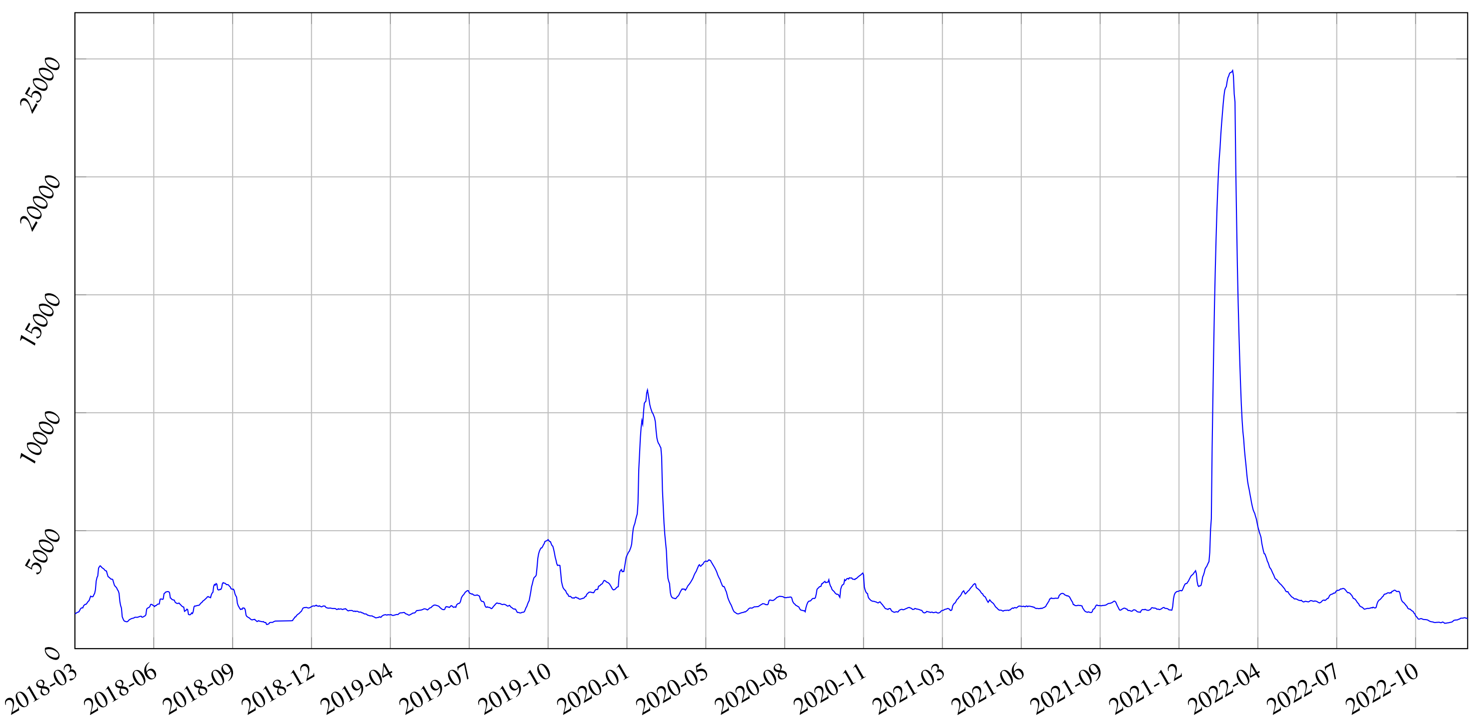

Figure 9: Number of daily tweets obtained through Twitter stream that mention Russia.

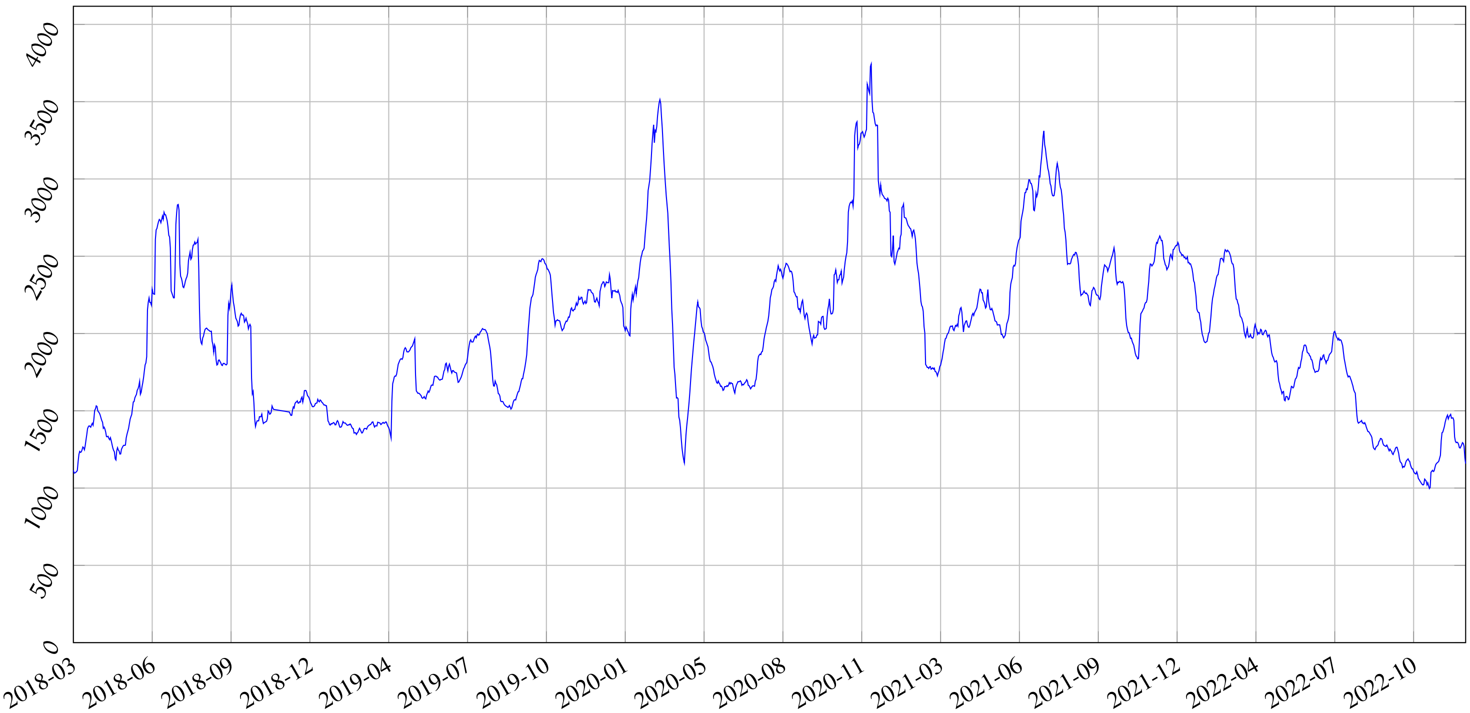

Figure 10: Number of daily tweets obtained through Twitter stream that mention Germany.

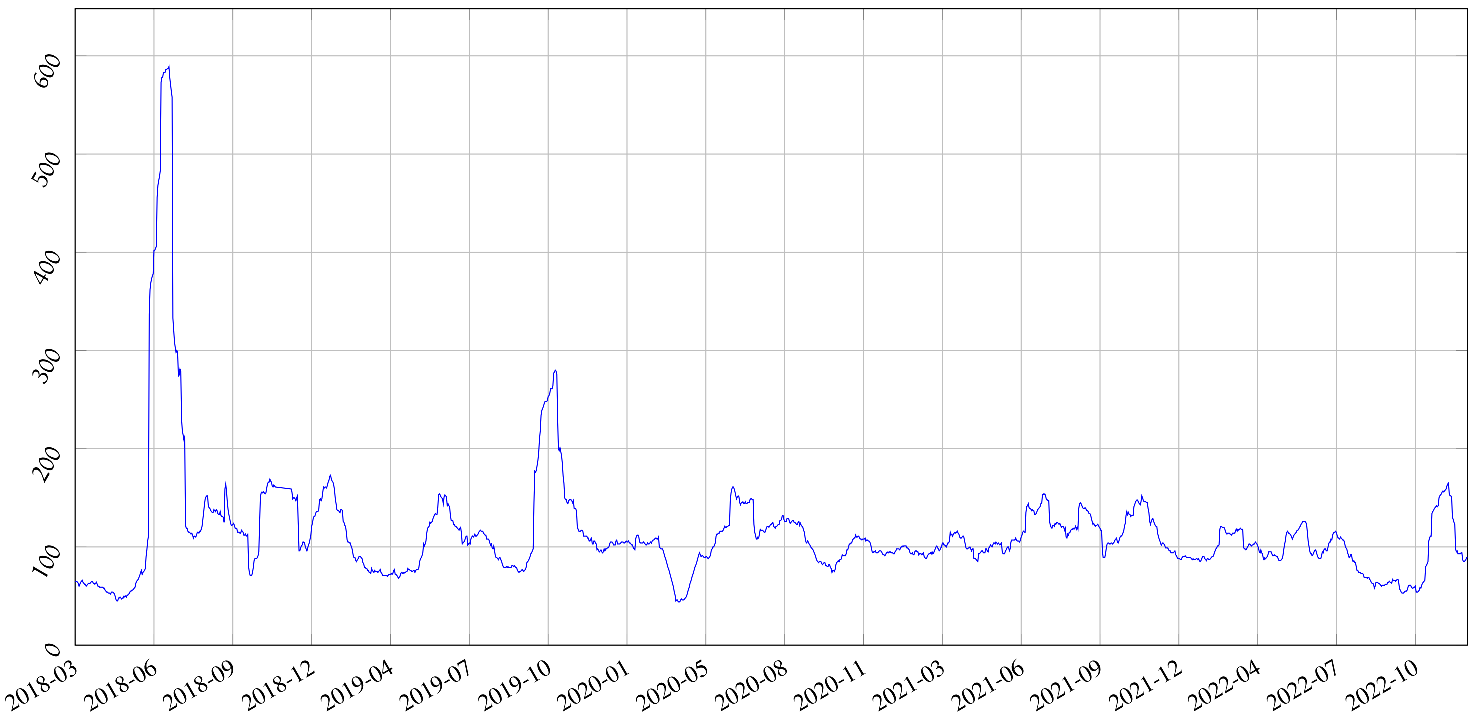

Figure 11: Number of daily tweets obtained through Twitter stream that mention Mexico.

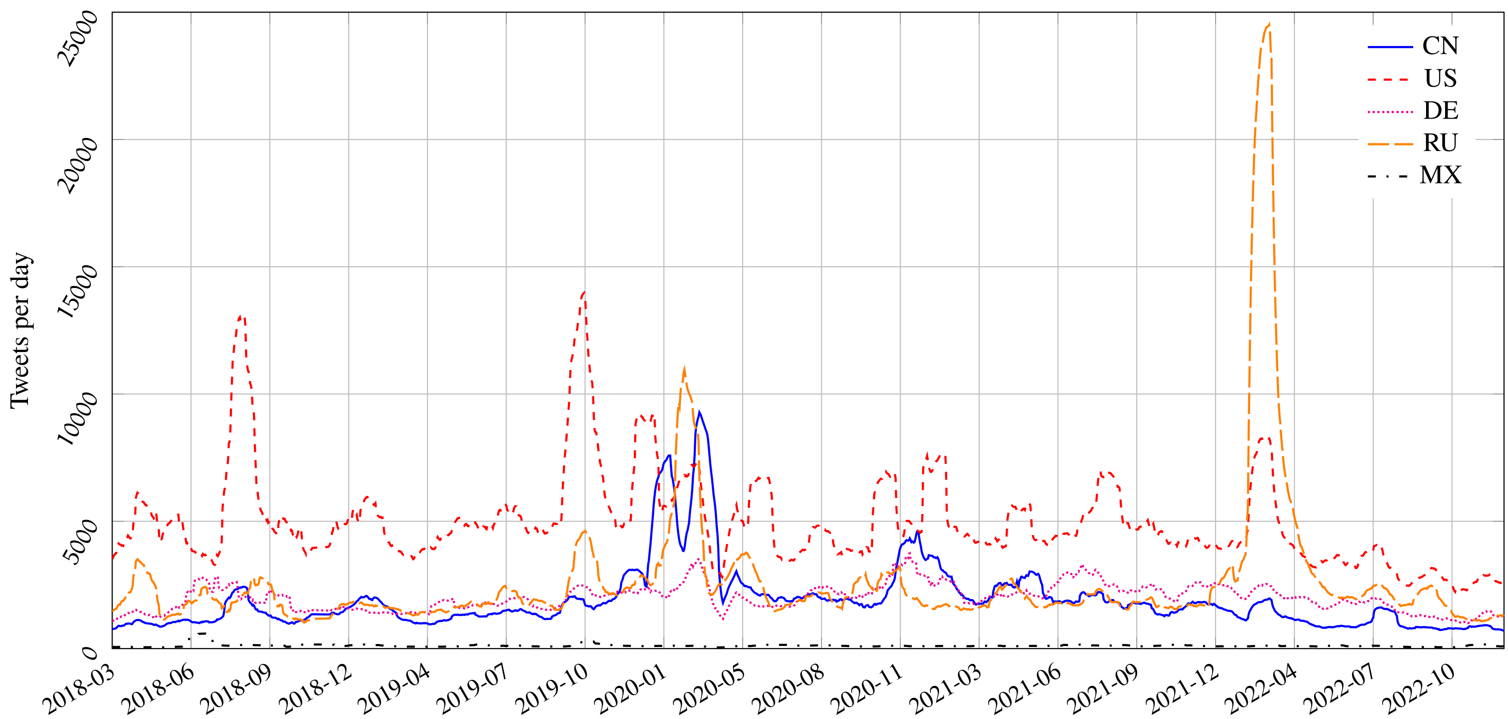

Figure 12: Number of daily tweets obtained through Twitter stream that mention the countries of interest.

1 Sentiment scores

We use a BERT-based deep learning sentiment analyzer for generating the sentiment scores.[2] The model is based on BERTurk (Schweter, 2020), a Transformers-base language model pre-trained on very large Turkish data. The sentiment model uses data from movie and product reviews (Demirtas and Pechenizkiy, 2013; Yıldırım, 2020), and tweet data Hayran and Sert, 2017. An earlier version of the model classifies the sentiment classes between 70–80% accuracy depending on the type of the data (Yıldırım, 2020). We normalize the scores assigned by the classifier between -1 (very negative) and +1 (very positive).

We visualize the average sentiment scores over time. It should be noted that what is measured is the overall sentiment of the complete post, which does not necessarily reflect the sentiment, or stance, towards the country of interest (e.g., a statement of support on a sad event may result in a negative sentiment score). Furthermore, the accuracy of the analyzer may also be lower than the cited score above, since most of the training data of the classifier is out of the domain of our data. However, as earlier studies note (Wang, Yuan, and Luo, 2015; Hu, Wang, Luo, Zhang, Huang, Yan, Liu, Ly, Kacker, She, et al., 2021), the large number of instances used in corpus based studies still capture overall trends since as verified by expected changes in trends based on well-known events.

Figure 13 presents the daily averages of the sentiment scores of the tweets from the general public as well as the politicians. The figure also includes the monthly averages of the sentiment scores of the speeches mentioning China in the parliament. However, the graph representing parliamentary speeches should be interpreted carefully because of the small number of instances per month, and regular missing data points from July to September each year.

There is, again, the clear COVID-19 effect, that causes a sharp drop in sentiment scores. The trends observed in tweets of politicians and the general public are mostly similar. The politicians on average seem to be more positive (or less negative), which may also be related to more formal / polite language, presumably more common in politicians' posts. Another possibility is the dominance of AKP and MHP members in the data, which are expected to be more pro-China.

Given we have sentiments expressed by both the politicians and the general public, an interesting question is whether the public sentiment affects the politicians, or the politicians affect the public sentiment. The cursory cross-correlation plotted in Figure 15 indicates that the peak correlation is with time a lag of zero days. As a result, at least with daily averages and without fine-grained classification of politicians and topics, there is no evidence for a clear direction of effect.

Figure 16 presents the comparison of daily average sentiment scores expressed in tweets mentioning China in comparison to the United States, Germany, Russia, and Mexico. The first three are included as countries with strong social/political ties that are an active part of the social media discussion. Mexico serves as a remote country with relatively

[2] `https://huggingface.co/savasy/bert-base-turkish-sentiment-cased`

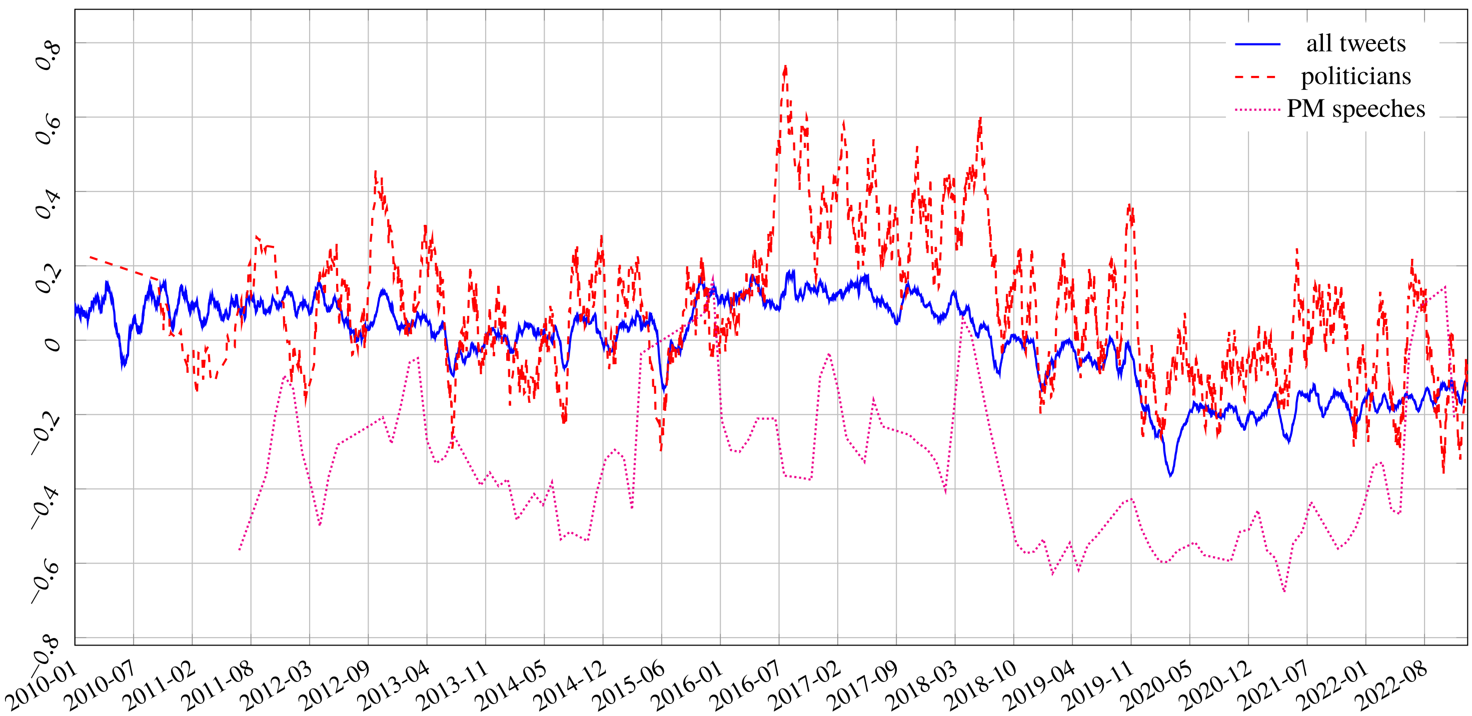

Figure 13: Daily average of the sentiment scores of the tweets mentioning China (30-day rolling average), and monthly average of the sentiment scores of the parliamentary speeches mentioning China (3-month rolling average).

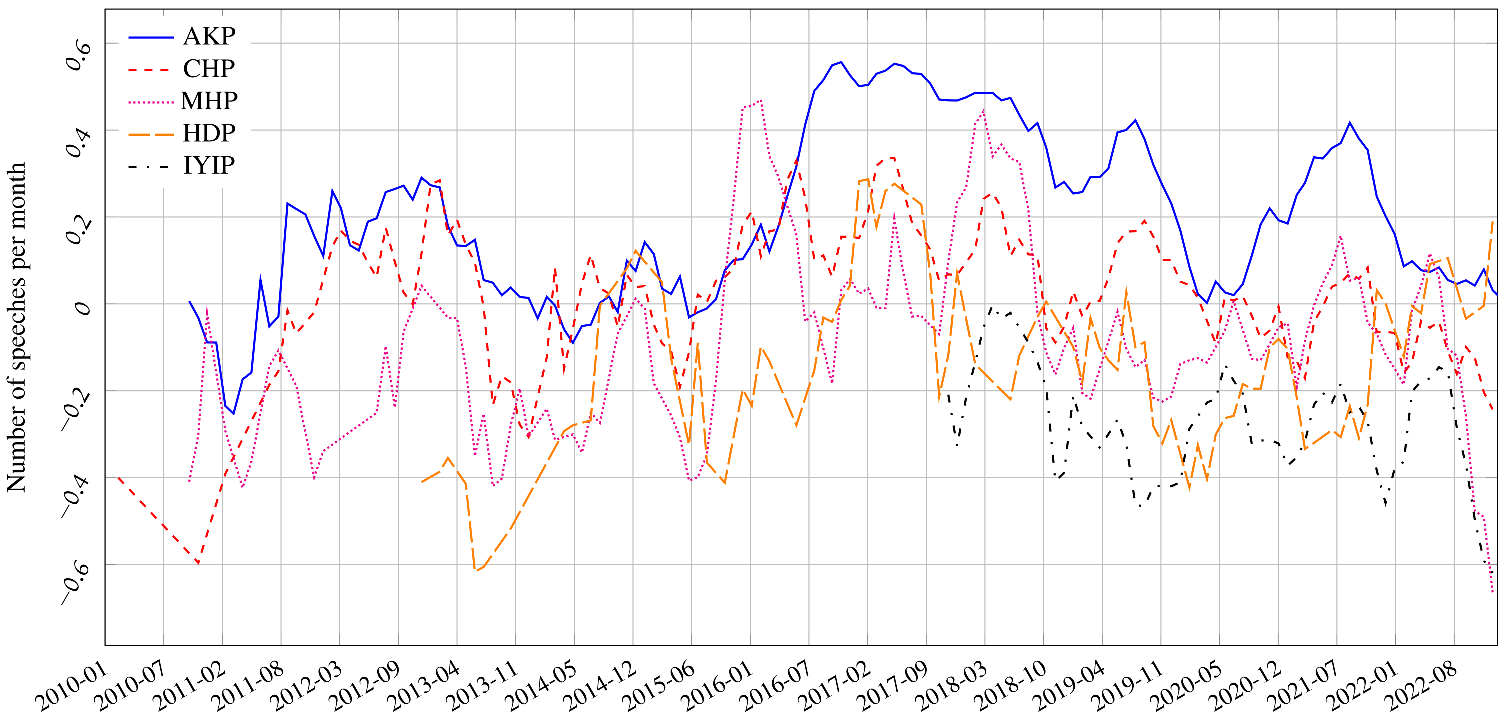

Figure 14: Daily average of the sentiment scores of politicians by party (3-month rolling average). The party identity for each politician is taken to be the last party membership recorded in the ParlaMint corpus.

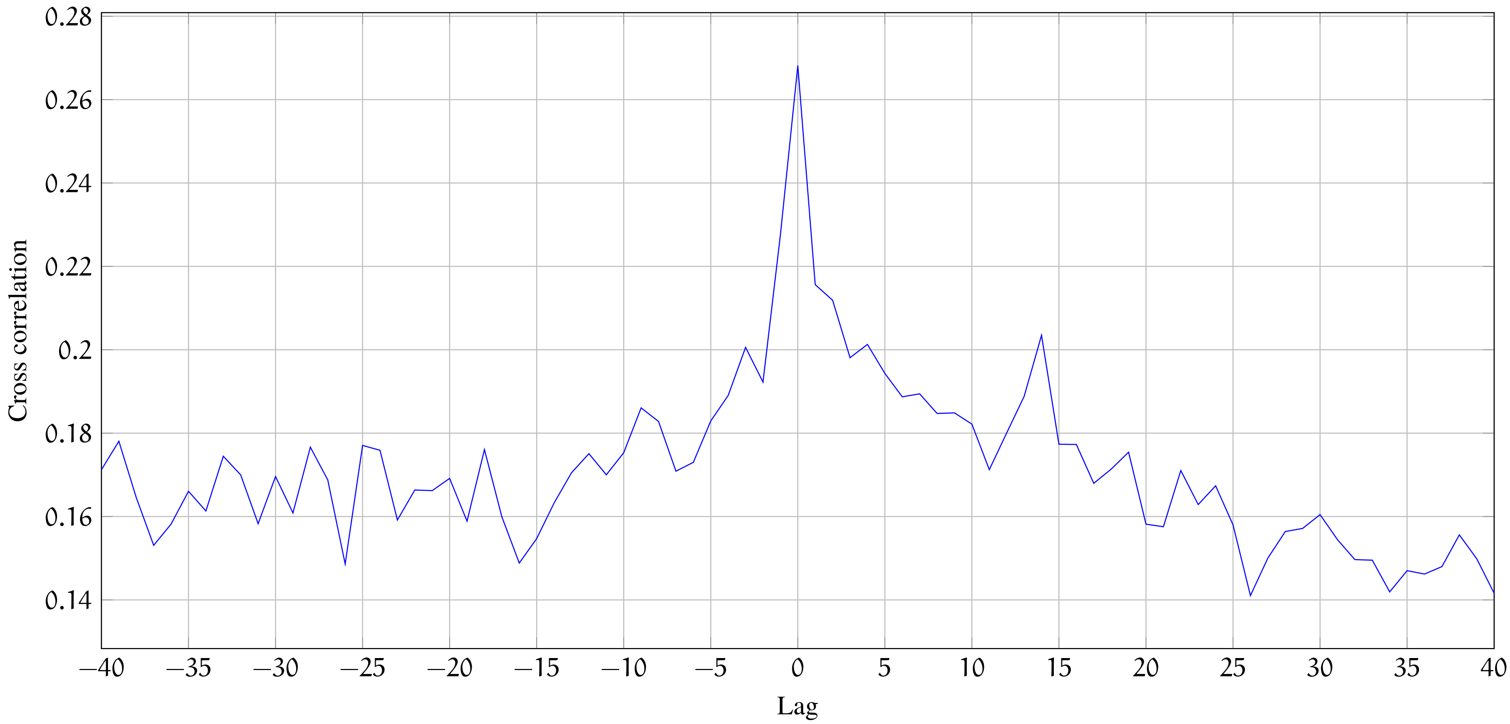

Figure 15: Cross correlation of daily average of the sentiment scores by public and politicians. We only display time lags up to 40 days.

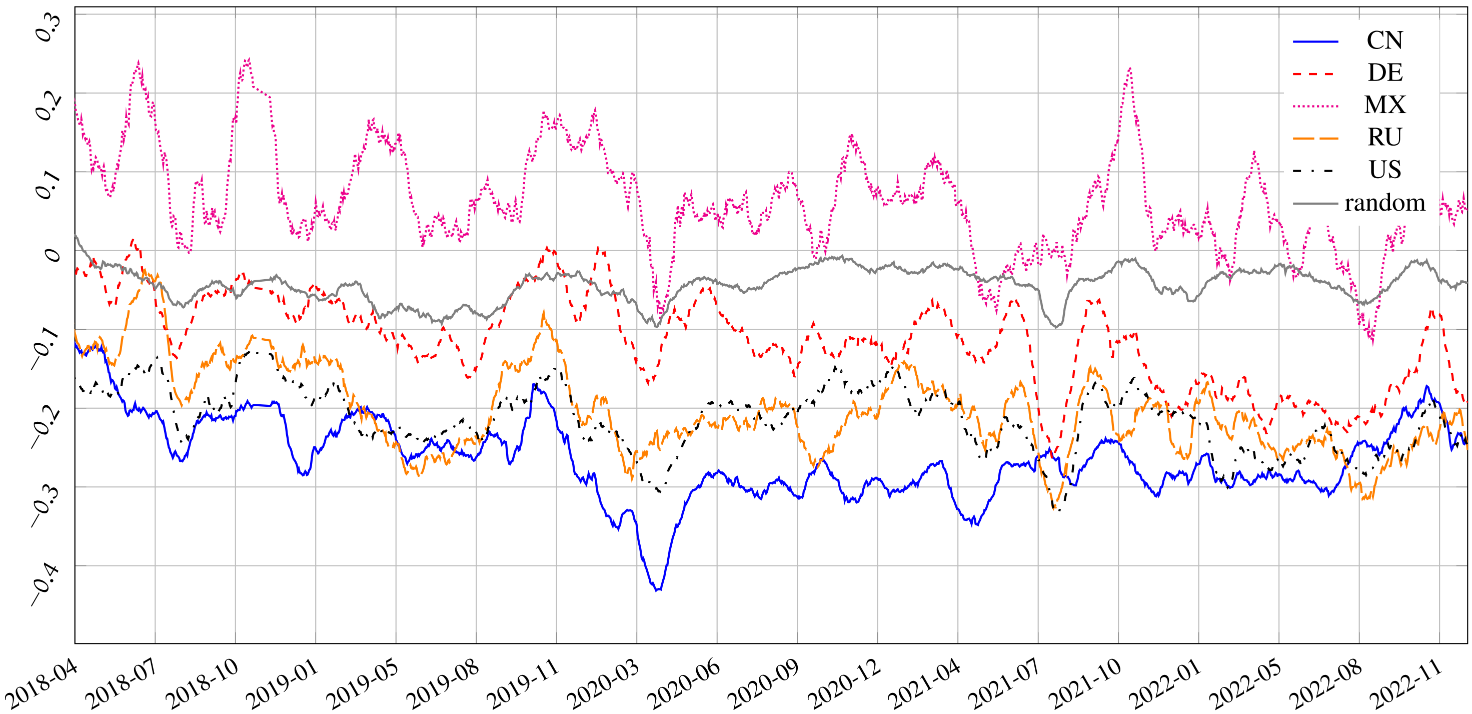

Figure 16: Daily average of the sentiment scores of the tweets containing China over time (30-day rolling average).

low political interaction, while having been mentioned on Turkish Twitter relatively frequently to allow us to collect a representative sample. In addition, the gray solid line represents the daily sentiment scores for randomly picked tweets from the Twitter stream. This graph uses a different data set than the graphs presented earlier. Since obtaining the full history of tweets for every country was not feasible, we selected these tweets from a corpus of tweets that has been collected from the live Twitter stream since April 2018.

The timeline of the sentiment scores towards tweets including China is similar to the earlier graph (Figure 13). A downwards trend since 2018, which became even lower with early 2020. It should, again, be noted that the data collection methods between the two graphs differ. However, the trends are similar for the overlapping period. All sentiment scores, including the ones for the random tweets, see a dip at the beginning of 2020, presumably due to COVID-19. The sentiment scores for other countries seem to recover to their earlier levels soon after the start of the pandemic. However, the sentiments of tweets that mention China stays lower than before after the beginning of 2020, despite a slight increase from its lowest point.

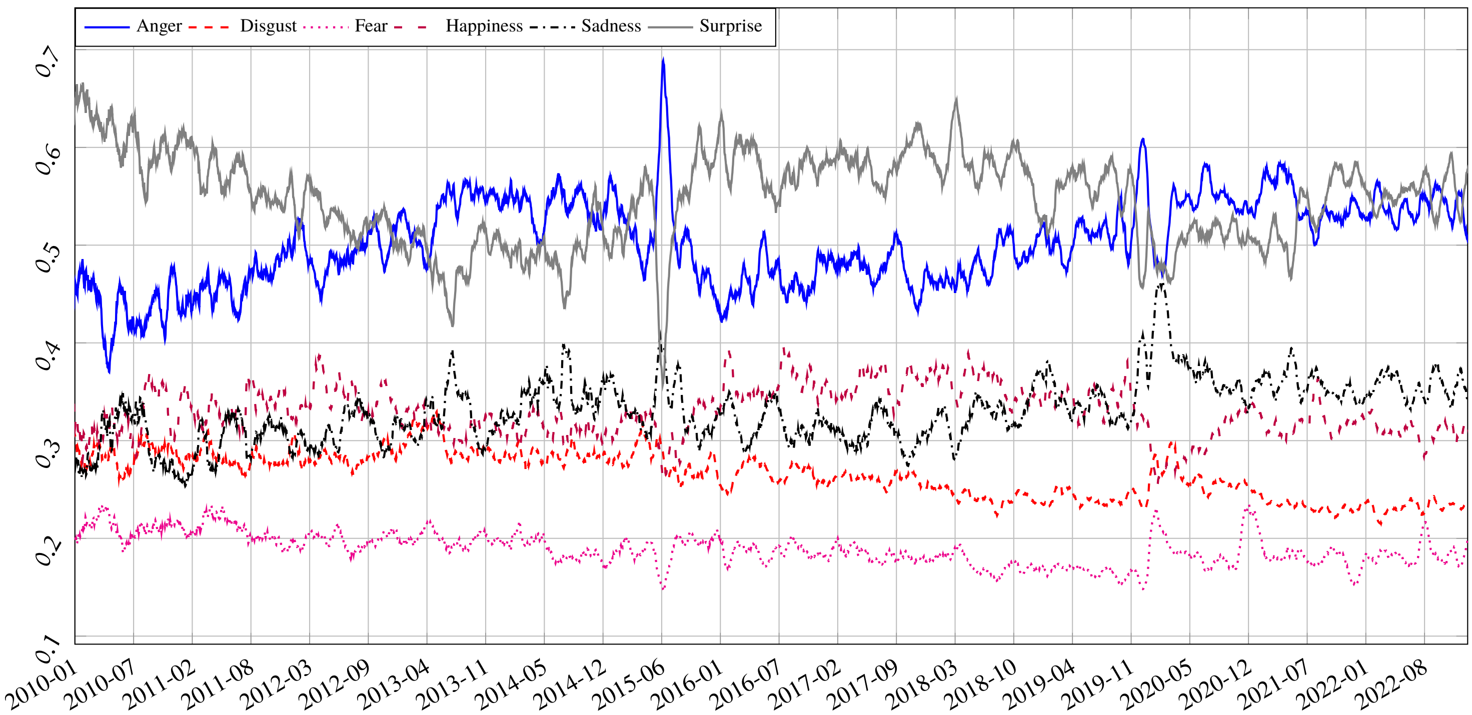

Figure 17: Daily average of the emotion scores of the tweets containing China over time (30-day rolling average). The scores range in range [0,1], from no indication of indicated emotion to strong indication of the emotion.

2 Emotion analysis

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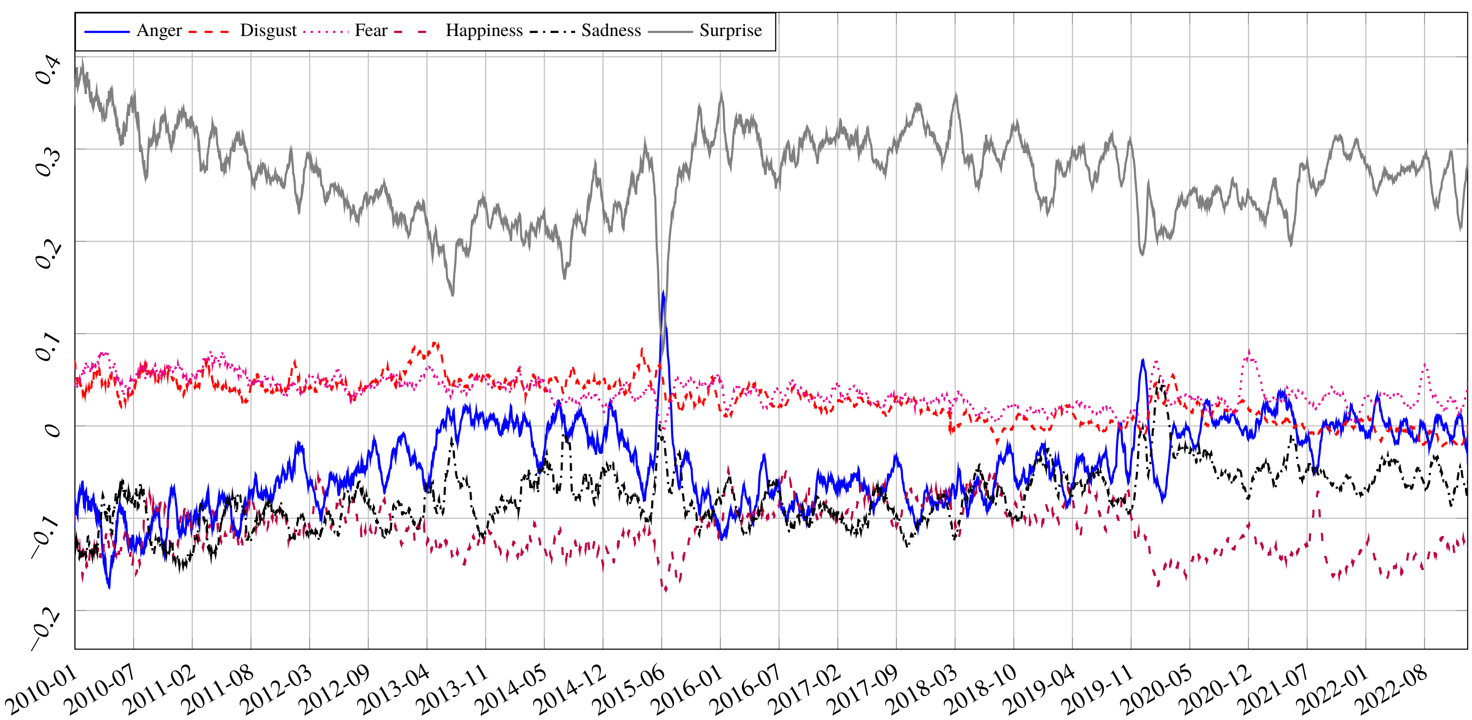

Figure 18: Normalized daily average of the emotion scores of the tweets containing China over time (30-day rolling average). The scores are subtracted from the average scores of random tweets. As are result, original scores over baseline (random tweets) are mapped to a positive score, while scores less than baseline are negative.

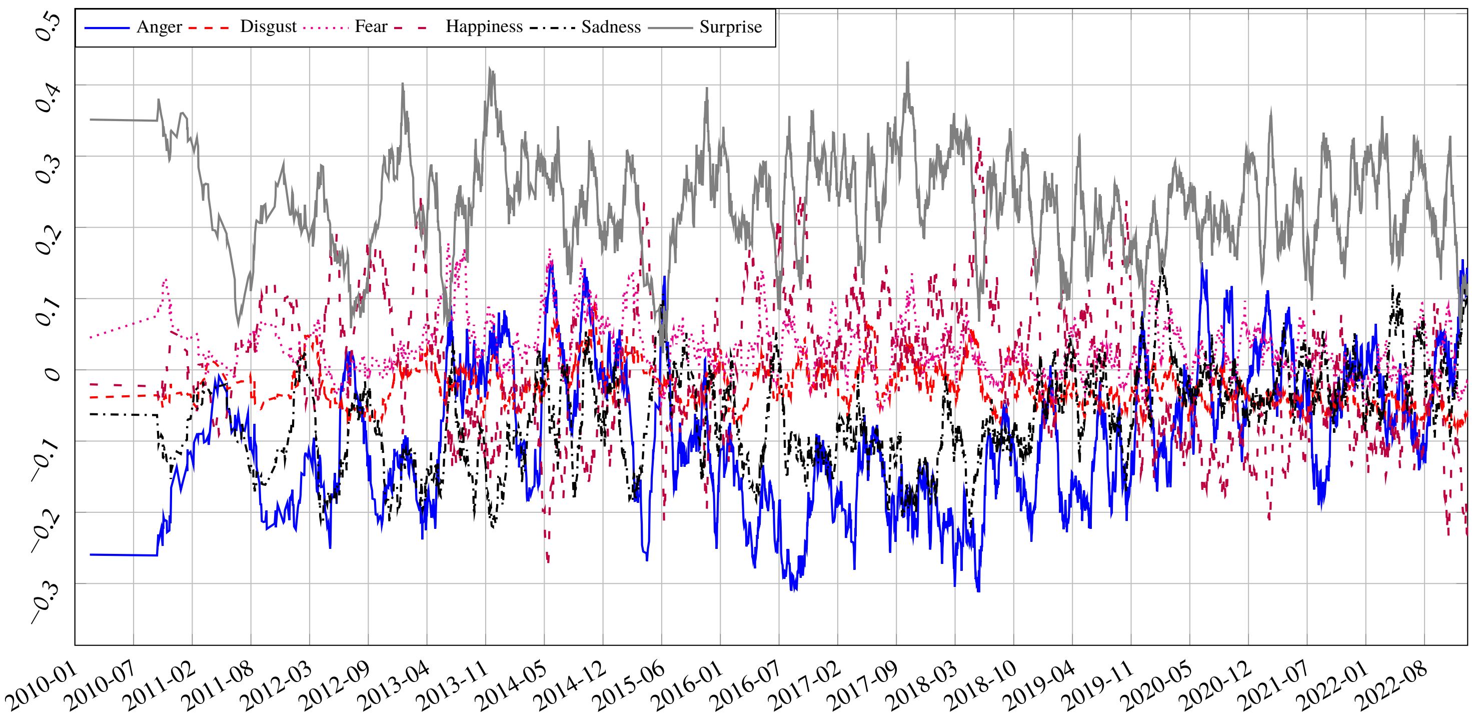

Figure 19: Normalized daily average of the emotion scores of the tweets from politicians on China over time (30-day rolling average). The scores are subtracted from the average scores of random tweets. As are result, original scores over baseline (random tweets) are mapped to a positive score, while scores less than baseline are negative.

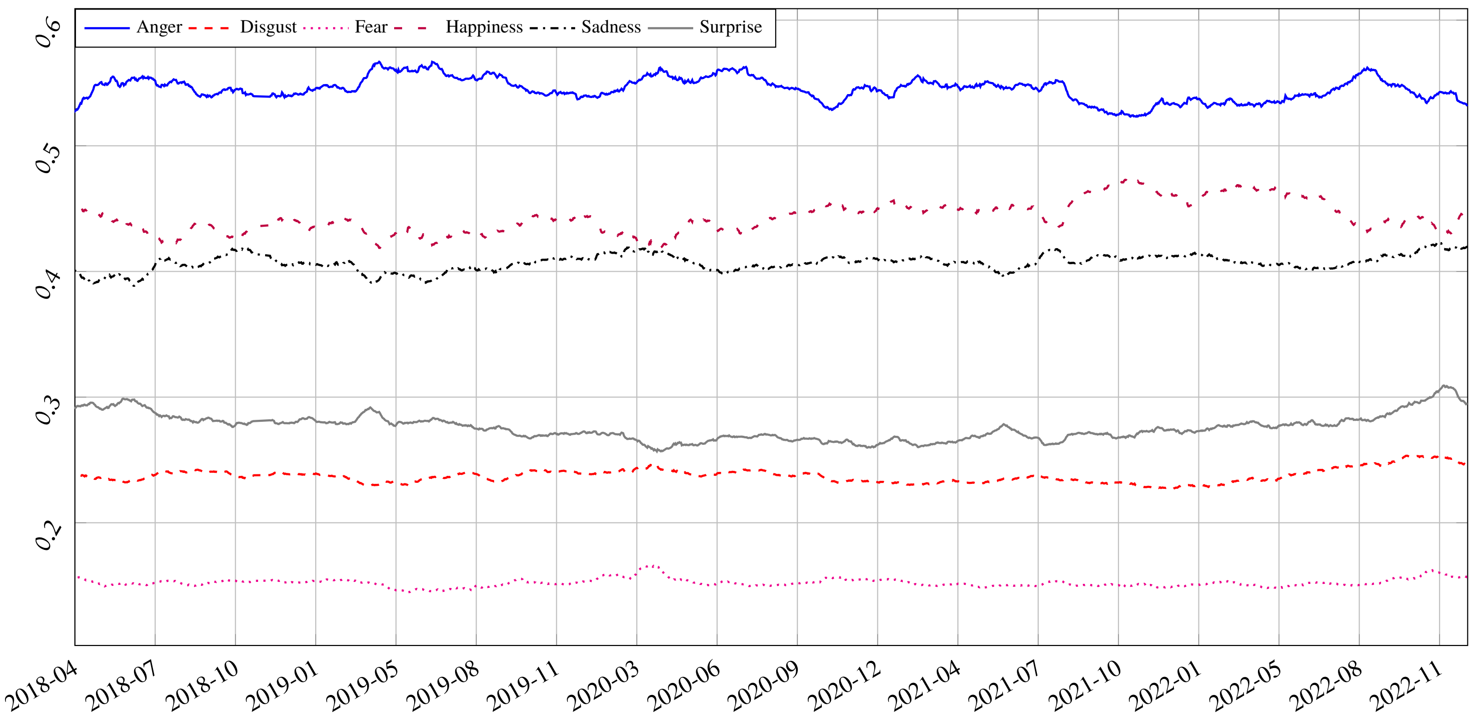

Figure 20: Daily average of the emotion scores of random tweets over time (30-day rolling average).

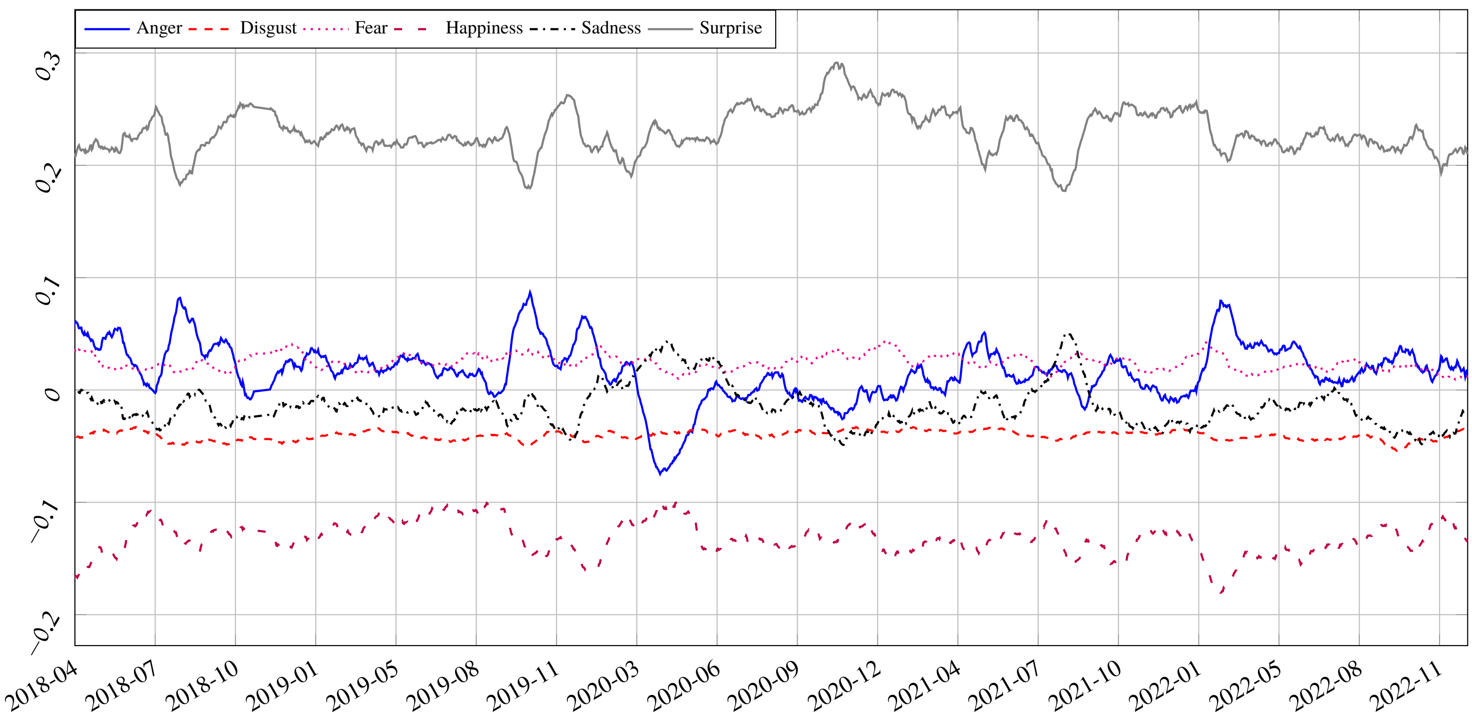

Figure 21: Normalized daily average of the emotion scores for USA (30-day rolling average).

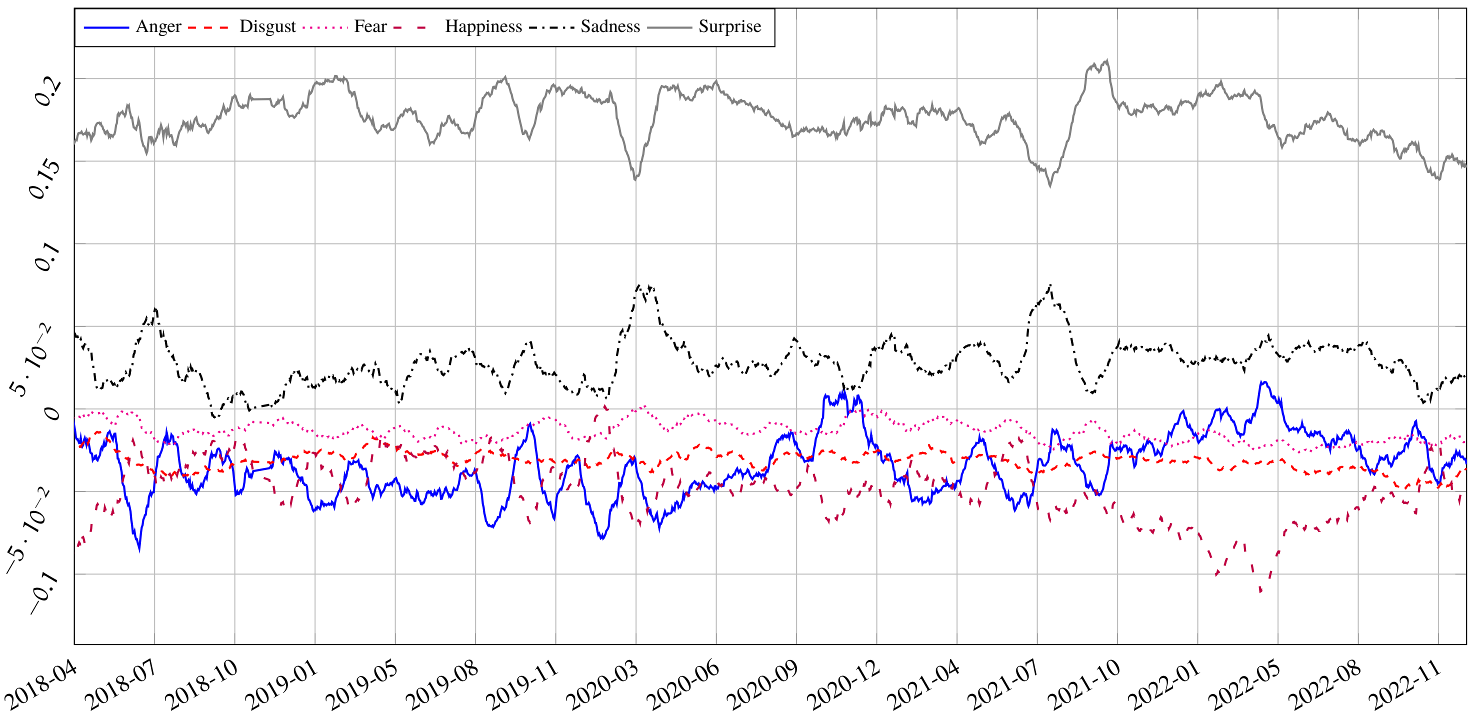

Figure 22: Normalized daily average of the emotion scores for Germany (30-day rolling average).

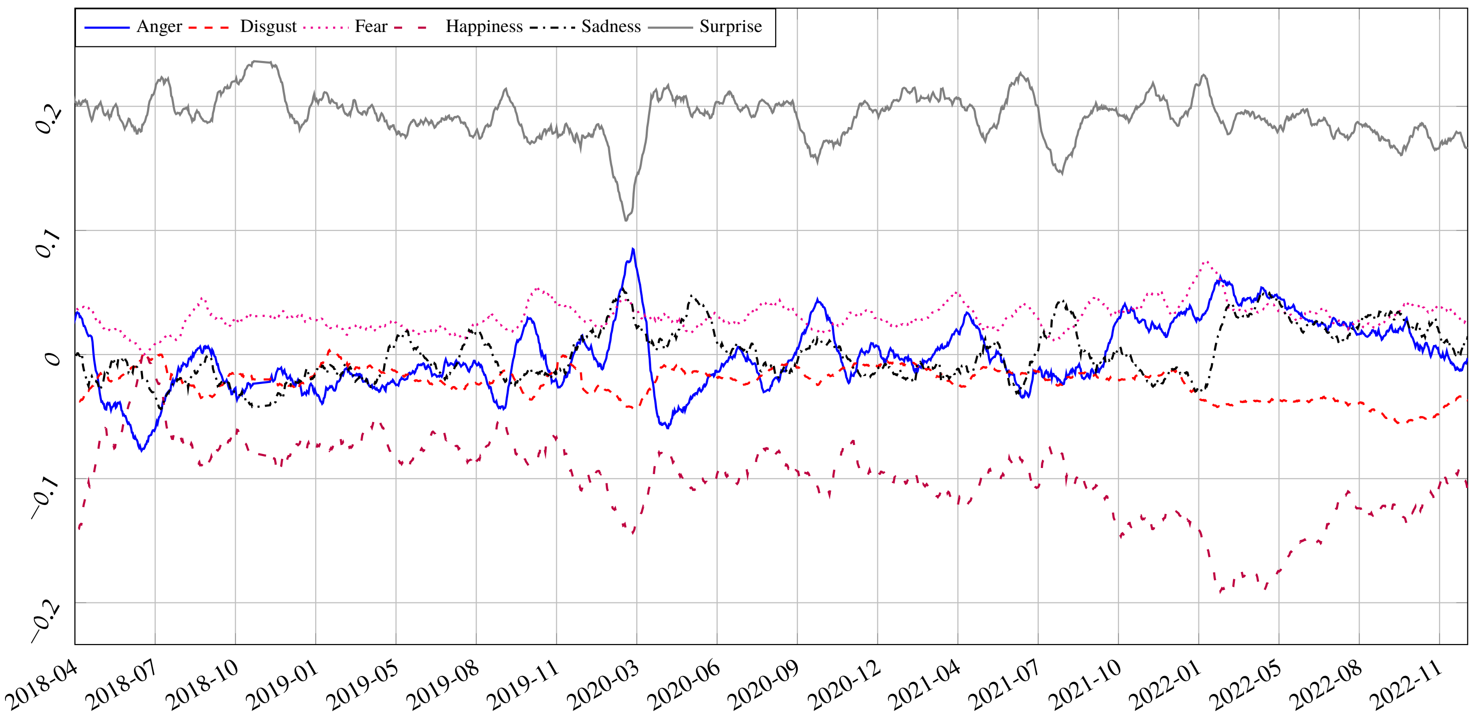

Figure 23: Normalized daily average of the emotion scores for Russia (30-day rolling average).

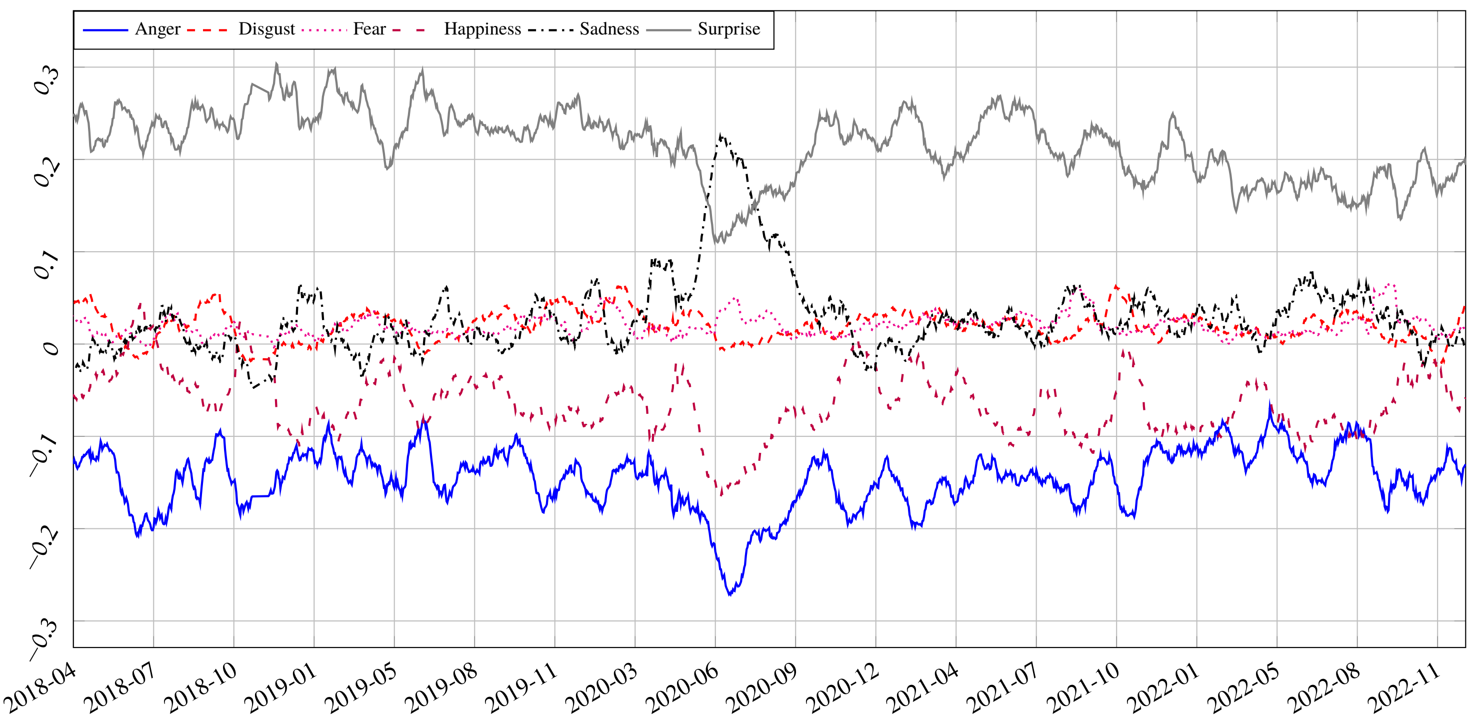

Figure 24: Normalized daily average of the emotion scores for Mexico (30-day rolling average).

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