Growing climate polarisation on social media

Max Falkenberg¹, Alessandro Galeazzi², Maddalena Torricelli³, Niccolò Di Marco³, Francesca Larosa⁴,⁵, Madalina Sas⁶, Amin Mekacher¹, Warren Pearce⁷, Fabiana Zollo², Walter Quattrociocchi⁸,* and Andrea Baronchelli¹,⁹,*

¹ City University of London, Department of Mathematics, London EC1V 0HB, (UK)
² Ca’ Foscari, University of Venice — Department of Environmental Sciences, Informatics and Statistics, Via Torino 155, 30172 Venezia (IT)
³ University of Firenze, Viale Morgagni, 40/44 - 50134 Firenze (IT)
⁴ Institute for Sustainable Resources, University College London, London WC1E 6BT, (UK)
⁵ Euro-Mediterranean Center on Climate Change (CMCC), Via delle Industrie, 13 - 30175 Venice (IT)
⁶ Centre for Complexity Science, Imperial College London, London SW7 2AZ, (UK)
⁷ iHuman, Department for Sociological Studies, University of Sheffield, Sheffield, S10 2TN, (UK)
⁸ Sapienza University of Rome — Department of Computer Science, Viale Regina Elena, 295 — 00161 Roma (IT)
⁹ The Alan Turing Institute, British Library, London NW1 2DB, (UK)

*Corresponding authors: quattrociocchi@di.uniroma1.it, abaronchelli@turing.ac.uk

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Climate change and political polarisation are two of the critical social and political issues of the 21st century. However, their interaction remains understudied. Here, we investigate the online discussion around the UN Conference of The Parties on Climate Change (COP) using social media data from 2014 to 2021. First, we highlight that cross-platform engagement peaked during COP26. Second, focusing on Twitter, we reveal low ideological polarisation between COP20 – COP25, with a large increase in polarisation during COP26. Finally, we show that this is driven by growing right-wing engagement (a 4-fold increase since COP21) and find no evidence of polarisation driven by individuals moving between ideological groups. With future climate action reliant on negotiations at COP27 and onwards, our results highlight the importance of monitoring polarisation in the public climate discourse and how this may impact political action.

I. INTRODUCTION

In its 2021 Global Risks Report, the World Economic Forum (WEF) highlights climate action failure as “the most impactful and the second most likely long-term risk” for humanity [1]. Simultaneously, the report notes the impact of “growing fragmentation in many societies” as a factor amplifying the effects of the Covid-19 pandemic (e.g., by inhibiting global cooperation), and stresses that “further polarisation” may create new obstacles “hindering financial, political, technical and international cooperation commitments on global issues such as climate change”.

In this paper, we study the interaction between these issues by analysing the online discussion around the Conference of the Parties (COP). COP has been the supreme decision making body of the United Nations Framework Convention on Climate Change (UNFCCC) since its establishment in 1992, and represents the leading international forum for climate diplomacy. This makes the online discussion around COP particularly well suited to gauging public views on climate action, allowing us to quantify the polarisation which may hinder climate action.

Various studies have considered the polarisation of climate ideologies from a sociological standpoint [2]. Previous work has found that the polarisation is particularly high amongst science-literate individuals [3], and that views can be strongly influenced by politicised content from the media [4] and corporate action [5]. Other studies investigate attitudes to climate change and polarisation on social media [3][4][9][9]. In most cases, they focus on interactions during a specific event such as Pearce et al. [10] on the 2014 IPCC report, and Hopke and Hestres [11] on COP21, while Williams et al. [12] study a particular four month time period in 2013. Others, such as Chen et al. [7] focus on a particular region, focusing on climate polarisation in the Finnish Twittersphere, and the alignment of climate ideology with other political views. However, by focusing on relatively short time periods of a few weeks or months, these studies have not focused on the evolving nature of climate polarisation.

In the wider literature, there has been major growth in the study of online polarisation, misinformation, and the
recently coined “infodemic” [13–20]. Historically, the dominant focus of these studies has been political polarisation in the United States and Europe [18, 21], with a recent shift towards studying the online discussion around Covid-19 [15, 19, 20].

Three gaps stand out when assessing the literature on climate polarisation: (1) quantitative longitudinal studies which span a multi-year period and address the evolving nature of polarisation beyond a particular event, (2) studies analysing very large datasets (with the recent exception of [22]), and (3) studies where polarisation is measured quantitatively.

Here, we address these gaps by studying the online discussion around COP across a seven year period, from COP20 in 2014 to COP26 in 2021, focusing on three social media platforms: Twitter, Youtube, and Reddit. Our focus serves two purposes. Firstly, rather than studying a general, context-free climate discussion, the COP discussion can be characterised as a single online event which lends itself to a quantitative analysis of climate polarisation. While studying the broader climate discussion is of course important, the discussion is so broad, involves such a wide range of social groupings, and covers so many topics, that it is practically impossible to study this discussion coherently in a single paper. Secondly, COP is the pre-eminent international forum for climate diplomacy. Therefore, the online discussion around COP is more representative of public engagement with the politics of climate change, as opposed to the wider climate discussion. Understanding polarisation in this arena may be more useful for understanding how ideological polarisation could impact political action on climate.

Our results show that the COP discussion can be partitioned into an ideological majority, including most politicians, climate activists, journalists and individuals, and an ideological minority. From COP20 – COP25, influential accounts in the ideological minority are climate focused and self-identify as falling outside the climate mainstream. However, only a small number of users engage with this cluster. Polarisation is low and largely flat between COP20 and COP25. In COP26, we show that polarisation increased dramatically, driven largely by growing right-wing engagement, as well as a significant overlap with the online discussion on Covid-19. Fewer than 3% of users fall in the ideological minority between COP20 – COP25, rising to 12% in COP26. With future commitments on climate action reliant on political progress at COP27 and onwards, monitoring polarisation will be critical to ensuring that ideological rifts do not grow so large as to create a climate action deadlock.

Before proceeding with the analysis, it is important to highlight a point on terminology. Since the online discussion around climate involves millions of individuals, defining suitable terminology to describe their ideological views is difficult. Previous studies have manually labelled users as pro-climate, sceptics, or otherwise; this approach is practically impossible with large datasets. Here, we refer to the two opposed groups as the ideological majority and minority. Acknowledging the need to justify that these groupings represent differences in views on climate, we label the ideology of influential users using information provided by the user themselves where possible and appropriate.

II. RESULTS

A. Engagement with COP

We start by showing the evolving nature of content creation and engagement from COP20 to COP26, see Figure 1. Panel (a) shows the number of posts for Twitter and Reddit, and video uploads for Youtube, from 2014 to 2021. In the inset, data are plotted showing general online engagement with COP measured using Google trends. This shows that social media engagement closely reflects wider online attention.

Within our study period, COP21 and COP26 are of particular significance, with the Paris Agreement signed at COP21, and the Glasgow Climate Pact agreed at COP26. Consequently, content creation and engagement are larger for COP21 and COP26 than in the intermediate years (COP20, COP22 – COP25). In addition to large global engagement with COP21 and COP26, our data shows the important influence of local engagement. This is shown in the Figure 1 inset where overall Google Trends scores are shown alongside country specific scores for France (the host of COP21) and Great Britain (the host of COP26). This highlights that local factors are an important driver of the discussion around COP, with high French engagement and low British engagement during COP21, and vice versa during COP26.

Alongside content creation, panels (b) – (d) show content engagement on Youtube, Twitter and Reddit respectively. Each panel shows increased engagement from COP20 to COP26. Additionally, total engagement on Twitter is around two orders of magnitude larger than on the other platforms. Unfortunately, the low volume of data on Youtube and Reddit limits our ability to robustly study polarisation around COP on these platforms. However, we do find a range of Youtube channels and Subreddits from across the ideological spectrum, see supplementary Information (SI), including multiple channels and Subreddits which fall outside the ideological mainstream.
FIG. 1. Content creation and user engagement on Twitter, Youtube and Reddit from COP20 to COP26. (a) Total number of posts/videos created each day. Inset: Google trends (GT) popularity score for “COP2x”, with country specific scores showing local enhancement of public engagement. (b) The retweet distributions for COP21 and COP26; inset: total number of retweets. (c) Equivalent for Youtube, and (d) Reddit comments. Each time series is normalised relative to the time series maximum for that platform. Other COPs shown in SI.

**B. Ideological polarisation during COP**

Here we investigate the evolving nature of ideological polarisation between COP20 and COP26 on Twitter. Using quantitative measures, we find that polarisation has increased significantly during COP26, after having been low, and largely flat, from COP20 to COP25.

To study polarisation quantitatively, we first assume that the ideological leaning of an individual, $i$, can be expressed as a single number, $x_i$, for a particular issue (e.g., their views on climate change) [16]. Then, the concept of polarisation refers to the properties of the probability distribution, $P(x)$, of ideological leanings across a population of individuals. We can assume ideological leanings are embedded in one dimension and fall in the range $x \in [-1, +1]$, and specify that users with similar ideological views should be close to each other on the spectrum. It follows that individuals with the most extreme ideological differences should map to opposing ends of the spectrum; in the current paper, this means the ideological mainstream which are generally supportive of climate action map to +1, whereas groups who generally do not support climate action map to −1; we acknowledge that individual views are far more complex than this simple characterisation, although a one dimensional spectrum is a useful tool for measuring polarisation quantitatively. Within this framework, an ideological issue is polarised if the distribution $P(x)$ contains multiple well-defined peaks (i.e., the distribution is bimodal or multi-modal).

To extract ideological scores from the Twitter retweet network, we use the “latent ideology” method introduced in [18, 23, 24], which partitions accounts into a set of influencers, and a set of users who retweet those influencers (see Methods for a technical definition). As an analogy to the mathematics, we can think of the method as starting with an arbitrary ordering of influencers in one dimension. Then for each user, the method looks at all the influencers retweeted by that user and attempts to shuffle the influencer ordering to bring those accounts closer together. By repeating this shuffling process iteratively, influencers which share a large set of common retweeters move progressively closer to each other on the ideological spectrum; indirectly, influencers who do not share a common set of retweeters move progressively apart. After iterating through all users, the method produces an optimum ordering where neighbouring influencers have the greatest overlap in their set of retweeters, whereas influencers at the opposite ends of the ordering are most extreme in the differences between their common retweeters. Finally, the influencers at opposite ends of the
ordering are mapped to +1 and −1 on the ideology spectrum; for consistency, we specify that the ideological majority are mapped to +1 and the minority to −1. The extent of retweeter overlap between two neighbouring influencers is captured by their numerical separation on the ideological scale. User ideology scores are calculated relative to the set of influencers they retweet.

This method produces ideological scores for individual Twitter accounts. Polarisation is then quantified using Hartigan’s dip test for unimodality [25] (see Methods). This outputs the test statistic $D$ and a corresponding statistical significance, $p$. If $D$ is small and not statistically significant, there is little to no polarisation in our network; increasing $D$ signifies increasing polarisation.

Figure 2 shows the latent ideology applied to the COP21 and COP26 networks. At the top of each panel we show the distribution of user and influencer ideology scores. Influencers are selected as the top 300 most retweeted accounts, excluding a small number (< 2% for each COP) which confute the results (see Methods). The top thirty influencers are shown in the lower panels of Figure 2. Statistical analysis is performed using the top 300 influencers, and is robust to variable influencer number (see SI).

![Figure 2](image_url)

**FIG. 2.** The ideological spectrum for COP21 (left) and COP26 (right). Top: A histogram of the influencer and user ideology scores for COP21 and COP26. The ideological minority map to −1, whereas the majority group map to +1. Bottom: The 30 most retweeted influencers and accompanying user ideology distributions. Influencers who are primarily retweeted by the ideological minority are written on the left, and influencers primarily retweeted by the ideological majority are on the right. The distributions shown alongside each influencer show the distribution of user ideologies who retweeted that influencer. For COP21, no members of the ideological minority are found amongst top influencers, in contrast to COP26 where we observe ideological polarisation. Expanded figure with all 300 influencers is available here.

Qualitatively, the user ideology for COP21 appears unimodal, whereas for COP26 the user ideology appears multimodal. This is in part due to a limited number of influencers in the ideological minority for COP21; exactly three minority influencers are detected as indicated by the arrows on the COP21 ideology distributions. This results in the ideology distributions exhibiting a single peak of around 99% of influencers in the ideological majority (clustered at +1 on the ideology scale), and a handful of minority influencers (~ 1% of total influencers) spread across the rest.
of the spectrum. In contrast, approximately 18% of the top 300 most retweeted accounts are part of the ideological minority during COP26.

These observations are confirmed by applying Hartigan’s diptest to the latent ideology distributions. For the influencer set, the polarisation statistic, \( D \), increases from COP21 to COP26 (COP21: \( D = 0.022, 95\% \text{ CI}: [0.016, 0.031], p = 0.41 \); COP26: \( D = 0.070, 95\% \text{ CI}: [0.055, 0.088], p < 2.2 \times 10^{-16} \)). Likewise, polarisation increases for the user set (COP21: \( D = 0.0078, 95\% \text{ CI}: [0.0072, 0.0084], p < 2.2 \times 10^{-16} \); COP26: \( D = 0.045, 95\% \text{ CI}: [0.044, 0.046], p < 2.2 \times 10^{-16} \)). Polarisation is higher for the user set than for the influencer set, likely due to higher majority user engagement.

The set of influencers used in Figure 2 varies between COP21 and COP26, limiting our ability to assess whether increasing polarisation is driven by shifting ideological views amongst users, or by changes in the number of users engaging with the ideological majority and minority. To test this, we recompute the ideology using a balanced influencer set (see SI), where we only select influencers who appear in both the COP21 and COP26 discussions. This shows that the ideological scores of users who appear in both the COP21 and COP26 discussions are largely unchanged. The increase in polarisation appears to be driven by users who were not engaged in the COP discussion from COP20 – COP25, but engaged with minority influencers during COP26. We find minimal evidence that users who were part of the COP21 discussion changed their ideological views by COP26. Finally, we note that similar polarisation is observed for the intermediate COPs (COP20, COP22 – COP25) as for COP21. This is shown in Figure 3 where we observe largely flat polarisation, before a large increase in COP26. In the SI, we show that bot activity and deleted accounts on Twitter are unlikely to have a substantial impact on this result.

Before considering the ideological minority in more detail, we should acknowledge that individual scores extracted using the latent ideology are a gross simplification of reality. Clearly, individual views on climate action are more nuanced than anything that can be expressed by a single number. However, previous studies using the latent ideology have shown the utility of the method for detecting ideological views, and have shown a good correlation between the numerically derived ideology score, and third party ideology scores taken from surveys [18].

Despite this, the method does incorrectly label some accounts, as is inevitable with computational methods on big datasets. A critical example is the case of prominent journalists who cover COP, but produce material which may have broad appeal across ideological groups. This is seen in Figure 2 where the British journalist @C4Ciaran is labelled as part of the ideological minority, a direct consequence of a prominent tweet observing the side streets of Glasgow “choked up with chauffeur-driven cars and vans, many with their engines idling”. This tweet was seen by many in the ideological minority as a sign of political hypocrisy, resulting in significant minority engagement. However, @C4Ciaran is the only account in the top 30 influencers which appears incorrectly labelled, although we note that some influencers primarily focus on Covid-19 related issues, referring to COP indirectly, rather than explicitly focusing on climate. Examples in the minority include @JamesMelville and @BernieSpofforth who campaign in the UK against...
vaccine passports, and @doctor_oxford in the majority who generally supports Covid-19 restrictions including the use of masks.

To some extent, this means that the ideological spectrum in Figure 2 more or less conflates climate ideology with Covid-19 ideology. However, we see this as important in itself given that Twitter algorithms likely recommend content to an individual based on the interactions of other users with similar interests. This means that even if some users in the ideological minority are there due to their views on Covid-19, not climate, they may be recommended content from users whose views do fall in the ideological minority on climate [26]. This observation chimes with public criticism of Twitter where users noted that they were recommended material by Twitter which were publicly perceived as climate sceptical [27].

Finally, it is important to stress that the latent ideology reveals the most extreme axis of ideological polarisation. Consequently, the ideological majority during COP21 and COP26 appear to be homogeneous groups (with the exception of the outlying Korean cluster for COP26). However, this may hide within majority group polarisation. For example during COP21, the views of groups like @Greenpeace likely differ from the views of @ObamaWhiteHouse. Investigating polarisation within the ideological majority should be considered in future work.

C. Understanding the ideological minority

We have previously referred exclusively to ideological majority and minority groups. Here we justify that these groups correlate with climate ideology. For COP21, three of the three hundred influencers selected fall in the ideological minority: @BjornLomborg, @Tony_Heller, and @JunkScience. Manual inspection of these user profiles suggests that these individuals self-identify as falling outside the mainstream on climate issues. The user @JunkScience quotes a Nature Climate Change article which refers to him as “the most influential climate science contrarian” [28], @BjornLomborg refers to himself as a “skeptical environmentalist” and references his book “False Alarm: How Climate Change Panic Costs Us Trillions, Hurts the Poor, and Fails to Fix the Planet”, and @Tony_Heller links to his blog “realclimatescience.com” which includes titles such as “There is no climate crisis”.

Focusing on COP26, we find that 56/300 influencers are in the ideological minority. Of these, 6/56 self-identify as climate focused and outside the mainstream ideology, based only on their Twitter biography and pinned posts. A large number of the remaining influencers are news media organisations or journalists (e.g., @newsmax, @nypost, @GBNEWS, @talkRADIO, @spikedonline, @PrisonPlanet, @darrengrimes_, @Nigel Farage, @bennyjohnson, @zerohedge), politicians (@SteveBakerHW, @MartinDaubney, @laurenboebert, @davidkurten, @lavern_spicer), or accounts campaigning against Covid-19 restrictions (@BernieSpofforth, @JamesMelville).

This growth in right-wing engagement is confirmed by analysing the URLs shared in minority group tweets. Using NewsGuard to classify domains gives the following distribution of political leanings: Far Right: 10.2%, Slightly Right: 70.2%, Slightly Left: 19.2%, Far Left: 0.4%. This is in contrast to leanings for the ideological majority: Far Right: 0.2%, Slightly Right: 9.7%, Slightly Left: 84.3%, Far Left: 5.8% (see SI for further details). This also highlights the dominance of the left-wing media in the majority discussion around COP.

D. Validating ideological polarisation through alternative methods

To ensure that the derived ideological spectrum is not a mathematical artefact, here we validate our results using two alternative methods: (1) by applying community detection to the retweet network (excluding influencers), and (2) by comparing the latent ideology with the credibility of news sources used by each ideological group.

Figure 3 shows the network of communities detected in the (a) COP21 and (b) COP26 retweet networks using the Louvain algorithm [29]. Each node represents a community of users, with edges representing inter-community links. Here, “community” refers to a structural property of a network where nodes are grouped together in such a way that the ratio of the number of intra-community links to inter-community links is maximised. As such, a community represents a group of accounts who interact frequently with each other, but less often with other accounts. Nodes are coloured according to the average community ideology score.

Panels (c) and (d) show heatmaps for individual user ideology against average neighbour ideology. These figures reveal a clear separation between the ideological majority and minority, and reveal the presence of echo chambers for both COP21 and COP26, using the framework outlined in [16]. In this context, an echo chamber can be defined as an environment in which users reinforce their opinion about a topic by repeated interactions with content showing similar attitudes [16]. Note, the COP26 minority includes multiple large communities, whereas for COP21 we find only one small minority community. In total, around 3% of users fall in the minority group for COP21, with this rising to 12% for COP26.
FIG. 4. The network of communities in COP21 and COP26, alongside visualisations of the ideological echo-chambers and correlation with distinct groups of media outlets. Top: The communities formed in the (a) COP21 and (b) COP26 retweet networks, coloured according to their average ideological score. Each node represents a community of users, with edges between nodes representing inter-community interactions. The figure reveals a large number of communities who are part of the ideological majority, alongside two major communities which are part of an ideological minority for COP26 and only one community for COP21. Communities in the ideological minority correspond to \( \sim 3\% \) of users in COP21 and \( \sim 12\% \) of users in COP26. Middle: Heatmaps showing the density of individual ideology scores vs average neighbour ideology for (c) COP21 and (d) COP26. The isolated clusters observed illustrate the presence of echo-chambers, see [16]. Bottom: Heatmaps showing the density of news media reliability scores provided by NewsGuard, against the average ideological score of each media outlet’s Twitter audience for (e) COP21 and (f) COP26.
The measures shown so far are derived from structural features of the retweet network; to show that these measures reflect real-world interpretations of ideology, panels (e) and (f) show heatmaps of the latent ideology against independent third party measures of news media reliability. Taking all the tweets of users with an assigned ideology score, we extract the URLs in the tweet text and cross-reference the extracted domains with a database of news source “reliability scores”, provided by NewsGuard (see Methods). This reveals that users in the ideological majority preferentially reference news domains with high reliability scores, whereas the ideological minority often reference domains with low reliability scores.

E. Key COP themes

To support observations of structural polarisation, here we show the distinct topics referenced by each ideological group during COP21 and COP26. Figure 5 shows the key hashtags used by each group in COP21 and COP26, ranked using the Shiftiterator approach [30] (see Methods). The method compares two bodies of text, computing the difference in probability that a hashtag appears in one text or the other. Hashtags are ranked according to the absolute probability difference, with terms on the left appearing more often in minority tweets, and those on the right appearing more often in majority tweets.

FIG. 5. The top hashtags used by the ideological minority and majority during (a) COP21, and (b) COP26. In each panel, hashtags used predominantly by the ideological majority are shown on the right in yellow, and those used by the ideological minority and shown on the left in yellow. Hashtags are ranked from top to bottom based on the absolute difference in their frequency in majority versus minority tweets.

Conference specific. Several hashtags are specific to the COP process. COP21 includes treaty references (#parisagreement, #climatetreaty), terminology (#indc), and references to particular conference groupings (#lpaa, #adp2). For COP26, majority terms are more general, but minority terms refer to the G20 preceding COP26 (#g20romesummit), and the prominence of the #netzero theme. There are also references to specific blog channels which were critical of the COP process (#flop26).

Climate urgency. Between COP21 and COP26, there is the shift in the urgency of climate language, with terms like #climatechange and #globalwarming becoming less prominent, and new terms such as #climatecrisis emerging.

Climate activism. Hashtags associated with climate activism are prominent in both COP21 (e.g., #climateaction, #actonclimate, #climatejustice, #climatemarch) and COP26 (e.g., #togetherforourplanet, #climateactioninyourarea). For COP26, there are also hashtags associated with the Korean K-Pop group BLACKPINK who acted as climate ambassadors during the conference (e.g., #blackpink, #blinks).

Local politics. Specific regional hashtags illustrate the intersection of local engagement with COP. In the minority group, COP21 has references to Canadian, Ontarian and Albertan politics (e.g., #polcan, #cdnpoli, #opolni, #ableg), while in COP26 we observe the prominence of the host country with critical references to Scottish First Minister Nicola Sturgeon (e.g., #resignsturgeon, #greatpretender, #elsiemcselfie, #fmqs). Scottish politics is also referenced
by the majority group in COP26 with the pro-independence hashtag #yesscots. The majority also reference #auspol, highlighting criticism of the Australian Government’s climate policy.

Covid-19. A core theme in the ideological minority during COP26 is #covid19 and #novaccinepassports. This is emphasised if we filter minority tweets according to their use of the term “covid” (see SI), where we find a core set of tweets with a strong focus on climate specific themes, and a broader secondary group with minimal reference to climate issues, but broader reference to other issues of relevance to the political right.

III. DISCUSSION & CONCLUSION

In this paper, we have studied how polarisation in the online discussion around COP has evolved between 2014 to 2021. Although our study aimed to analyse Twitter, Youtube and Reddit, in practice we find that the COP discussion on Twitter is significantly more active than on the other social media platforms. However, our results do show that content creation and engagement went up between COP21 and COP26 on all three platforms, and that all platforms include prominent accounts, channels, or subreddits, which fall outside the mainstream climate ideology.

On Twitter, we find that ideological polarisation was low and largely flat between COP20 – COP25, before a significant increase in COP26 driven by growing right-wing engagement, as well as a degree of overlap with the online discussion around Covid-19. The analysed time period is important, spanning the start and end of the Trump presidency; on Reddit the US election in 2016 was found to be a major polarising event [31]. However, our data shows almost no change in climate polarisation at the time. Rather, our increase in polarisation coincides with the Covid-19 pandemic; how the pandemic is affecting online polarisation remains a hotly debated topic.

Previous studies have suggested that right-wing engagement may be partially driven by bot activity [32]. In the SI, we show that this is unlikely to be the case for the COP discussion on Twitter, where for COP26 the number of posts from sources which may host bots is larger for the ideological majority than for the minority. We also show that there are minimal differences between the prevalence of deleted accounts in the minority and majority groups; in late 2021 Twitter stated that they would start implementing measures against climate scepticism, but did not refer to the option of suspending accounts [27].

Our assessment of structural polarisation reveals majority and minority groups in the COP discussion. Within the minority group, the key influencers during COP21 are individuals with a strong focus on environmental issues, many of whom self-identify as falling outside the mainstream climate ideology (e.g., @JunkScience who quotes a Nature Climate Change article calling him “the most influential climate science contrarian” [28]). While several such accounts reappear in the COP26 data, minority influencers are largely right-wing media organisations and politicians. Most of these accounts do not appear to have been engaged with COP prior to COP26. This is reflected in an increase in users engaged with the ideological minority from 3% in COP21 to 12% in COP26. This shows that, while the political right on social media largely ignored COP in the past, there is a growing online community who oppose the climate mainstream and engage with the international politics of climate change. It is possible that this increase in polarisation is in part driven by local engagement with COP which enhanced English language engagement with COP26, but not with COP21. However, an analysis on French language Twitter (see SI) reveals similar (although somewhat smaller) increases in polarisation between COP21 and COP26. This suggests that observed increases in polarisation cannot be explained purely by enhanced local engagement. French Twitter also reveals similar themes to the English language analysis, particularly the overlap of the ideological minority with the Covid-19 discussion, and groups resistant to vaccine passport measures.

The current study suffers from similar limitations as other studies on social media. Although we aimed to comprehensively study three social media platforms, the bulk of our analysis focuses on Twitter, as is the case for most studies on climate change and social media [9]. Future work should acquire even larger datasets than the one used in the current study, and could consider a wider range of platforms, including Gab and Parler which may better reflect the uncensored views of the ideological minority than the public discussion on Twitter [33]. Our data suggests that the COP discussion is not particularly active on Youtube or Reddit, although we note this may not necessarily be the case for other climate events; further analysis of the climate discussion on these platforms would be warranted in the future. Access to data from Facebook and Instagram would also be valuable for studies on climate polarisation, but so far the availability of data for research has been very limited. Across these platforms, a detailed analysis of content would be valuable, in addition to the structural analysis used in this paper. Focusing on technical aspects, we note that how to best measure polarisation quantitatively is an open problem. The latent ideology method used here is one promising measure. However, we acknowledge that a one dimensional ideology score is probably not enough to encapsulate the nuance of ideological views on complex social and political issues. Future work may wish to consider how best to quantify polarisation in these more complex scenarios.

Finally, given the very recent increase in polarisation observed during COP, future work should continue to monitor the evolving nature of polarisation during COP27 and onwards, and assess whether recent increases in polarisation are
sustained, or whether these structural changes are temporary. It will be important to understand whether polarisation in the public discussion around COP affects the outcome of future negotiations, and whether, as the World Economic Forum note, further polarisation is creating new obstacles to climate action.

REFERENCES

[1] World Economic Forum, *The Global Risks Report 2021. 16th Edition*, Tech. Rep. (World Economic Forum, 2021).
[2] C. H. Lucas, Concerning values: what underlies public polarisation about climate change?, Geographical Research 56, 298 (2018).
[3] C. Drummond and B. Fischhoff, Individuals with greater science literacy and education have more polarized beliefs on controversial science topics, *Proceedings of the National Academy of Sciences* 114, 9587 (2017). https://www.pnas.org/content/114/36/9587.full.pdf
[4] S. Chinn, P. S. Hart, and S. Soroka, Politicization and polarization in climate change news content, 1985-2017, *Science Communication* 42, 112 (2020) https://doi.org/10.1177/1075547019900290
[5] J. Farrell, Corporate funding and ideological polarization about climate change, *Proceedings of the National Academy of Sciences* 113, 92 (2016) https://www.pnas.org/content/113/1/92.full.pdf
[6] E. M. Cody, A. J. Reagan, L. Mitchell, P. S. Dodds, and C. M. Danforth, Climate change sentiment on twitter: An unsolicited public opinion poll, *PloS one* 10, e0136092 (2015).
[7] T. H. Y. Chen, A. Saliboum, A. Gronow, T. Yli-Anttila, and M. Kivelä, Polarization of climate politics results from partisan sorting: Evidence from finnish twittersphere, *Global Environmental Change* 71, 102348 (2021)
[8] J. R. Fownes, C. Yu, and D. B. Margolin, Twitter and climate change, Sociology Compass 12, e12587 (2018).
[9] W. Pearce, S. Niederer, S. M. Özkula, and N. Sánchez Querubín, The social media life of climate change: Platforms, publics, and future imaginaries, *Wiley Interdisciplinary Reviews: Climate Change* 10, e569 (2019).
[10] A. Bessi, M. Coletto, G. A. Davidescu, A. Scala, G. Caldarelli, and W. Quattrociocchi, The spreading of misinformation online, *Proceedings of the National Academy of Sciences* 113, 554 (2016).
[11] M. Cinelli, W. Quattrociocchi, A. Galeazzi, C. M. Valensise, E. Brugnoli, A. L. Schmidt, P. Zola, F. Zollo, and A. Scala, The covid-19 social media infodemic, *Scientific Reports* 10, 1 (2020).
[12] M. Cinelli, G. D. F. Morales, A. Galeazzi, W. Quattrociocchi, and M. Starnini, The echo chamber effect on social media, *Proceedings of the National Academy of Sciences* 118 (2011).
[13] A. Bessi, M. Coletto, G. A. Davidescu, A. Scala, G. Caldarelli, and W. Quattrociocchi, Science vs conspiracy: Collective narratives in the age of misinformation, *PloS one* 10, e0118093 (2015).
[14] J. Flaminio, A. Galeazzi, S. Feldman, M. W. Macy, B. Cross, Z. Zhou, M. Serafini, A. Bovet, H. A. Makse, and B. K. Szymanski, Shifting polarization and twitter news influencers between two us presidential elections, arXiv preprint arXiv:2111.02505 (2021).
[15] R. Gallotti, F. Valle, N. Castaldo, P. Sacco, and M. De Domenico, Assessing the risks of ‘infodemics’ in response to covid-19 epidemics, *Nature Human Behaviour* 1, 1285 (2020).
[16] J. Zarocostas, How to fight an infodemic, *The lancet* 395, 676 (2020).
[17] C. A. Bail, L. P. Argyle, T. W. Brown, J. P. Bumpus, H. Chen, M. F. Hunzaker, J. Lee, M. Mann, F. Merhout, and A. Volkovsly, Exposure to opposing views on social media can increase political polarization, *Proceedings of the National Academy of Sciences* 115, 9216 (2018).
[18] T. J. Cann, I. S. Weaver, and H. T. Williams, Ideological biases in social sharing of online information about climate change, *PloS one* 16, e250656 (2021).
[19] P. Barberá, J. T. Jost, J. Nagler, J. A. Tucker, and R. Bonneau, Tweeting from left to right? Is online political communication more than an echo chamber?, *Psychological science* 26, 1531 (2015).
[20] P. Barberá, Birds of the same feather tweet together: Bayesian ideal point estimation using twitter data, *Political analysis* 23, 76 (2015).
[21] J. A. Hartigan and P. M. Hartigan, The dip test of unimodality, *The annals of Statistics* , 70 (1985).
[22] J. Hannon, M. Bennett, and B. Smyth, Recommending twitter users to follow using content and collaborative filtering approaches, in *Proceedings of the Fourth ACM Conference on Recommender Systems* RecSys ’10 (Association for Computing Machinery, New York, NY, USA, 2010) p. 199–206.
[23] D. Vetter, Revealed: How facebook, google platformed climate lies during cop26 and beyond, *Forbes* (2021)
[24] J. Farrell, K. McConnell, and R. Brulle, Evidence-based strategies to combat scientific misinformation, *Nature climate change* 9, 191 (2019).
IV. METHODS

A. Datasets

Twitter data including tweets and user information was collected using the official Twitter API for academic research ([https://developer.twitter.com/en/docs/twitter-api](https://developer.twitter.com/en/docs/twitter-api)), using the search query “cop2x”, $x \in \{0, \ldots, 6\}$. For each COP, data was collected from July 1st in the year of the conference, to May 31st the following year, with the exception of COP26 where data was collected up to and including November 14th, 2021. Statistics for each COP are provided in Table I. Each dataset was downloaded between October and November 2021.

| Conference Date | Data collection range | # Tweets | # Users | # Filtered Tweets | # Filtered Users |
|-----------------|-----------------------|----------|---------|-------------------|-----------------|
| COP20           | 01/12/2014 to 12/12/2014 | 282,472   | 87,780  | 137,215           | 47,404          |
| COP21           | 30/11/2015 to 12/12/2015 | 3,571,515 | 768,598 | 1,995,140         | 467,652         |
| COP22           | 07/11/2016 to 18/11/2016 | 734,001   | 202,853 | 477,364           | 137,334         |
| COP23           | 06/11/2017 to 7/11/2017  | 783,242   | 219,882 | 570,072           | 151,441         |
| COP24           | 03/12/2018 to 14/12/2018 | 932,909   | 337,072 | 649,408           | 226,622         |
| COP25           | 02/12/2019 to 13/12/2019 | 1,908,744 | 599,391 | 751,898           | 286,054         |
| COP26           | 31/10/2021 to 12/11/2021 | 7,809,303 | 1,816,918| 5,963,639         | 1,264,932       |

For YouTube, we collected videos using the official YouTube Data API ([https://developers.google.com/youtube/v3](https://developers.google.com/youtube/v3)), searching for videos matching the keywords "cop2x", $x \in \{0, \ldots, 6\}$. Then, an in-depth search was performed by crawling the network of related videos as provided by the YouTube algorithm. Next, we filtered the videos that contained the keywords in the title or description from the gathered collection. Finally, we collected the comments of each video from our collection. Note however that, unlike the Twitter API, the YouTube API only returns a sample of videos and comments for any given search query, typically around 10% of the total.

Reddit data was collected using the pushshift.io API ([https://pushshift.io/](https://pushshift.io/)) and official Reddit API ([https://www.reddit.com/dev/api/](https://www.reddit.com/dev/api/)). For each COP, we downloaded all the submissions containing "cop2x" from the pushshift repository, and then downloaded the corresponding engagement statistics, such as the number of comments and crossposts, through the official Reddit API. This choice guarantees that submission statistics are up to date since pushshift.io mirrors Reddit in near real-time, and thus statistics on pushshift are often unreliable.

B. Network construction

The Twitter interaction network is constructed by taking the full corpus of tweets for each COP and focusing exclusively on retweets. Such an approach is typical in the Twitter analysis literature, where retweets are considered evidence of a user endorsing the message of the original poster [31]. This is in contrast to quote tweets or comments which are less likely to represent a clear endorsement of a tweet. After selecting all the retweets from the full Twitter dataset, we filter by language using the Twitter API language metadata, selecting only those retweets written in English.

From this set of English language retweets, a network is constructed by defining a node for each unique user in the dataset. This includes any user who authored an original English tweet, or retweeted an English tweet, containing
the keyword “cop2x”, $x \in \{0, \ldots, 6\}$. A directed edge is formed from node A to node B if user A retweeted a post authored by user B. Edges are weighted according to the number of unique retweets between those two users.

### C. Latent ideology

The latent ideology estimation was developed in [23, 24] and adapted for exploiting retweet interactions in [18]. Following [18], we infer ideological positions of Twitter users using correspondence analysis (CA) and retweet interactions.

First, we build a matrix $A$ such that each element $a_{ij}$ is the number of times user $i$ retweeted influencer $j$. To select only users that are interested in the COP26 debate, we prune out users that retweeted less than two influencers.

We then execute the CA method according to the following steps. Given the adjacency matrix normalized by the total number of retweets as $P = A(\sum_{ij} a_{ij})^{-1}$, the vector of row and column sums respectively as $r = P1$ and $c = 1^T P$, and considering the matrices $D_r = \text{diag}(r)$ and $D_c = \text{diag}(c)$, we can compute the matrix of standardized residuals of the adjacency matrix as $S = D_r^{-1/2}(P - rc)D_c^{-1/2}$. The usage of the standardized residual matrix allows the methods to account for differences in users’ activity and influencers’ popularity. Next, single value decomposition is applied to the matrix $S$ as $S = UD\alpha V^T$ with $UU^T = VV^T = I$ and $D\alpha$ being the singular values diagonal matrix. The standard row coordinates $X = D_r^{-1/2}U$ can be considered as the estimates of the users. In our study, we only consider the first dimension that corresponds to the largest singular value. Users’ ideological position is computed by rescaling the row estimates into the set $[-1, 1]$, while the influencers’ ideological position is calculated by the median of the weighted position of their retweeters.

1. **Hartigan’s dip test**

The Hartigan’s dip test is a nonparametric test to reveal multimodal distribution in a sample [25]. It calculates the maximum difference over all sample points between the unimodal distribution function that minimizes that maximum difference and the empirical distribution function. The test produces a statistic $D$ which quantifies the magnitude of multimodality, and a statistical significance $p$. If $p < 0.01$, we say that the ideology distributions show statistically significant multimodality. Conversely, if $p \geq 0.01$, we cannot reject the unimodality of the distribution.

2. **Selecting influencers**

Applying the latent ideology to a set of influential accounts on Twitter does not guarantee that those accounts will arrange themselves in the latent space based on political or climate ideology. In a number of cases, the dominant factor which determines the principal ideological axis is geography. By focusing exclusively on English language twitter, the effect of these geographic factors is reduced. However, some additional filtering is required to avoid the latent ideology partitioning based on geography.

Factors which may conflate ideological scores include (1) language (e.g., English vs. non-English), (2) geography (e.g., accounts focused on Indian politics), and (3) prominent topics outside the core discussion (e.g., discussions in the blockchain community), see SI for details. These factors are mitigated by selecting English language tweets, and by performing some minor filtering of the influencer set. For each COP, $< 2\%$ of accounts are removed from our set of influencers in this process (see SI).

### D. Text analysis

After separating Twitter users into an ideological minority and majority, we selected all the English language hashtags related to the users in each ideological group, analysing the COP21 and COP26 tweets separately. We then pre-processed the data in which we normalised the text (removing capitalisation, Unicode characters, punctuation, and English stop words).

After cleaning, we used the Shiftiterator package [30] to analyse each set of aggregated hashtags, comparing the different ideologies for a given COP. This package allows us to quantify which words contribute to a pairwise difference between the two texts and how they contribute to understanding their differences. The comparison method is word shift analysis, based on the frequency counts of how often words appear in each of the two texts. For each word
In the text, the method evaluates the probabilities \( p_1(w) \) and \( p_2(w) \), that the word \( w \) appears in texts 1 and 2 respectively. It then calculates the proportion shift as their difference:

\[
\delta p_w = p_2(w) - p_1(w).
\] (1)

If the difference is positive \( (\delta p_w > 0) \), then the word is more common in the second text. If it is negative \( (\delta p_w < 0) \), then it is relatively more common in the first text. The method ranks words based on the absolute difference.

To ensure that hashtags are information, we filter out some frequent hashtags related to COP, such as the location (e.g., ‘paris’, ‘glasgow’, ‘france’, ‘scotland’) and the year (e.g., ‘cop21’, ‘cop26’, ‘2015’, ‘2021’, ‘paris2015’, ‘glasgow2021’).

E. News media URL classification

To highlight the different types of sources used by the minority and majority audience, we exploited data retrieved from NewsGuard [https://www.newsguardtech.com/]. NewsGuard is a tool that provides trust ratings for news and information websites. NewsGuard assesses the credibility and transparency of news and information websites based on nine journalistic criteria. We exploit these information to classify links shared by twitter users matching the domains with the ones provided by NewsGuard. For COP21, we classified the 16% of all links, while for COP26 we classified the 17%.
SUPPLEMENTARY INFORMATION: RESULTS

The supplementary results include an expanded discussion of engagement with COP, including more detail on summits other than COP21 and COP26.

We also provide a brief discussion of ideological polarisation on Youtube and Reddit to support the findings on Twitter. The bulk of the supplementary results expands on the latent ideology introduced in the main manuscript. We also provide extended text analysis for each COP, with a particular emphasis on COP21 and COP26. Finally, we provide a brief analysis of French language Twitter to show that changes in polarisation are not specific to English language Twitter.

In the supplementary methods, we outline the preliminary filtering required for the latent ideology and discuss the issue of deleted material and bots for the validity of our results.

A. Engagement with COP

Supplementary Figure 1 shows the total number of daily posts referring to COP since Twitter was founded in March 2006. The first three COPs during this period (COP12 – COP14) were not discussed on Twitter during this time. Between COP15 and COP19, some discussion around COP was active on Twitter, although the total number of posts are generally small compared to all COPs since COP20. Given the small datasets up to and including COP19, we exclude these conferences from our analysis in the main paper.

Supplementary Figure 1. The daily number of posts on Twitter making reference to COP since the founding of the platform in March 2006. Until COP15, there is not measurable activity on Twitter discussing the COP summits. From COP15 – COP19 there is some engagement, but overall content creation is far below the values observed during any subsequent conference. The limited size of the dataset prior to COP20 warrants this paper restricting our dataset to COP20 and onwards.

Supplementary Figure 2 shows the engagement with COP between COP20 and COP26 on (a) Twitter, (b) Youtube, and (c) Reddit. Each subfigure shows the distribution of retweet counts or comments on each post or video that makes reference to that specific COP. In all cases, the data shows that COP engagement on Twitter is significantly higher than on the other two platforms. This is most clearly seen during COP20 where Twitter saw a total of $3.1 \times 10^5$ posts making reference to “cop20”, while only $10^3$ Youtube comments were on COP related videos, and 30 Reddit comments. This lack of data on Youtube and Reddit prevents a robust analysis of ideological polarisation on these platforms. However, we offer some brief qualitative observations in the following section.
Supplementary Figure 2. Engagement with COP from COP20 in 2014 to COP26 in 2021 on (a) Twitter, (b) Youtube, and (c) Reddit. The total number of retweets/ comments is shown in the inset. Engagement on Twitter is consistently at least one order of magnitude larger than on Youtube or Reddit. The lack of data for Youtube and Reddit prior to COP26 prevents a robust analysis of the evolving nature of ideological polarisation on these platforms.
B. Ideological polarisation on Youtube and Reddit: A qualitative analysis

As previously seen in the engagement section, many users take part in the online debate around COP on Twitter, Reddit and Youtube. For Reddit and Youtube, we can qualitatively confirm the presence of fringes belonging to the ideological minority, their number in terms of users is too low to allow us to deepen their study by applying the latent ideology method. In fact, for Twitter we observe in Supplementary Figure that the latent ideology only gives consistent results if the number of influencers exceeds 200 accounts. On Youtube and Reddit, we are unable to extend the influencer set beyond ca. 60 and ca. 30 accounts respectively in a principled manner. A lack of data and other limiting factors therefore prevent a robust, quantitative analysis of ideological polarisation on Youtube and Reddit. It is important to highlight that while it is possible to collect all posts on Reddit about a certain topic, the YouTube API provides only a sample of videos. One confounding factor comes from the fact that the majority of Youtube channels in our dataset are not about climate, but their contents cover a wide range of topics (e.g. music, religion, news channels, tech). To get an idea of this effect, among the 100 channels with the most comments in our dataset, only 5 are climate specific. In our dataset, videos from those channels collect about 3% of the total comments. Therefore, ideology results for them are poorly related to climate debate. Another issue for YouTube comes from the fact that, after selecting only English-language channels, many have a strong geographical focus presenting news specific to a given region (e.g. Al Jazeera English, South China Morning Post, WION). In this case, the geography of the channel is an important limiting factor that confounds the latent ideology. Another problem concerns the different number of comments in climate actions channels vs. climate sceptics channels. On our Youtube dataset the channel with the most interactions is Blackpink, a korean k-pop group. They publish climate activism videos on their channel and the comments on their videos about COPs correspond to approximately 8% of all the comments in our dataset. Among the 100 channels with most comments, other channels which appear to be part of the ideological mainstream are UN Climate Change, Just Have a Think, Nick Breeze ClimateGenn and Facing Future. They collect about 2% of the total comments. Conversely, Friends of Science is the most prominent channel which appears to oppose climate action, but only receives around 0.1% of all comments. This difference between engagement with channels with contrasting ideological views limits the efficacy of the latent ideology. Finally, it is important to note that several important channels have comments turned off (e.g. the official COP26 Youtube channel).

On Reddit, although we found subreddits dedicated to the climate discussion from both mainstream and minority points of view, only a small number of users refer to COP explicitly. Indeed, the share of submissions related to COP for the most debated conference (COP26), is below 4% for Subreddits focused on climate topics endorsing the mainstream perspective such as “climate” (3.8%), “climatechange” (2.9%), and “environment” (1.8%), as well as for Subreddits adhering to alternative views, such as “cimatedisalarm” (2%) and “climateskeptic” (1.8%). Moreover, Reddit data show a high separation in terms of geography with the presence of country-oriented subreddits. For example, in COP21 the third most used subreddit is “france”, while in COP26 we find subreddits as “Scotland”, “NewsOfTheUK”, “unitedkingdom” and other lesser referenced geographical Subreddits.
C. News Source Orientation

Here, we report the distribution of the political orientation of the news media sources referenced by majority and minority ideological groups on Twitter. We rely on NewsGuard data to classify urls by domains and assign them a political orientation. Results are shown in Supplementary Figure 3. This shows that the ideological majority are dominated by left-leaning news sources, whereas the ideological minority are dominated by right-leaning sources. Note, that the figure shows the fraction of news sources from each leaning category. The absolute number of links in the minority group is much larger in COP26 than for COP21.
D. Ideological polarisation on Twitter

Supplementary Figure 4 shows how the polarisation statistic, $D$, changes with the number of influencers used to calculate the latent ideology in COP21 and COP26. We evaluate the $D$ statistic for the users and the influencers starting with 20 influencers and increasing the number of influencers by one each time step, until 500, ordered according to the number of retweets of each influencer (the influencer with the largest number of retweets first). The bold lines represent the mean of $D$ values for each number of influencers. The shadow area around them lies between the 2.5 and the 97.5 percentile of the $D$ values.

The figure shows that the latent ideology produces consistent polarisation measures if the number of influencers is larger than around 200 influencers. Larger influencer sets produce more consistent, but for COP20, it is difficult to extend the influencer set beyond 300 accounts. Hence, we use 300 influencers for each COP.

Supplementary Figure 4. The polarisation statistic, $D$, as a function of the number of influencers used to calculate the latent ideology for COP21 and COP26. For each COP we plot the influencer and user distribution $D$ statistics. The shaded area around each line indicates the 95% confidence interval as calculated using 1000 bootstrap samples. Values are approximately constant if the number of influencers used exceeds 200 accounts.

Now we show the latent ideology calculated for the intermediate COPs (COP20, COP22–COP25). These are shown in Supplementary Figures 5–9. Each figure appears qualitatively similar to the results for COP21. The exact value of the $D$ statistics for each value is shown in Figure 4 of the main paper.
Supplementary Figure 5. The latent ideology for COP20. Top: user and influencer ideology distributions using the top 300 influencers. Below: the top 30 (of 300 total) influencers with distributions showing their retweeters on the ideology scale. Enlarged figure with full 300 influencers is available for download [here](#).
Supplementary Figure 6. The latent ideology for COP22. Top: user and influencer ideology distributions using the top 300 influencers. Below: the top 30 (of 300 total) influencers with distributions showing their retweeters on the ideology scale. Enlarged figure with full 300 influencers is available for download here.
Supplementary Figure 7. The latent ideology for COP23. Top: user and influencer ideology distributions using the top 300 influencers. Below: the top 30 (of 300 total) influencers with distributions showing their retweeters on the ideology scale. Enlarged figure with full 300 influencers is available for download here.
Supplementary Figure 8. The latent ideology for COP24. Top: user and influencer ideology distributions using the top 300 influencers. Below: the top 30 (of 300 total) influencers with distributions showing their retweeters on the ideology scale. Enlarged figure with full 300 influencers is available for download [here](#).
Supplementary Figure 9. The latent ideology for COP25. Top: user and influencer ideology distributions using the top 300 influencers. Below: the top 30 (of 300 total) influencers with distributions showing their retweeters on the ideology scale. Enlarged figure with full 300 influencers is available for download [here](#).
There are two plausible explanations for the increase in ideological polarisation seen during COP26:

1. Users who were previously part of the ideological majority have now become a part of the ideological minority.
2. The ideological views of users already engaged with COP haven’t changed. However, engagement from new users, who were previously not part of the COP discussion, has strengthened the ideological minority.

Assessing which of these explanations is most likely is difficult with the imbalanced influencer sets between COP21 and COP26. Therefore, we recompute the ideology using a balanced set of influencers. This requires (1) that an influencer takes part in both the COP21 and COP26 discussion, and (2) that the influencers selected are split equally between the ideological majority and minority groups. Given that the ideological minority is much larger for COP26 than COP21, we choose influencers based on their COP26 ideological score. Note, this does not mean that these influencers will, by necessity, fall into the same ideological group for COP21.

Supplementary Figure 10 recomputes the latent ideology with this balanced set of influencers, merging the top 15 minority and majority influencers who appear in both the COP21 and COP26 discussion.

Hartigan’s diptest shows that influencer polarisation is similar between COP21 and COP26 using the balanced influencer set (COP21: \( D = 0.20 \), 95% CI: [0.14, 0.23], \( p < 2.2 \times 10^{-16} \); COP26: \( D = 0.21 \), 95% CI: [0.14, 0.23], \( p < 2.2 \times 10^{-16} \)). This indicates that the minority influencers from COP26, who also engaged with COP21, were already part of the ideological minority (and likewise for majority influencers). However, user polarisation increases significantly between COP21 and COP26 (COP21: \( D = 0.014 \), 95% CI: [0.013, 0.015], \( p < 2.2 \times 10^{-16} \); COP26: \( D = 0.046 \) (95% CI: [0.44, 0.48], \( p < 2.2 \times 10^{-16} \)).

It is interesting to note that if we focus on minority influencers that appear in both the COP21 and COP26 discussions, 7 of 15 have a specific climate focus. This exceeds the number of climate focused influencers in the
minority if we simply use the 300 most retweeted accounts.
E. Ideological polarisation on French language Twitter

Retweet networks are constructed for COP21 and COP26 where tweets are filtered for French language only.

For the influencer set, the polarisation statistic, $D$, increases from COP21 to COP26 (COP21: $D = 0.023$, 95% CI: [0.016, 0.034], $p = 0.33$; COP26: $D = 0.042$, 95% CI: [0.028, 0.058], $p = 0.0005$). Likewise, polarisation increases for the user set (COP21: $D = 0.0090$, 95% CI: [0.0076, 0.0102], $p = 2.2 \times 10^{-16}$; COP26: $D = 0.012$, 95% CI: [0.010, 0.013], $p = 2.2 \times 10^{-16}$). This shows a clear increase in ideological polarisation on French language Twitter, despite the effect of local enhancement during COP21. The increase in polarisation is smaller than for English language Twitter, although there is evidence that, as in English, the change in polarisation is reflected in an increase in far right engagement with COP.

For the COP21 influencer set, although none of the influencers self-identifies as being climate focused, a majority of them self-identify as being right-wing partisans in France. @ntwolfmother and @Sisf94 mention being supporters of the former French president Nicolas Sarkozy and @f_philippot is the president of the political movement Les Patriotes, which notably aims at cancelling the climate emergency France declared in 2019. Moreover, a large number of these influencers have been actively voicing their opposition to the sanitary pass, which has been implemented in France from the 9th June 2021, by using popular hashtags from the French opposition such as #AntiPass. One of these accounts, namely @EugenieBastie, works as a journalist for Le Figaro, which is one of the most consulted newspapers in France. She has also used her Twitter account to voice her skepticism regarding the vaccination campaign and her opposition to left-wing social movements.

Regarding the COP26, more influencers fall within the ideological minority. One of them, @philippeherlin, published a book titled “Cancel economy : Pourquoi la transition énergétique est une catastrophe économique”. This influencer set also contains some of the most influential French political actors in the far-right, such as Marine Le Pen (MLP_officiel) and Eric Zemmour (@ZemmourEric). During the last opinion polls for the 2022 French presidential election, 16% and 15% of the voters expressed their support respectively for Marine Le Pen and Eric Zemmour, which means that they are more likely to end up in the second round of elections than their left-wing counterparts. Two of these influencers are also the official pages of media companies, namely Russia Today (@RTenfrancais) and Sud Radio (@SudRadio). The latter one has been hosting lately several French personalities who expressed their hesitancy regarding the vaccination campaign. Some of the other influencers, such as @AnonymeCitoyen and @Carene1984, are also voicing their disagreement against the sanitary pass and sharing conspiracy theories about the Covid vaccines. Overall, we notice that the contemporary debates about the sanitary crisis has become viral in the ideological minority, leading a set of notable political actors, media sources and lambda citizens to rally around a homogeneous social cause, which is the fight against the sanitary pass.
F. Extended discussion of tweet content

1. English hashtags: comparison between COP21 and COP26

In Supplementary Figure 11, we show the results of the Shiftiterator applied to aggregated Twitter hashtags from COP21 and COP26 editions. In both Figures, we report the hashtags used by Twitter accounts that are part or not of the ideological majority on climate, in COP21 (left side) and in COP26 (right side).

(a) COP21 vs COP26 - ideological majority

(b) COP21 vs COP26 - ideological minority

Supplementary Figure 11. Pairwise comparisons between hashtags from different COP editions. The results show the comparison between Twitter hashtags used in the online discussion in COP21 (left side) and in COP26 (right side). Figure (a) presents the comparison of hashtags tweeted by users afferent to the ideological majority and Figure (b) presents the comparison of hashtags tweeted by users external to this ideology.

In Supplementary Figure 11 (a), the hashtags used by accounts afferent to the ideological majority are in general related to climate discussion themes. While during COP21 (left side) the hashtags refer to neutral themes, during COP26 (right side) are more frequent hashtags linked to local politics, climate activism (such as ”blackpink”) and climate action and awareness (”climateaction”, ”fridaysforfuture”). A different situation can be found in Supplementary Figure 11 (b). COP21 hashtags are once again related to climate issues and a lesser extent, to local politics, while those of COP26 report massively to the topics associated with COVID19, vaccines, local politics and only to a more secondary extent, to climate change.

In Supplementary Figures 12,13 we present the evolution over time of the most used hashtags in COP21 and COP26, respectively used by Twitter user afferent to the ideological majority. In Supplementary Figure 12 hashtags related to activism, the perception of the threat of climate change, and the promotion of its mitigation (such as ”climateaction” or ”climatecrisis”) become predominant in the online discussion, displacing more neutral hashtags from the top positions (such as ”climate”, ”parisagreement”). Supplementary Figure 13 shows hashtags related to the climate debate giving way to new hashtags such as those related to covid or netzero, testifying that the discussion outside the ideological majority has been divided into various fields, even those unrelated to climate change.
Supplementary Figure 12. Evolution in time (from COP21 to COP26) of the use of hashtags relative to the ideological majority debate.

Supplementary Figure 13. Evolution in time (from COP21 to COP26) of the use of hashtags relative to the debate falling outside the ideological majority.
Supplementary Figure 14. Pairwise comparisons between French hashtags within the same COP edition. For Figures (a) and (b), the results show the comparison between French Twitter hashtags used by the ideological majority (right side) and by the minority (left side).

2. French hashtags

In this Section, we want to show the results of studying French Twitter hashtags. The second edition with the most engagement among those analysed here is that of COP21. For a fair comparison of the editions of COP26 and COP21, it is necessary to explore what happens on the French online Twitter as well as on the English one (we showed the results for that in the main article). The findings confirm what we have already observed in the case of the English Twitter hashtags. Within COP21, the debate is around climate and climate changes topics, while for COP21 the online discussion shifts to non-climate related themes, in particular in the discussion falling outside the ideological majority.

In Supplementary Figure 14 we show the results of the Shiftiterator applied to aggregated French Twitter hashtags from COP21 and COP26 editions. In Supplementary Figure 15 (a), the hashtags used by accounts afferent to the ideological majority are in general related to climate discussion themes. While during COP21 (left side) the hashtags refer to neutral themes, during COP26 (right side) are more frequent hashtags linked to local politics, climate action and awareness (“climatecrisis”, “justiceclimate”). A different situation can be found in Supplementary Figure 15 (b). COP21 hashtags are once again related to climate issues and a lesser extent, to local politics, while those of COP26 report massively to the topics associated with COVID19, vaccines, local politics and only to a more secondary extent, to climate change.

Supplementary Figure 18 further dissects the ideological minority by separating tweets which make explicit reference to “Covid-19” from those which do not, both in English and in French hashtags. As we can observe, the separation between climate themes and non-climate themes is neat.
Supplementary Figure 15. Pairwise comparisons between French hashtags from different COP editions. For Figures (a) and (b), the results show the comparison between French Twitter hashtags used in the online discussion in COP21 (left side) and in COP26 (right side). Figure (a) presents the comparison of hashtags tweeted by users afferent to the ideological majority and Figure (b) presents the comparison of hashtags tweeted by users external to this ideology.

Supplementary Figure 16. COP21 vs COP26 (French hashtags): ideological majority - alluvial diagram
Supplementary Figure 17. COP21 vs COP26 (French hashtags): ideological minority - alluvial diagram

Supplementary Figure 18. Comparison of hashtags about COP26 (ideological minority debate) containing references to COVID19 (left side) and not containing references to it (right side), both in English (Figure (a)) and in French (Figure (b)).
V. SUPPLEMENTARY INFORMATION: METHODS

The latent ideology can be conflated by geographical factors, as well as niche topics outside the main COP discussion. Therefore, in order to ensure that the latent ideology splits influencers based on climate ideology, rather than, for example, geography, we must remove some accounts from the top 300 most retweeted accounts used as our set of influencers. In some cases, it is also necessary to filter out accounts whose set of unique retweeters have no overlaps with any of the unique retweeters for the remaining influencer set. This is typically only an issue for small datasets.

The accounts filtered out of the influencer set for each COP are listed below:

- COP20: @GreenLifeStory due to disjoint set of retweeters. (Total removed: 1/300 influencers)
- COP21: @narendramodi due to prominent cluster of accounts associated with Indian politics which have minimal overlap with the wider English language discussion. (Total removed: 1/300 influencers)
- COP22: @BoardshortsBen, @Anggun_Cipta, @lekimastores and @jpussmann. All of these accounts are non-US/UK/Australia/Canada, which between them dominate the COP discussion. This conflation occurs in part due to very few accounts in the minority climate ideology. (Total removed: 4/300 influencers)
- COP23: @earthtokens, an account which primarily interacts with the blockchain community. (Total removed: 1/300 influencers)
- COP24: No filtering required. (Total removed: 0/300 influencers)
- COP25: No filtering required. (Total removed: 0/300 influencers)
- COP26: @narendramodi and @naftalibennett due to association with Indian and Israeli politics respectively. @cop26token and @Earthtoken_io who primarily interact with the blockchain community. Note, a significant Korean cluster is observed in the latent ideology, but this does not obscure the divide between the minority and majority ideological positions on climate. Hence, following a principle of minimal interference with the data, we do not remove any of the accounts in this Korean cluster. (Total removed: 4/300 influencers)

A. Deleted material

The Twitter API does not allow access to tweets which have been deleted, or to accounts which have been suspended or removed. If a user retweets a tweet which is later deleted, individually, or because the account of the original author is suspended, then the retweet will also be removed. As a result, our datasets, particularly for earlier COPs, are likely to be missing some tweets. However, it is not possible to measure exactly how many tweets/ users have been deleted, and how this missing data will affect our results.

To roughly approximate how missing data may affect our results, we note that if a tweet mentions a user, i.e., by using the tag @realDonaldTrump, that user tag remains even after the tagged users account is removed or suspended. Conveniently, these tags appear in the tweet metadata that is downloadable via the Twitter API, including those corresponding to suspended or removed accounts. Consequently, we can gauge the propensity of missing information by checking whether the accounts mentioned in our datasets were active on Twitter at the time our data was downloaded. The fraction of mentions corresponding to accounts which are suspended or removed are given below:

- COP21. 2.57%
- COP22. 1.90%.
- COP23. 1.56%.
- COP24. 1.06%.
- COP25. 0.45%.
- COP26. 0.15%.

Note that for the COP21 dataset, approximately 2.5% of mentions refer to deleted accounts for both the majority and minority groups. Given that this is not larger for the minority group, it is reasonable to suggest that deleted material can only have a minor influence on the changes in polarisation we observe.
B. Enhancement of ideological groups from bots

Supplementary Figure 19 shows the number of tweets from the ideological minority and majority which come from official Twitter sources, e.g., “Twitter for Android”. Tweets from these official sources cannot be used to run bots which artificially enhance content engagement. The figure shows a steady increase in the overall fraction of tweets from official sources between COP20 and COP26, with minimal differences between the majority and minority groups, with the exception of COP20 where the minority group only sends around 55% of tweets from official sources. In COP26, more tweets in the ideological minority are from official sources than for the majority. Hence, it is unlikely that engagement with the minority is principally driven by bots, with official sources accounting for well over 90% of all tweets.

Supplementary Figure 19. Percentage of tweets from the ideological majority (yellow bars) and the ideological minority (blue bars) coming from Twitter clients. The percentage is calculated over the total count of tweets from both official and non official sources.