Is it all talk: do politicians that promote environmental messages on social media actually vote-in environmental policy?

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ORIGINAL ARTICLE

Is it all talk: Do politicians that promote environmental messages on social media actually vote-in environmental policy?

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Abstract Government policies are key to combating climate change and biodiversity loss. Here, we examine whether environmental messages on Twitter by UK politicians can be used to predict the probability of politicians voting-in pro-environmental policy. Using historical Twitter data and voting records, we determine that the number of tweets by UK politicians regarding environmental subjects has increased over the last decade, although this is not consistent across all parties. The probability of voting environmentally has not increased, instead, voting trends are highly heterogeneous over time, varying by political party. This suggests that there is little association between politicians that promote environmental messages on social media and the odds of them voting-in environmental policy. However, in some cases, politicians do deviate from political party lines, and so we assessed whether politicians that posted more environmental messages were more likely to break party lines and vote-in environmental measures. We found evidence that, after accounting for party, politicians who tweet more frequently about environmental subjects are more likely to vote against party lines in favour of environmental measures. This work suggests that politicians' that post more environmental messages are more likely to support pro-environmental policy, but this signal is low relative to the predominant driver—political party association.

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Article highlights

- Environmental tweeting by UK MPs has increased over the past decade but environmental voting has not.
- Party lines account for much of the variation in environmental vote patterns.
- Political association is a stronger predictor of vote intentions than whether an MP tweets about environmental issues.

Keywords Twitter · Politicians · Environment · Messaging · Communication · Vote

1 Introduction

In 2019, the UK Parliament passed a motion to declare an environment and climate change emergency (UK-Parliament 2019). The motion was proposed by the then opposition leader Jeremy Corbyn stating: "*This is no longer about a distant future, we're talking about nothing less than the irreversible destruction of the environment within our lifetimes*". Despite a recent increase in climate action (Davidson et al. 2020), there have been criticisms that these actions are outweighed by discussion and not enough is actually being done to protect the environment (zu Ermgassen et al. 2021). These suggestions are supported by the fact that both climate and the environment have been talking points across the political spectrum for decades with limited action taking place: "The danger of global warming is as yet unseen, but real enough for us to make changes and sacrifices, so that we do not live at the expense of future generations" Margaret Thatcher, 1990; "Our effect on the environment, and in particular on climate

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change, is large and growing", Tony Blair, 2004; "Whether you like it or not it is a matter of when, not if, your country and your people will have to deal with the security impact of climate change," Boris Johnson, 2020.

There is increasing global pressure on governments to address the effects of anthropogenic changes to biodiversity and climate (Sala et al. 2000; McGill et al. 2015; Newbold et al. 2015). This change in attitude has largely come about due to high profile international conventions and reports (e.g. IPCC 2018; IPBES 2019; Convention on Biological Diversity 2020), as well as a rising public awareness through increasing mainstream media coverage (Schmeller et al. 2009; Legagneux et al. 2018). This in turn led to the Paris Climate Change Agreement (UNFCCC 2015), a legally binding international agreement to limit global warming to below 2 °C compared to pre-industrial levels. There is, therefore, a political will to address the current biodiversity and climate crisis, supported by both the scientific community (Ripple et al. 2020) and members of the public (IPSOS 2020).

Government policies are a key measure in combating climate change and biodiversity loss, yet political action requires support from the electorate (McCrea et al. 2016). As a result, there is an incentive for politicians to demonstrate that their views on particular subjects (e.g. biodiversity loss) are in alignment with targeted sections of the electorate. Enter Twitter. Since its creation in 2006, Twitter has rapidly become a core part of political messaging and strategy across the world (Golbeck et al. 2010; Grant et al. 2010; Graham et al. 2013; Frame and Brachotte 2015), allowing politicians to self-promote and curate a favourable public persona (Kruikemeier 2014). Whilst the ability to predict electoral outcomes using Twitter data is debated (Gayo-Avello 2012), some studies have shown that social media activity can be closely related to electoral outcomes (Tumasjan et al. 2010; DiGrazia et al. 2013; Kruikemeier 2014; Buccoliero et al. 2020). This is despite the fact that social media users are not an unbiased sample of the population (DiGrazia et al. 2013). Politicians are therefore motivated to manage accounts in a way that demonstrates their character and personality — traits that interest potential voters (Buccoliero et al. 2020). For example, in the 2008 US presidential election Barack Obama became the first President to use Twitter as an official form of communication to reach voters, with the majority of tweets composed by a professional team (Aharony 2012). Obama subsequently became the most followed person on Twitter, with 133 million followers at the time of writing. By the 2016 US election Twitter was a core part of both Hillary Clinton's and Donald Trump's election campaigns, despite contrasting styles (Enli 2017; Ross and Caldwell 2020).

The use of Twitter in politics is open to abuse. It is theoretically possible for politicians to curate a persona that does not accurately reflect their views or voting intentions. A simplified example of this would be a member of the public voting for a politician because of a perceived view as a result of a curated online persona, and the politician then voting in the opposite direction once elected. As such there is a question of trust that needs addressing. Whilst both trust in the media and in politics are well studied topics (see Enli and Rosenberg 2018, and references within for a summary), the advent of social media has blurred the lines between news content and delivery, with politicians creating and distributing their own messaging. This increased use of social media for political messaging has occurred during a period of declining trust in politics in contemporary democracies (Stein et al. 2021). Despite a general decline in trust, politicians are seen as more honest on social media than in traditional news interviews or appearances (Enli and Rosenberg 2018). Therefore, it is important to determine whether this trust is well-placed and if statements made on Twitter are backed up by actions in parliament. This is particularly important on environmental issues with some critics already highlighting the gap between words and actions (zu Ermgassen et al. 2021).

Social media data is increasingly being used in research to answer societal questions. Twitter, in particular, has become a valuable tool for researchers providing insight into topics ranging from islamophobia and football (Alrababa'H et al. 2021), to species conservation (Roberge 2014). As well as being an analytical tool, Twitter itself has a role in shaping our society as demonstrated by its use in protests and activism (Bosch 2017; Ince et al. 2017). Using Twitter to gain political insight is nothing new (Tumasjan et al. 2010; Gayo-Avello 2012; DiGrazia et al. 2013; Kruikemeier 2014; Buccoliero et al. 2020); however in this study we take a more focused approach, using MPs' Twitter accounts to study a specific theme: environmentalism. This method could easily be applied to any number of topics e.g. healthcare, with the same aim in mind—is what politicians write on Twitter reflected in their votes in parliament?

Here, we explore in three stages whether UK politicians that are more vocal about environmental matters on Twitter are more likely to vote pro-environmentally (vote in favour of measures that would benefit the environment). By environmental we use the Collins Dictionary definition i.e. concerned with the protection of the natural world of land, sea, air, plants, and animals (Collins Dictionaries 2018). We have used this term as it allows us to adopt a broad range of subjects including biodiversity loss and climate change as well as mitigation measures that could reduce greenhouse gas emissions.

(1) *Twitter Model*—To what extent has the rate of tweets by Members of Parliament (MPs) mentioning environmental terms changed over the past decade?

We expect to see an increase in tweets with environmental terms due to the aforementioned increasing political pressure to combat climate change and biodiversity loss (Sala et al. 2000; McGill et al. 2015; Newbold et al. 2015).

(2) *Vote Model*—To what extent has the number of MPs voting for environmental measures (measures aimed at benefiting the environment) changed over the same time?

We expect a similar result here as we find in question one, as the pressures are the same.

(3) *Deviance Model*—Are MPs that are more outspoken on Twitter regarding environmental issues more likely to vote for the environmental policies?

If we assume that politicians' views on Twitter are an accurate representation of their political views and voting intentions, we would expect to see MPs more outspoken on Twitter to have voted in favour of more environmental legislation. However, the analysis of this final point is complicated by two important factors. First, as MPs are representatives of their constituents, their vote record could be more influenced by the views of their constituents, rather than their own personal views (which they may express on Twitter). As such we take constituency demographics into account in this analysis, as environmental concern has been shown to change depending on factors including rural-urban gradients (Berenguer et al. 2006). Second, under the UK political system MPs are often "whipped" into voting along party lines, with clear career benefits to "toeing the party line" (conforming with the party) and negatives to "breaking the whip" (dissenting from the party) (Willumsen and Öhberg 2017). In some cases, however, MPs may dissent as a result of ideological differences (Willumsen and Öhberg 2017). Since the Climate Change Act in 2008, environmental and climate issues have become an increasing part of political agendas, with cross party support for a number of measures (Carter 2014). However, this is not always the case (Carter and Clements 2015), meaning that party affiliations are likely to be a key factor in vote patterns. As a result, we control for the whip by determining how likely it is for each MP to deviate from their party line and vote for pro-environmental measures when the party is predicted to vote against (or *vice-versa*) i.e. whether MPs are "rebelling" against the majority of their party to vote in favour of environmental measures. We expect to see that the majority of variation around vote patterns is explained by political party, but also that those who tweet more prolifically about the environment are more likely to vote in favour of environmental measures. If, however, we find no relationship between environmental messaging (tweets regarding environmental matters) and voting intentions, it raises questions about the relationship between the social media persona of politicians and the reality of voting patterns at a key moment in terms of climate change, biodiversity loss and trust in politics.

2 Methods

2.1 Data

2.1.1 Twitter data

To first determine changes in environmental tweeting over time (Question 1), we collated posts on Twitter (where accounts were available—588 out of 650) from all current MPs (since the 2019 general election). Due to a high turnover of MPs at recent general elections, the ten longest serving MPs (for each political party) that either lost their seat or stood down at or after the 2015 general election were also included to maximise the number of MPs that took part in multiple environmental votes. Where parties had more than ten former MPs, an arbitrary random sample was taken to make up the ten former MPs per party. In these instances, an additional number of high-profile former MPs (party leaders, cabinet, or shadow cabinet ministers) were also included to account for MPs that may have had relatively short parliamentary careers but had large social media followings and therefore online influence. Independent MPs were treated on a case-by-case basis and assigned to a political party if they were former members of the party for the majority of the period between October 2008 and present, or until their exit from parliament. This information was taken from the UK Parliament website (https://members.parliament.uk/members/Commons). Independent MPs were assigned as independent if they sat as Independents for the majority of the above period. MPs that changed parties were removed from the analysis, as were any belonging to parties with fewer than five MPs over the analysis period. Sinn Féin MPs were also removed due to their policy of abstentionism, preventing comparison of tweets and votes. A total of 653 MPs were included in the Twitter analysis, 579 of which are currently sitting as MPs.

The last (up to) 3200 tweets over the last 10 years (2010–2020) were downloaded for each MP using the *rtweet* R package (Kearney 2019). These tweets were all in the public domain. For some MPs, the 3200 tweets covered their entire tweet history. For other, more prolific tweeters, the 3200 tweets only covered a proportion of their tweet history; therefore not all historic tweets are included in the analysis (Supplementary Fig. S1). Not all tweets occurred whilst an individual was an MP, with some tweets occurring prior to election or after leaving parliament.

Using this dataset, all tweets were classified as containing environmental terms or not. An initial list of classifying terms was used to automatically classify tweets based upon the presence/absence of terms. The initial terms used were: climate, nature, wildlife, conservation, carbon, emissions, global warming, renewable, flood, drought, ocean acidification, coral bleaching, wildfire, pollution, poaching, fossil fuel, insect decline, extinction, deforestation, microplastic, greenhouse, environment, and terms that stemmed from the following: recycl*, pollinat*, sustain*, and biodivers*. However, as there was no guarantee these terms were actually discussing the environment, we manually classified (by humans) a random 1000 subset of the environmentally classified (from the automation) tweets, categorising them as environmental or not. To determine the reliability of manual classification, a subset of 100 randomly selected tweets from the 1000 were then reclassified by four people, two of which were independent of the research and Krippendorff's alpha was calculated ($\alpha = 0.70$), providing a high level of confidence in the manual classification. After testing the manual classification reliability, we calculated the proportion of tweets from the 1000 tweet subset, that were manually classified as environmental and compared this to the automatic assignments (Supplementary Table S1).

All terms where the manual classification revealed that fewer than 90% of tweets were related to the environment (i.e. the automation performed poorly), as well as terms that did not occur in the 1000 subset, were excluded. The original tweet dataset was then refined using this reduced series of terms (biodivers*, carbon, climate, deforestation, emissions, extinction, flood, fossil fuel, global warming, greenhouse, poaching, pollinat*, pollution, renewable, wildlife). Whilst this list covers a broad range of environmental subjects and provides a fast way of assessing tweets, it should be noted that this is not an exhaustive list of environment-based terms and that some tweets regarding the environment will have been missed. Additionally, not all tweets containing these search terms may be about environmental matters, but a very high proportion will be.

We are also making the assumption that the majority of tweets with environmental content will regard the environment positively or with concern. Whilst anti-environmental tweets are likely to exist they are almost certainly outweighed by environmental ones. We can anecdotally confirm this from our review of terms using the subset of 1000 tweets. All tweets in the 1000 subset were coded as being environmental (1: tweets refer to the environment, or environmental issues including but not limited to climate, biodiversity, and environmental solutions), anti-environmental (-1: tweets refer to need for environmental destruction, denial of environmental issues, prioritisation of other factors over environmentalism), or irrelevant (0: automatic assignment of term in the wrong context e.g. toxic work environment, tweets that are ambiguous or there is insufficient information to determine a position). A total of 805 tweets were classified as environmental and 195 as irrelevant, whilst no tweets were classified as anti-environmental. As has been shown in other work, environmental tweets fall into two broad groups: Anti-environmental tweets—tweets that show a distaste or dislike for the environment (e.g. 'Foxes affecting my ability to rear sheep'), or advocate against environmental measures, perhaps prioritising other factors like the economy, or denying environmental issues exist (e.g. climate change denial); and environmental tweets—which includes all tweets expressing an interest or positive engagement with the environment, as well as tweets describing when action is required to protect the environment. In both cases, the content of the tweet should determine its classification, not its sentiment, as sentiment is a poor predictor of the environment classification. For instance, the tweet 'I am distraught at all this environmental destruction—something must be done' would receive a negative sentiment but should be labelled as pro-environment (Johnson et al. 2021).

In the full tweet dataset a total of 12,714 tweets contained at least one environmental term out of a total of 910,214. These tweets were classified as environmental messaging and assigned a score of 1. Tweets without environmental terms i.e. not environmental messaging, were assigned a score of 0. An exploratory analysis of the Twitter data is available in Supplementary Materials (Supplementary Figs. S2 and S3). We provide here an example of three randomly selected tweets that were classified as environmental. Tweets have been paraphrased for anonymity.

1. Area is disadvantaged by delaying flood defence plans.
2. Free bus travel has multiple benefits including reduced congestion and carbon emissions, as well as cleaner air and sustainable transport networks.
3. Declaration of climate emergency. No longer able to have business as usual. Party aims for Green Industrial Revolution to increase employment, reduce emissions, reduce bills, and improve homes.

2.1.2 Parliamentary data

To determine changes in environmental voting over time (Question 2), we compiled 16 environment-related votes dating from 2008 to 2018. Votes were selected from a Guardian newspaper investigation of MP climate vote records (Duncan et al. 2019). The 16 votes selected (Table 1) were chosen by the Guardian in consultation with a number of environmental groups and researchers. Their

Table 1 Sixteen environmental divisions (votes) used in the analysis

Division	Date	Aye votes	No votes	Rebels
Climate change bill—third reading (and other amendments)	28-10-2008	463	5	5
Airport expansion (parliamentary approval)	24-02-2009	246	203	26
Government to sign up to 10:10 climate change campaign—rejected	21-10-2009	226	297	13
Energy bill—clause 42—energy efficiency requirement for landlords of private rental properties	14-09-2011	277	127	14
Energy bill—clause 11—subsidy of nuclear power generation	03-06-2013	20	503	16
Energy bill—clause 1—requirement to set a decarbonisation target range	04-06-2013	267	290	25
Energy bill—third reading	04-06-2013	396	8	10
Energy bill—clause 10—financial incentives for larger small scale low carbon generation plants	04-06-2013	245	312	1
Infrastructure bill—new clause 9—moratorium on onshore unconventional petroleum—review impacts of exploitation	26-01-2015	52	308	20
Infrastructure bill—new clause 1—environmental permits for hydraulic fracturing activities	26-01-2015	223	319	1
Finance bill—application of climate change levy tax to electricity generated from renewable sources	08-09-2015	310	245	3
Finance bill—clause 42—vehicle tax—relation to carbon dioxide emissions—surcharge for vehicles costing over £40,000	26-10-2015	255	302	0
Energy bill—new clause 3—carbon capture and storage strategy for the energy industry	14-03-2016	229	268	0
Energy bill—new clause 8—setting a decarbonisation target range	14-03-2016	227	272	0
Energy bill—clause 79—onshore wind power—delay exclusion of onshore wind contribution to renewable electricity generation requirements	14-03-2016	183	270	0
National policy statement: airports—Heathrow north-west runway	25-06-2018	415	119	104

Date in day-month-year. Votes in favour (Aye) and against (No) are show for each division, as are the number of rebels (MPs voting against the majority of their party)

selection of votes aimed to cover a range of policies affecting UK carbon emissions (Duncan and Watts 2019). Political partisanship is well established in the UK press (Brandenburg 2005, 2006); therefore using any single newspaper as a basis of vote selection is open to potential political bias, The Guardian, for example, self identifies as "left leaning" and "a liberal voice". Whilst using votes selected by a national newspaper raises the possibility of vote selection being biased towards one side of the political spectrum, the methodology used by Duncan and Watts (2019) included environmental groups and academics to determine the votes used, with some disagreement between contributors. We acknowledge here that the classification of what constitutes an environmental vote is highly subjective. As such we believe that using the pre-determined set of votes selected above is a more reproducible method than if we were to select votes ourselves with our own views and biases. It should also be noted that this study makes no attempt to discuss the political, practical, social or financial aspects of each vote and purely looks at the proposed environmental aspects in relation to how MPs tweet about the environment.

MP vote records were taken from the division repository on www.publicwhip.org.uk an independent, not-for-profit, open-source database of divisions in the Houses of Parliament and Lords dating back to 1997. For each division (item to be voted on), MPs that voted pro-environmentally (voted in favour of legislation that would benefit the environment) were given a score of 1 and MPs that voted negatively (voted against legislation that would benefit the environment) were scored 0. Abstentions, absences and votes for both Aye (meaning yes) and No in a single division were not included in the analysis. MPs that voted in fewer than five votes were removed from the analysis as were any MPs belonging to parties with fewer than five MPs during the analysis period. A total of 374 MPs and 3790 votes were included in the analysis. An exploratory analysis of these data, in combination with the Twitter data, is available in Supplementary Materials (Supplementary Fig. S4).

2.2 Models

2.2.1 *Change in environmental messaging on twitter and environmental voting*

All analyses were performed in R (R Core Team 2020). To assess how environmental messaging (which we define here as tweets containing at least one environmental term) and voting patterns have changed over time (Questions 1 and 2), we developed two logistic regression models. Both models contained a binary value indicating whether (1) Twitter Model: tweets contained environmental terms, or (2) Vote Model: whether MPs voted for environmental measures. For both models, date (at the scale of years), was used as a predictor and treated as a continuous variable. For the Twitter Model, MPs were included as a random intercept nested within political party. This was done to account for the expected increase in environmental tweets over time by all MPs, but takes the different baseline number of environmental tweets for individual MPs into consideration i.e. all MPs are expected to increase the frequency of environmental tweets over time, but some MPs will tweet more or less than others. For the vote model, a visual inspection of the vote data showed inconsistent vote trends over time, with some MPs increasing environmental voting over time, and others decreasing. These trends tended to be grouped by party. To account for this, a random intercept and correlated random slope were included in the model to allow votes to vary over time for MPs nested within political parties.

As an accompaniment to the Twitter Model, we also characterised overall word use within tweets by identifying the most used words. We then repeated this, using only tweets that contained at least one environmental term. All punctuation and numbers were removed, as well as all stop words (e.g. common words like 'the' and 'a') specified by the 'tm' R package (Feinerer et al. 2008; Feinerer and Hornik 2020).

2.2.2 *Link between environmental vote records and environmental messaging*

To determine if there was a relationship between environmental voting and messaging (Question 3), we first had to control for the effect of the whip. As a result, we used the Vote Model above to extract the predicted probability of voting environmentally at each vote, for each party—in essence, the party averages over time. Next, we developed individual logistic regressions for each MP, with vote as the response and date of vote as a predictor. From this, we extracted the predicted probability of voting environmentally at each vote, for each MP. We then subtracted each MP's predicted environmental voting probability from the respective party average, deriving each MP's deviance from the party line, over time. We then averaged this deviance across the votes and multiplied by 100, creating a percentage deviance score whereby 100% means an MP deviates completely from the party to vote in favour of environmental measures, and -100% means an MP deviates completely from the party to vote against environmental legislation. We only estimated these values for parties with five or more MPs, leaving only five political parties (Conservative $n = 203$, Labour $n = 130$, Scottish National Party $n = 5$, Liberal Democrats $n = 15$ & Democratic Unionist Party $n = 6$).

We developed a generalised least squares regression to understand how environmental messaging and constituency demographics affected the probability of deviating from a party and voting environmentally (Deviance Model). Party deviance (inverse hyperbolic sine transformed to meet residual normality assumptions) was used as a response variable and the following predictors (z transformed; with a mean of 0 and a standard deviation of 1) were included to account for differences in constituency demographics and Twitter usage: proportion of environmental tweets per MP, number of Twitter followers per MP (log10 transformed), average weekly wages (available from the ONS: Office For National Statistics 2019) and population densities (log10 transformed) in each MPs constituency—available from ONS (England and Wales) (Office For National Statistics 2020), National Records of Scotland (Scotland) (National Records of Scotland 2020), and Northern Ireland Statistics and Research Agency (Northern Ireland) (Northern Ireland Statistics And Research Agency 2019)—published 2020, 2020 & 2019, respectively. Proportion of environmental tweets was included as the main metric of interest. The number of followers was included to determine whether online influence had any effect on accountability i.e. are those more popular on Twitter more likely to deviate from party lines to vote for environmental measures. The constituency demographics were included as MPs represent constituents and constituents' views on environmental matters vary due to multiple factors, including levels of rural–urban differences and social class (Gifford and Nilsson 2014) (proxied by population density and average wage, respectively). Predictor variables were tested for correlation using the *ggpairs* function from the R package

GGally (Schloerke et al. 2020), predictors had low pairwise correlation (Fig. S5). There was no evidence of multicollinearity, with all VIFs less than 1.4. A random intercept for party was included to control for the non-independence of MPs within parties. As all MPs are scaled within parties these intercepts will be very similar. We selected an intercept model rather than a random slope model as we hypothesised that these relationships (effect of wage, followers, population density) would be observed across all parties instead of varying by party. An exponential spatial correlation structure (using the constituencies' latitude and longitude centroid) was also included to account for the spatial autocorrelation of MPs from neighbouring constituencies sharing similar voting patterns as a result of similar demographics and environments. In order to compare effects sizes between predictors we present standardised betas which required z transforming predictors. To see the non-standardised effects see Fig. 4.

3 Results

3.1 Change in environmental messaging and vote records

No broadly environmental words occurred within the 55 most common words across all tweets (Fig. 1a). In tweets with at least one environmental term, 16 of the 55 most used words were related to the environment (Fig. 1b). Of these words, the most frequently used were related to negative events such as climate change or flooding, suggesting an appreciation of the urgency of environmental issues.

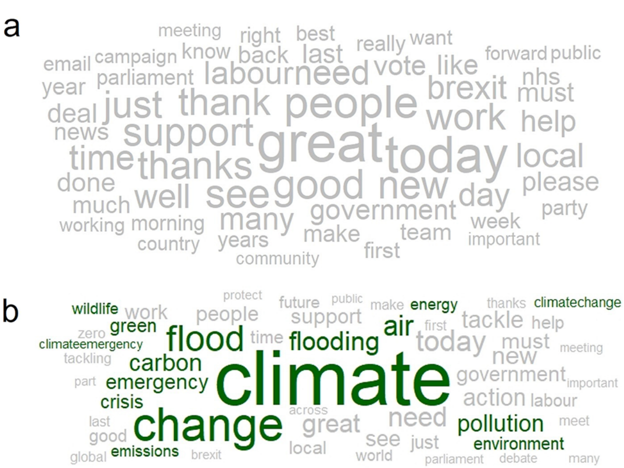

Fig. 1 Twitter word cloud. The most frequently used words **a** across all tweets in the analysis, **b** across all tweets in the analysis containing at least one environmental word. Broadly environmental words are coloured green. Word size is proportional to frequency

The probability of environmental messaging (i.e. posting tweets containing environmental terms) increased over time (Twitter Model OR = 1.24, 95% CI = 1.22–1.25, $z = 29.30$, $p < 0.001$; Fig. 2), where on average, MPs increased environmental messaging by 24% per year. However, in the majority of cases, the probability of a tweet including environmental messaging remained low (less than one tenth of tweets).

The probability of an MP voting environmentally did not change significantly over time (Vote Model: OR = 0.83, 95% CI = 0.54–1.28, $z = -0.816$, $p = 0.414$, Fig. 3). In both the Tweet and Vote Models the fixed effect (date) explained relatively little of the variation within the data (marginal R^2 of 0.04 and 0.02, respectively). Including random effects for party greatly increased the model fits with a conditional R^2 of 0.29 and 0.74, respectively. The random slopes were particularly important in the Vote Model, as MPs followed similar patterns to the party line.

3.2 Link between environmental voting and environmental messaging

The probability of deviating from party lines by voting environmentally increased with environmental messaging (coef = 0.460, SE = 0.109, $t = 4.22$, $p < 0.001$, Fig. 4a) and with average wage (coef = 0.315, SE = 0.119, $t = 2.65$, $p = 0.008$, Fig. 4b). Population density and number of Twitter followers had no effect on the probability of deviating from a party (Fig. 4c, d). As with the previous models, the party random intercept effect (as well as the spatial correlation structure) accounted for a greater proportion of the variation within the data than the fixed effects alone ($R^{2\text{Marginal}}$: 0.06, $R^{2\text{Conditional}}$: 0.30). We observed little spatial structure within party deviance, with the Party random intercept term accounting for almost 10 times more variance in the data than the spatial autocorrelation term.

4 Discussion

We explored how environmental messaging and environmental voting patterns of UK MPs have changed over time and assessed whether messaging was backed up by action on environmental issues, or whether the online presentation of environmental concern was distinct from the realised voting pattern of the MP. We found evidence that environmental messaging has increased over the past decade, but environmental voting has not. Instead, pro-environmental voting decreased in some parties and increased in others, with the vast majority of variation (74%) explained by political party membership. In spite of this, we found evidence that MPs with higher environmental messaging

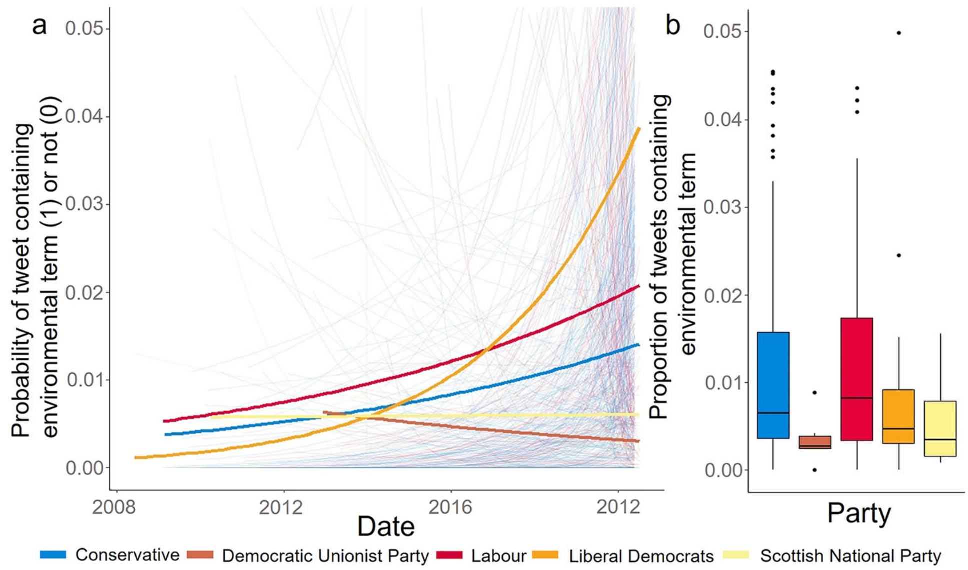

Fig. 2 Comparison of envrionmental tweets between political parties. **a** Probability of a tweet containing an environmental term (score = 1) over time. Individual MPs are coloured by party and bold lines indicate party averages. **b** Proportion of tweets containing environmental terms by party over the study period. *Y*-axes have been cropped to 0.05 to show major trends. Parties are coloured by official party colours

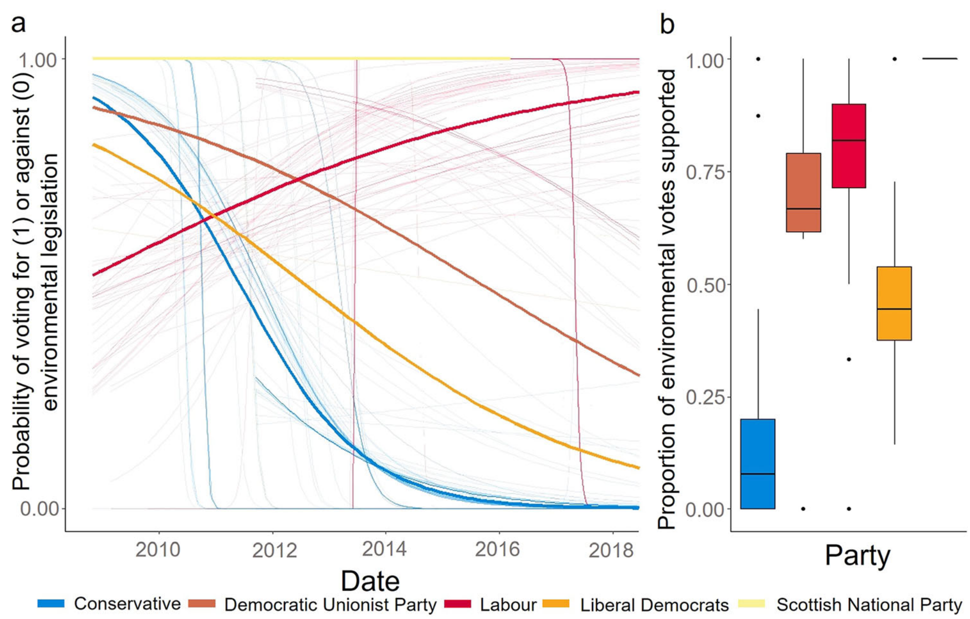

Fig. 3 Comparison of envrionmental voting patterns between political parties. **a** Probability of voting environmentally (score = 1) across 16 parliamentary votes. Individual MPs are coloured by party and bold lines indicate party averages. **b** Proportion of environmental votes voted for by parties over the study period. Parties are coloured by official party colours

were more likely to vote pro-environmentally, even when the party line was against the proposal, although the overall effect was small. This suggests that there is truth in the tweets to some extent, although party affiliation needs to be considered.

Our analysis of Twitter data showed that the probability of an MP publishing a tweet containing an environmental term has increased over the past decade from 0.001 in 2010 to 0.009 in 2020. Whilst significant, this increase still only accounts for a small number of tweets published by MPs, as highlighted by the fact that none of the 55 most used words across all tweets are broadly environmental (Fig. 1). The increase in probability is less surprising than the relative rarity of tweets containing environmental terms. Environmental matters have become increasingly important to both members of the public and political agendas (Pidgeon 2012; Carter 2014); therefore it makes sense to see an increase in the probability of environmental tweets. As we enter a critical period for climate and environmental policy (UNFCCC 2015), it is likely that the prevalence of such tweets will increase in the years to come.

There was no overall increase in the probability of MPs voting for environmental measures over time. As described earlier, political party accounted for the majority of the variation within the data. This is strong evidence to suggest that the best way to determine how an MP is likely to vote on an environmental matter is to determine the party line. It is interesting to note that the two major parties (Labour and

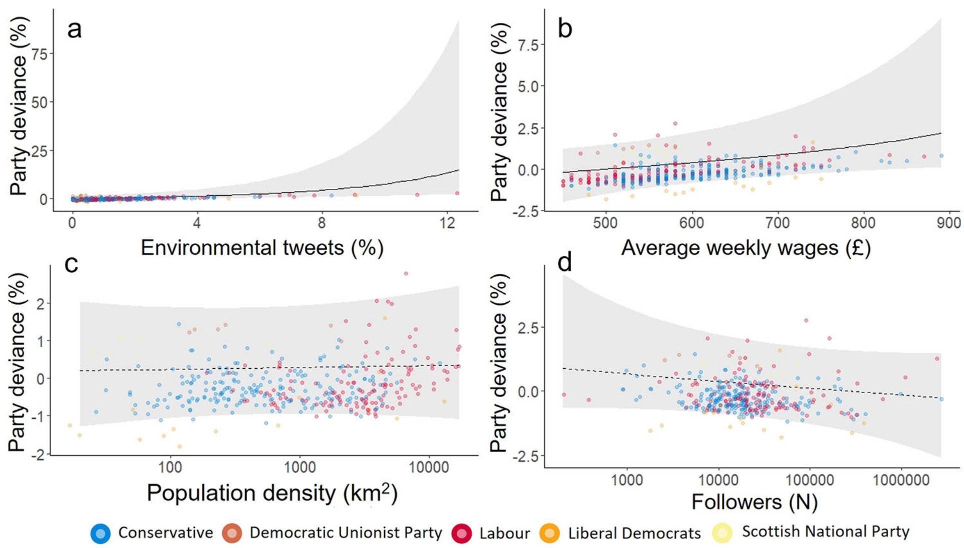

Fig. 4 Effect of predictors on environmental messaging. Marginal effects and 95% confidence intervals of fixed effects in the environmental voting vs tweets and constituency demographics model, with all other variables held at their mean. Fixed effects: **a** percentage of tweets that contain environmental messaging (at least one environmental term). **b** Constituency average weekly wage (£). **c** Constituency population density (km^2). **d** Number of followers on Twitter. Points indicate raw values and are coloured by official party colours. Solid lines indicate a significant effect. For **c** and **d** *x*-axes are on the log10 scale

Conservative) see a switch in voting intentions, with Labour MPs initially being less likely to vote for environmental matters and Conservative MPs more likely to vote favourably. The switch in voting patterns appears to occur after 2010; therefore it is possible that this switch is due to the results of the 2010 general election that saw a Labour government replaced by a Conservative-Liberal Democrat coalition. Whilst we do not wish to be drawn into the economics and politics of environmental policies, these data may suggest that environmental policies are more favourable to opposition parties than those in power.

The final stage of our analysis investigated the remaining variation within the voting patterns data. Our model found that the probability of voting against party lines, in favour of environmental measures was higher when MPs were more vocal about environmental matters on Twitter. It should be noted, however, that the probability remains small, with only a 0.28% increase in the probability of voting with every 1% increase in environmental tweets. Average weekly wage was also positively associated with voting pro-environmentally, with a 0.40% increase in probability per £100 increase in constituency-average weekly wages. At the national level it has been shown environmental interest is correlated with wealth (Franzen and Vogl 2013), despite environmental impacts being seen as lower risk (Lo and Chow 2015). It is interesting to see some evidence for this trend at a local level, with MPs representing wealthier constituents more likely to vote in favour of environmental measures. The conditional R^2 value of this model is only 0.057, suggesting that many additional factors, not included in the analysis are likely to be relevant.

A limitation of this work is the selection of votes used in the analysis. Using a single national newspaper as a source of votes could result in political bias as it would be possible to cherry pick votes that cast a particular party in a pro or anti-environmental light. However, this concern does not seem relevant in this case, as both major political parties voted for and against environmental matters and the differing opinions of stakeholders involved in the original article by Duncan and Watts (2019) suggest a balance of opinion.

A further limitation of the work is the classification of tweets. As mentioned in the methods not all tweets containing the key terms selected will be related to environmental matters. Additionally, the sentiment of tweets has not been included in the analysis. An assumption of this work is that people mentioning environmental matters are more likely to vote in favour of the environment. However, if someone is consistently vocally opposed to environmental matters it is unlikely that they would vote for them. New tools built to analyse the content of tweets e.g. Johnson et al. (2021), could be used to add further nuance to the analysis.

Finally, we must consider that there may be issues with missing variables or endogeneity. For example, there are likely to be latent features within the model that remain uncaptured. The core purpose of this study is to identify if politicians' words (tweets) match their actions (votes), but thinking casually, a willingness to deviate from a party will likely be influenced by an array of things which are hard (impossible) to measure e.g. how interested a politician is in the environment, their career ambitions (going against the whip slows down a career), whether they have conflicts of interest, etc. As we are unable to test these factors, we have endeavoured to be cautious in our choice of language when describing the results and encourage readers to be cautious in their interpretations.

As has been amply demonstrated in recent years, when it comes to politics, not everything posted on social media is true (Allcott and Gentzkow 2017). However, the use of Twitter by MPs in terms of environmental messaging allows some cautious optimism. We found that MPs that tweet more frequently about environmental matters are more likely to vote in favour of the environment. However, because the vast majority of variation within the data is explained by which political party an MP belongs to, environmental tweeting only accounts for a small, but significant fraction of the variation within the data. These results mean that even if an MP has a high probability of tweeting environmentally, the party they belong to is a far better predictor of whether they will vote along environmental lines. This is not to say that MPs that tweet environmentally are feigning interest in order to win votes, just that environmental interests are likely to be over-ruled by the party system and the benefits that arise with toeing the line vs the negatives for rebelling (Willumsen and Öhberg 2017). Our analysis shows that there are occasions where MPs are willing to vote against the party line in favour of environmental measures, and this is more likely to be the case if they are vocal about environmental matters on Twitter.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40974-022-00259-0.

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Declarations

Conflict of interest Between 2017 and 2020, TFJ was a member of the Labour party. TFJ no longer holds any political memberships. MPG declares no conflict of interest. Research met institutional ethics guidelines with all data in the public domain. We opted to preserve MPs' anonymity. The Twitter data are protected and so cannot be shared but can be sourced independently at https://github.com/ropensci/rtweet. Vote records are freely available from https://www.publicwhip.org.uk/. The code used in the analyses can be found at: https://github.com/mgreenwell/enviro-tweets-votes.git.

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