Emotional Reactions and the Pulse of Public Opinion: Measuring the Impact of Political Events on the Sentiment of Online Discussions

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Abstract

This paper analyses changes in public opinion by tracking political discussions in which people voluntarily engage online. Unlike polls or surveys, our approach does not elicit opinions but approximates what the public thinks by analysing the discussions in which they decide to take part. We measure the emotional content of online discussions in three dimensions (valence, arousal and dominance), paying special attention to deviation around average values, which we use as a proxy for disagreement and polarisation. We show that this measurement of public opinion helps predict presidential approval rates, suggesting that there is a point of connection between online discussions (often deemed not representative of the overall population) and offline polls. We also show that this measurement provides a deeper understanding of the individual mechanisms that drive aggregated shifts in public opinion. Our data spans a period that includes two US presidential elections, the attacks of September 11, and the start of military action in Afghanistan and Iraq.

1 Introduction

Public opinion is a proxy for the way citizens perceive political issues and react to current affairs. Scandals or controversial policies, natural disasters or international conflicts, can all provoke shifts in the opinions of the public and cast shadows over the authority of their representatives. Public opinion can impact on the political process by means of electoral accountability, or by means of propaganda and media manipulation (Glynn, Herbst, O’Keefe, and Shapiro 1999; Jacobs and Shapiro 2000; Lewis 2001; Zaller 1992). Both channels offer a link connecting the people with their leaders that is central to the democratic process and to the legitimacy of policy making (Lippmann 1922). Citizens can use public opinion to articulate their interests and reward or punish their representatives for their actions; and political leaders can adapt their discourse and performance to the interests of their constituents by tracking their opinions (Delli Carpini and Keeter 1996; Hutchings 2005). Knowing what the people think and what prompts changes in those opinions is a core element
of democratic governance, and the reason why vast amounts of efforts and resources are being employed to measure it.

Several barometers are designed to track shifts in public opinion. Approval ratings, for instance, offer monthly measures of support to government; and several sample surveys gauge public opinion around a range of controversial issues like abortion, arms control or gay rights (Erikson, MacKuen, and Stimson 2002; Stimson 1998; Stimson 2004). While approval rates offer a continuous but shallow measure of what the public thinks, surveys are richer but usually designed to capture long-term dynamics on very specific areas of public concern. In this paper we propose a new approach to the study of public opinion that aims to complement these previous efforts and move forward our understanding of how the public thinks. The novelty of our approach is twofold: we analyse what the public decides to discuss about, as opposed to their opinions on a battery of predetermined topics; and we extract and analyse the emotional content of their discussions on a large scale, for which we use the Affective Norms for English Language Words (Bradley and Lang 1999; Dodds and Danforth 2009). Emotions have been theorised as a fundamental antecedent of human action: they affect how individuals process information, but also how they form their preferences, desires and beliefs (Elster 1999; Frank 1988; Frijda 1986; Turner and Stets 2006). Appraisal and affective intelligence theories have long considered the cognitive effects of emotions and their role in public opinion formation (Lazarus 1991; Lazarus and Lazarus 1994; Marcus, Neuman, and MacKuen 2000). Our approach builds on this line of research, but shifts attention from the level of individual reaction to the aggregated patterns of general sentiment.

This paper aims to show that online communication, in the form of public discussions, offers new empirical insights into how the public responds to political events. The main assertion this paper makes is that online discussions are an untapped domain in political communication research, and it offers a strategy to start mining that domain. The analyses that follow make two main contributions: first, they show that online discussions, although not demographically representative of the population, are representative of public opinion trends (as measured by presidential approval rates); and second, that emotions can be used as consistent indicators of political attitudes. The paper proceeds as follows. First, it reviews previous attempts to track public opinion, focusing on findings about the volatility and polarisation of public views; and it summarises political psychology research on how emotions mediate information processing and attentiveness to political events. Then, it presents the data and methods used to track general sentiment, involving tens of thousands of discussions held in several Usenet political newsgroups during a six-year period (1999-2005). Section four shows that the political events that took place in this period were accompanied by different emotional responses as measured in terms of valence, arousal, and dominance; it also shows that changes in these three emotional dimensions correlate (albeit to a different degree) with changes in presidential approval ratings. The paper ends with a discussion of the implications that these findings have for public opinion research, qualifying arguments about polarisation and opinion tides, and confirming some of the findings of affective intelligence theory.

2 Research on Public Opinion and Emotional Reactions

Changes in public opinion follow different frequencies: there is the slow pace of issue evolution and ideological alignment, which tracks the distribution of political preferences in the population over decades of generational shifts (Erikson, MacKuen, and Stimson 2002; Page and Shapiro 1992); and there is the fast responsiveness of approval rates, which offer a volatile measure of what the public thinks (Clarke, Stewart, Ault, and Elliott 2004; Kriner and Schwartz 2009; Mueller 1973). Research on issue alignment and issue evolution has focused on the changing salience of conflicts over public policy, and on how the electorate position themselves with regard to those issues. This includes policies about education, race, welfare or health care, but also gun control, capital punishment or abortion, all of which generate public debates that change in intensity and visibility over the years (Adams 1997; Carmines and Stimson 1989; Layman 2001; Schuman, Steech, and Bobo 1985; Stimson 2004; Wolbrecht 2000). While most of these issues are not a priority for the vast majority of the public (whose knowledge about politics is consistently low anyway, Delli Carpini and Keeter 1996), they are closely monitored by minorities that turn those issues into decisive electoral factors and stir awake the “sleeping giant”, as some have called the general public (Hutchings 2005). These issues define the electoral boundaries of public opinion because they open the competition space for political parties (Carmines and Stimson 1989; Petrocik 1987; Repass 1971; Stokes 1963): parties want
to be aligned with what the electorate think and match the policy expectations of as many voters as possible. The composition of those expectations, however, changes over time.

One of those changes is the increasing levels of polarisation bred by public opinion during the last few years: today there are more people adopting extreme positions in their policy alignment than decades ago (Baldassarri and Gelman 2008; DiMaggio, Evans, and Bryson 1996; Evans 2003; Fiorina, Abrams, and Pope 2005; Layman 2001). There is no consensus about the reach or extent of that polarisation: recent literature suggests that it affects only the most contended issues (like, for instance, the war in Iraq), and that the gap between extremes is actually being widened by political parties, who are becoming better at sorting individuals along ideological lines (Baldassarri and Gelman 2008; Fiorina, Abrams, and Pope 2005). Polarisation has not taken place around “valence” issues (those that are uniformly liked or disliked by the electorate, regardless of their ideological leaning, like for instance corruption, Stokes 1963); and recent findings show that the basic correlation structure that links issues into belief systems has in fact remained pretty stable over time (Baldassarri and Goldberg 2010): the way people think about some issues (i.e. abortion) is not independent of their opinions about other issues (i.e. gay rights), and the structure of this interdependence does not seem to have shifted that much over the last few decades.

The debate around polarisation has been accompanied by a parallel debate on the measurement problems associated to survey research. Research on public opinion often assumes that people’s preferences are well defined and consistent, and if they are not, that their inconsistencies are cancelled out on the aggregate level (Converse 1964; Page and Shapiro 1992; Zaller and Feldman 1992; Zaller 1992). This assumption derives from the way opinions are elicited, namely using a battery of issues (primed by the media, the political discourse, or the researcher) on which respondents are asked to give their views. This measurement strategy generates the problem of non-attitudes: respondents might not have an opinion formed around the issues they are being asked about; it also ignores a wide range of topics in which the public might be more interested. Surveys using the open ended “most important issue” question, on the other hand, have other measurement problems, mostly their inability to differentiate the importance of an issue from the degree to which issues are a problem (Wlezien 2005). This means that research on public opinion that relies on those surveys have some intrinsic limitations in what they can say about the origins and shifts of mass opinion.

Research on approval rates puts together the opinion of the public into a single measurement: their satisfaction with the management of government. This approximation to what the public thinks is not flawed by the problems identified above because it does not go into the reasons why respondents approve (or not) the President’s job. On the aggregate, this measurement is rich enough to help identify inertias that systematically appear during the life cycles of all administrations. Previous research has identified consistent “honeymoon” periods during the first months in office, when there is a general level of contentment and approval rates are higher; it has also identified an unavoidable attrition paired with the act of governing, which makes falling rates just a matter of time. In times of crisis, approval surges systematically, in support of leaders, and it tends to move in parallel with the national economy: when prosperous, rates are higher, but when the economy goes down, so do approval rates. Finally, research on approval rates shows that they also tend to equilibrate over time: when they are above or below 50 percent, they tend to converge back to it (Stimson, 2004: 144-148; also Mueller, 1973). Controlling for these trends, the rest of the variation in approval depends on particular political events, like the Watergate scandal in the 70s, or the Lewinsky case in the 90s. This line of research is based on the assumption that the public is well informed, that they follow the theory of affective intelligence, revolve around the cognitive effects of emotions, and how they act as heuristic devices that voters use to gather and process information (Marcus and MacKuen 1993; Marcus, Neuman, and MacKuen 2000; Neuman, Marcus, Crigler, and MacKuen 2007; Rahn 2000; Sniderman, Brody, and Tetlock 1991). One of the main findings of affective intelligence theory is that anxiety about political affairs makes people become more alert and vigilant, and more
inclined to gather and process relevant information; in other words, this negative emotion makes citizens more thoughtful and attentive (Marcus, Neuman, and MacKuen 2000). A more recent study has also shown evidence of the effects that anxiety and anger have on political attitudes in the context of the Iraq war. Both emotions increased attention to the war, but they had opposite effects on support: anger increased support to the military intervention, but anxiety reduced it (Huddy, Feldman, and Cassese 2007). One acknowledged weakness of these studies is that they rely too heavily on induced emotions and retrospective self-report, which makes them vulnerable to measurement errors, and difficult to generalise (Mutz 2007). This paper aims to overcome these weaknesses by proposing an alternative way to measure emotional reactions to political events like the war in Iraq.

Our analytical strategy consists on analysing real-time reactions to political events (i.e., as they happen, not as they are recalled) by measuring and aggregating the emotional content of opinions voluntarily expressed over time and on a large scale. This adds what we think is an unexplored dimension to the analysis of emotions and political behaviour: we know very little about which emotions prevail on the population level over time, or how long it takes for the effects of emotions to decay. The political psychology literature differentiates between “mood” and “emotional reactions” because the former refers to a much longer phenomenon than the latter, which is more focused and short-lived. By tracking general sentiment over time, our approach gives an empirical criterion to assess when emotional reactions crystallise into mood; it also offers a glimpse into the “dark matter” or unseen forces that operate in the background of public opinion (Stimson 2004: 144). Our approach, however, should be seen as complementary to other political psychology approaches: a topic as elusive and complex as the role of emotions in public opinion formation needs to sum, rather than subtract, sources of data. Enriching this essential toolbox is, ultimately, our goal.

There are two types of questions that motivate this research. The first, methodological, is can we solve some of the problems associated to survey research by implementing a bottom-up approach to the study of public opinion? By bottom-up we mean analysing the opinion voluntarily expressed by people in politically relevant discussions. For that, we propose exploiting the new forms of interpersonal communication enabled by Internet technologies. We have considered elsewhere whether online interactions can promote deliberation and encourage the construction of politically relevant discussion networks (Gonzalez-Bailon, Kaltenbrunner and Banchs 2010; Gonzalez-Bailon 2010). The purpose here is to determine whether the opinions expressed in those discussions can be used to assess emotional reactions to political events, and whether those reactions co-evolve with political attitudes. The second type of questions are theoretical: First, what can the analysis of general sentiment add to the polarisation debate? Does the way people react to political events suggest convergence or polarisation? Emotions are universal mechanisms, but the same stimuli might generate heterogeneous reactions; our aim is to find out how much variance different events generate. And second, what emotional dimension explains better political attitudes? Affective intelligence theory suggests that anxiety and anger have vigilant effects on citizens: they become more alert the more threatened they feel. Do our data support the prevalence of this type of emotion, and its higher predictive power of political attitudes? The analyses that follow are an attempt to answer these questions.

3 Methods and Data: Measuring Emotion in Online Discussions

The data we use tracks political discussions in the online forum Usenet, a distributed discussion system that has been active for over three decades (Hauben and Hauben 1997; Lueg and Fisher 2003). We use the dataset Nestscan (Smith 2003; Smith and Kollock 1999), a sample of Usenet that contains about 350 thousand discussion groups. Our analyses focus on the discussions held within the groups that contained the word “politics” in their hierarchy (hierarchies are used to organise newsgroups in nested categories); for the period September 1999 to February 2005, the time window we analyse, this totalled 935 groups, involving about 800 thousand unique participants. We chose to analyse political discussions in Usenet because they allow us to reconstruct patterns over a longer time period than more recent social media. The time window considered here includes some prominent events like two presidential elections, the attacks of 9/11 or the invasion of Iraq. The series we analyse are aggregated on a monthly basis. When preparing the data for the analyses, we excluded the threads that did not have at least three messages in order to avoid spam and non-significant discussions.
The discussions we track with this data involve users that are obviously not a representative sample of the population: representativeness is undermined not only by the digital divide (particularly important towards the beginning of the period, when Internet penetration rates were lower) but also by the self-selecting nature of these groups. Our discussants are probably more interested in politics than the average person: after all, we analyse the discussions of a minority (of hundreds of thousands) of users sufficiently engaged in politics to be active in these forums. However, this phenomenon is not specific to online data: political engagement is always the inclination of a few, and those that usually broadcast the signal of public opinion are a minority as well (Hutchings 2005). People who participate in the discussions we analyse are the equivalent to opinion leaders, or to the “passionate people” to which the literature on public opinion usually refers (Stimson 2004: 163): they are those who care a great deal about public affairs and have strong enough views to talk about them. If we assume that around this core of active discussants there is an even larger periphery of users that follow the discussions without participating, then the role of these opinion leaders in defining general sentiment becomes even more important. The signal of public opinion that we capture with this data is, nonetheless, strong and diverse: the discussion groups we track are positioned along the ideological scale, which can be assessed using the names of the discussion groups (i.e. alt.politics.democrat, alt.politics.republican).

We measure public opinion using the messages that users contribute to these forums. In particular, we analyse the emotional content of the discussions following the method proposed by Dodds and Danforth (2009). This method employs the ANEW (Affective Norms for English Language Words) list to quantify the emotional content of texts on a continuous scale. The ANEW list contains about a thousand words that receive a rating on a 9 point scale in three dimensions: valence, arousal, and dominance (Bradley and Lang 1999). The valence dimension associates words with feelings of happiness, pleasure, satisfaction or hope: the higher the score a word receives in this dimension, the happier it makes subjects feel, on average. The arousal dimension measures the extent to which words make subjects feel stimulated, excited, or frenzied as opposed to calm, dull, or sleepy: again, the higher the score of a word in this dimension, the more aroused it makes subjects feel. Finally, dominance focuses on feelings of domination or being in control versus feelings of submission or awe; the higher the score of a word in this dimension, the more it is associated with feelings of autonomy and prominence. On the grounds of the literature reviewed in the previous section, our assumption here is that the emotional response of citizens to political events precedes their rationalisation of opinions and attitudes.

There are other examples of large-scale text analysis that use alternative methods to gauge emotions or sentiment in public opinion. These examples use micro-blogging communication (i.e. Twitter messages) to measure what people think about politics (O’Connor, Balasubramanyan, Routledge, and Smith 2010) and movies (Asur and Huberman 2010), and use those opinions to make market-based predictions in the form of Box-office revenues and presidential popularity scores. We believe that our approach improves on these efforts not only because it covers a wider time window which, as mentioned above, helps us identify long-term shifts in public opinion; but also because it is based on a lexicon of emotional words that has been validated by psychologists (as noted by Dodds and Danforth 2009) and replicated in other languages (i.e. Redondo, Fraga, Padron, and Comesana 2007), which potentially widens the comparative dimension of the analyses across linguistic communities. We agree with these other approaches in that using online data is faster, less expensive and, crucially, more informative in important ways than traditional surveys or polls.

In our analysis, we use the subject line of the messages as a proxy to the topic of the discussions as well as a summary of their contents; for instance, one popular discussion had the subject line “Bigots for Bush” (with about 19,000 messages and 690 unique discussants), and one unpopular discussion had the subject line “John Edwards, weak but has nice hair” (with only 3 messages sent by 3 different discussants). In total, we analysed about 380 thousand subject lines containing about 2.3 million words, 6% of which (N 140,000) appeared in the ANEW list. The low percentage of words contained in the list means that this analytical strategy is only reliable when large corpuses of text are available (Dodds and Danforth 2009). Figure 1 contains the list of twenty most popular ANEW words aggregated per year in the form of tag clouds (i.e. the size of the word corresponds to the square root of its number of occurrences in the subject lines). The series at the top of the figure indicates the total number of discussions initiated on a monthly basis; the ANEW words at the bottom are sized in proportion to their relative weight within the discussions held every year, starting in September 1999. The figure shows two things: first, that there is an upward trend in
number of political discussions initiated in these forums: towards the end of the period there are
twice as many discussions around political issues than at the beginning; and second, that there is a
shift in the visibility of certain topics. After 9/11, “war” becomes the most prominent topic, clearly
outweighing the other topics in the discussions held between September 2003 and September 2004,
the year of the invasion of Iraq.

Every word in the ANEW list has an average score in the three scales (valence, arousal, and domi-
nance). Following Dodds and Danforth (2009) we counted the number of instances in which ANEW
words appear in the subject lines of the discussions, and calculated monthly averages and standard
deviations based on their frequency and scores. However, unlike Dodds and Danforth we not only
analyse valence values, but also those in the arousal and dominance dimensions. As the previous
section showed, these three dimensions represent different psychological mechanisms, and prompt
different behaviour (Marcus, Neuman, and MacKuen 2000; Neuman, Marcus, Crigler, and MacK-
uen 2007). Which of the three emotional dimensions (valence, arousal or dominance) explains better
political attitudes is one of the substantive questions we want to answer with this data. The second
question is how volatile emotional responses are, and how much disagreement or polarisation there
is around average values. If emotions play a substantive role in shaping preferences and behaviour,
as affective intelligence theory suggests, the heterogeneity of their distribution is also an important
element when it comes to inferring political outcomes: if the population grows increasingly angrier,
one should expect more informed and vigilant citizens.
4 Shifts in General Sentiment and Approval Rates

4.1 The Impact of Political Events on Emotional Reactions

This section pays attention to shifts in emotional reactions as measured by changes in the three dimensions: valence, arousal, and dominance. Figure 2 shows the emotional scores on these three dimensions, plotting averages (left y-axis), and standard deviations (right y-axis) in the same figure as they change over time. The grey vertical bars identify some of the most prominent events in this period: the two presidential elections (in November 2000 and November 2004), the attacks of September 11, the invasion of Iraq, and the abuses of Abu Ghraib. These series show two clear trends: first, that 9/11 marks a before and after, prompting a fall in the average values of valence and, to a lesser extent, dominance, and a rise in the scores of arousal; and, second the upheaval caused by the invasion of Iraq and the scandals associated to the conflict: these events are associated to the lowest peaks in valence and the highest peaks in arousal. After 9/11, the standard deviation around mean valence scores goes up significantly, signalling increasing levels of emotional polarisation, that is, a higher proportion of messages that fall closer to either of the two extremes of the happy-unhappy scale.

Before the attacks, discussions reflected higher levels of happiness and lower levels of excitement, right the opposite of what happens after the attacks; the two general elections that took place during this period did not provoke reactions comparable to those associated with the military interventions that followed the attack. These trends show that after 9/11 the public became gloomier and more irascible, but also that they had more diverse reactions around the average values. One of the predictions made by political psychology research is that anxiety and threats make people more alert: risk boosts the attention of the public. The rise of arousal levels after the attack indicates that this precondition for a stronger public vigilance is in place. What these trends add to previous research is the evidence that changes in emotional reactions still linger years after the stimuli that originated them took place. This suggests that emotional reactions to very specific and completely unexpected events can derive into the more permanent phenomenon of shifting public mood. The distinction between emotions and mood is important because the latter permeates the public’s perception of events, and affects their behaviour, for a longer period of time, even after the event that originated the initial reaction disappears down the time line. The political communication tracked in these online discussions shows that emotions are very volatile, but also that they crystallise into long-term mood. These time dynamics shed interesting insights into how permanent emotions shifts are and how long they take to decay.

4.2 Relationship with Presidential Approval Rates

The trends showed in Figure 3 reproduce the same information but this time in comparison to changes in presidential approval ratings, as obtained from the Gallup organisation’s website (for better visualisation, the standard deviation of valence has been offset by -1). The figure makes more explicit the relationship between the three series of emotional reactions and how these are related to changes in approval rates. As expected, approval reacts sharply to critical events, noticeably the attacks of 9/11, when support for the President reached a historical maximum, and the start of military action in Iraq. Yet when compared to the emotional scores of the discussions, interesting differences emerge. First, the sudden soar of approval rates brought about by 9/11 converges, a few months later, back to the equilibrium of about 50 per cent (in line with the equilibration cycle of approval rates identified by previous research, Stimson 2004: 145); yet the average emotional scores do not go back to normal after the event: as mentioned in the previous section, valence levels remain lower, and arousal levels higher, than before. This also applies to the levels of polarisation around valence: they not only remain higher, but keep on being slightly on the rise.

The shifts caused by this exogenous (and unpredictable) shock take place at the same time, causing a simultaneous reaction in the four series. However, different relationships emerge in other points of the period. The start of the Iraq war, for instance, generates highs and lows in the three emotional dimensions before it generates a response in approval rates, which go up shortly after military action starts (again, in line with what we would expect in times of war, Mueller 1973). This military intervention coincides with the lowest point in the valence series, that is, the moment with the unhappiest general sentiment; it is also one of the moments with the highest emotional polarisation. The invasion of Iraq also coincides with a peak in arousal: when the war started, discussions adopted
the angriest expressions of the period considered here. If we just measure public opinion using approval rates, this war did not bring such an extreme reaction in the public as the attack of 9/11 had done; but it definitively stirred more antagonistic feelings. One reason for this different reaction has probably to do with the unexpectedness of the attack. The possibility of a war was in the mind of the public for a longer period, and this gave them more time to digest the news and have a response ready when the war finally started; in other words, the public had more time to distil reasons out of their
Figure 3: Changes in valence, arousal and dominance compared to presidential approval rates.

passions. These findings also qualify previous approaches to the emotional reactions associated to the war (Huddy, Feldman, and Cassese 2007): anger might increase support, and Figure 3 suggests that the average feeling was that of an increased anger; but it also shows that there was quite a lot of divergence around that general feeling, at least as expressed in written opinion.

Compared to approval rates, these trends suggest that people increase or decrease their support to the President partly as a result of different emotional reactions. To identify the degree of association between the three emotional series and approval rates, we analysed monthly correlations, plotted in Figure 4. The coefficients show the degree of association between variables using 13-month time windows, centred in each corresponding month, to which we assign the coefficient. At the beginning and at the end of the period we truncate the time window so that for the first and last month the correlation coefficient is based on 7 months, for the second and second from the last, it is based on 8 months, and so forth. From month 7 to month 60 in our series, the correlation is based on the 13-month time windows. The red intervals depicted in Figure 4 correspond to the coefficients that proved statistically significant (according to Fisher’s \( p \)-value with \( p < 0.05 \), Fisher 1925). The first thing the figure shows is that the three emotional dimensions are not fully synchronised; the average values of valence and dominance are, for most of the period, highly correlated, with rates of change that go in the same direction: the happier the general feeling, the stronger is also the general sentiment of being in control; but changes in arousal only correlate sporadically with changes in the other two dimensions. The strongest correlation with the arousal series is the standard deviation of valence: excluding the early and late months of the period, as the standard deviation in valence goes up (that is, as polarisation increases), the average values of arousal also go up.

The second thing that Figure 4 shows is that the three emotional dimensions do not correlate to the same extent with presidential approval rates, shown in the last column of the matrix. While valence has a significant negative correlation around the period surrounding the attacks of 9/11 (a correlation that is positive with the standard deviation series) and a positive correlation during the scandals of Abu Ghraib, arousal shows the opposite relationship: around the time of 9/11, higher arousal levels coincide with higher approval rates, but the relationship is reversed by the time the Iraq invasion started. Of all three emotional series, dominance is the dimension that shows the weakest relationship with approval rates.
The analyses in the previous section show that some of the changes in approval rates seem to be the consequence of different emotional reactions, and that some of those emotions have a stronger relationship with the opinion expressed in the form of evaluations of the President. This section specifically addresses the question of which of the three dimensions (valence, arousal or dominance) explains better changes in presidential approval rates; in other words, the analyses that follow aim to identify if the emotional content of political discussions help predict presidential approval rates. Figure 4 showed that the three emotional dimensions do not correlate to the same extent with presidential approval rates; however, some of the most relevant variations in their trends occur simultaneously or closely in time, and seem to be related to salient political events. To better exploit the dependences among these variables, we move from linear correlations to a more complex analysis that takes into account the temporal dimension of the data. In this section we use time series analysis methods (Box, Jenkins, and Reinsel 2008) to predict presidential approval rates using the three emotional dimensions.

We use an ARMA (Auto Regressive Moving Average) model, which takes into account the recent history of both the response and explanatory variables (approval rates and the three emotional dimensions) for predicting approval rates. As the name implies, an ARMA model incorporates two fundamental components: an Auto Regressive part, which is able to exploit relevant information related to the auto-correlated nature of the time series we want to predict (i.e. presidential approval rates), and a Moving Average component, which is able to incorporate additional information from other external time series (in our case, the three emotional dimensions). The general form of ARMA
estimator can be expressed as follows:

\[
X(t) = \sum_{i=1}^{p} A_i X(t - i) + \sum_{j=1}^{m} \sum_{i=1}^{q} B_{i,j} Y_j(t - i)
\]  

where \(X(t)\) is the time series to be predicted (i.e. approval rates), \(p\) and \(q\) are the orders of the autoregressive and moving average models, respectively (their calibration is explained below), \(m\) is the total number of external sources of information (i.e. the three emotional series), \(Y_j(t - 1)\), \(t\) is the time index for each time series (i.e. the 66-month measurements), and \(A_i\) and \(B_{i,j}\) are the model coefficients that have to be computed during a training phase by using historical data. The aim of this model is to estimate if changes in the three emotional time series are significant predictors of changes in presidential approval rates, once we control for auto-regression, that is, for the fact that approval rates in time depend on their value in \(t - 1\).

ARMA models are trained by means of an optimisation procedure aiming at minimising the fitting error over the training dataset. In our case, we used the available 66-month data as the training dataset and evaluated the performance of the prediction models in terms of the mean absolute error over the training dataset. We use the current value of the presidential approval rate (AR component) and the 3-month previous history of the emotional dimensions (MA component) to generate predictions of the approval rate for the following month (that is, for \(t + 1\)). According to this, the orders of our ARMA model are \(q = 3\) and \(p = 1\). Prior to running the analyses, all time series were smoothed using a 4-month window, weighted following a Hamming distribution to minimise the effects of noise. Smoothing time series not only allows us to reduce the amount of noise in the data; it also yields a more robust performance of the prediction algorithms. Smoothing constitutes a common practice in this kind of analysis (e.g. O’Connor et al. 2010). A figure comparing the smoothed and unsmoothed versions of the series can be found in the Appendix.

In a first stage, we constructed and evaluated 10 different models. The first model, which we use as a benchmark, only incorporates the autoregressive (AR) component. This model only uses the information of the approval rate at the current month \(t\) to estimate the rate at the following month \(t + 1\). The model is used to compare the performance of the other nine models, which incorporate the moving average (MA) component and were constructed as follows: six of them include only one emotional time series \((m = 1)\), either the mean or the standard deviation of the three emotional variables (mean-valence, mean-arousal, mean-dominance, std-valence, std-arousal and std-dominance); the remaining three models include both the mean and the standard deviation time series \((m = 2)\) of one emotional variable at a time (both-valence, both-arousal and both-dominance). Figure 5 presents mean absolute errors and accumulated errors for the nine models.

The figure shows that all ARMA models perform better than the benchmark AR model, which suggests that the information derived from the three emotional dimensions increases predictive power. Figure 5 also shows that of all the models that only use one emotional variable, those considering the mean values generate better predictions (with the exception of the model with the standard deviation of arousal). The predictions obtained by the models that consider both the mean and the standard deviation are not necessarily better, again with the exception of arousal. Actually, the performance of the models that take into account arousal-related time series are always better than those considering valence and dominance.

The best model in terms of predictive power considers both the mean and the standard deviation of arousal. The prediction of this model produces the minimum mean absolute error (MAE=1.14\% of the approval rate), which is 27\% lower than the benchmark model that only takes into account the autoregressive component of presidential approval rates (for which the MAE=1.57\%). To assess the significance of this difference, we simulated a thousand ARMA models with random inputs that reproduced the same distribution of the arousal series. None of these models was able to produce a better prediction than the empirical ARMA model, which means that arousal variables do help us predict approval rates, and that this is not just an artefact of introducing more parameters in the model.

The detailed time evolution of the prediction errors are presented in the lower panel of Figure 5. The panel displays the prediction error for the benchmark AR model and the three ARMA models that consider both the mean and standard deviation of the emotional variables. These lines show the cumulative sum of the absolute values of the prediction errors, normalised by the number of
Figure 5: Mean absolute errors and accumulated errors for the ten predictive models.

evaluation points (i.e. the last points in the cumulative curves correspond to the mean absolute error displayed in the upper panel). Two important observations can be drawn from this plot: first, the significant contribution of the attacks of 9/11 to the accumulated prediction error for all prediction
models (related to the unexpectedness of the event); and, second, the consistently better performance of the arousal-related model for the whole time period.

In a second stage, we conducted a more detailed comparison between the benchmark AR model and the best ARMA model, which includes the two arousal time series. We compared the approval rates predicted by the two models with the actual approval rates (Figure 6, upper panel), and their corresponding estimation error curves (Figure 6, lower panel).

The predictions given by the benchmark model respond to a simple one-month shift strategy. The autoregressive coefficient obtained by this model is 0.989, which means that the best guess the model can make for the next month approval rate value is that it is about 0.99 times the current month value, revealing a global downward trend of approval rates. However, the important point revealed by Figure 6 is that the ARMA model is able to follow approval rate variations better than the AR model. The absolute errors curves presented in the lower panel of Figure 6 show that the largest peak in prediction errors occurs on 9/11 for the two models. In both cases, the peak is very similar in amplitude, showing that at this particular point in time both models are similarly unable to predict approval rates one month ahead. Again, this is due to the unexpectedness of this event: the attacks came as an exogenous shock that produced strong reactions in approval rates and emotional variables (as Figures 2 and 3 showed) but that is completely unpredictable from the information and previous history contained in the time series. Leaving this particular case aside, the figure shows that the information provided by the two arousal series (mean and standard deviation) certainly contributes to improve approval rate predictions: while the AR model prediction error ranges between -3% and 4%, the ARMA model’s error is bounded between -2% and 2%.

Figure 6: Predictions for approval rate with AR and best ARMA models and their corresponding estimation error curves.
6 Discussion and Conclusions

Can emotions, and their role in public opinion formation, be tracked using online communication? In the light of our results, the short answer is yes. We have shown that different political events incite different emotional reactions, and that these reactions shape political attitudes, here measured by means of presidential approval rates. Our findings suggest that arousal is the prevalent emotional dimension in shaping political attitudes: previous research on political psychology suggests that a political reality perceived as riskier and more threatening engenders emotions of arousal; we have shown that this emotional dimension is also the most significant in shaping attitudes over time. In line with previous research on public opinion, we have found evidence of increasing polarisation, at least since the 9/11 attacks, an event that marked a new era in the cycles of public opinion and, as our findings suggest, in the mood of the public. Our findings also show that there are nuances in the relationship between emotions and public opinion. The same political events unleash more disagreement in some emotional dimensions (valence, arousal) than in others (dominance), and they have different lasting effects: while approval rates tend to equilibrate in the long run, shifts in the emotional reactions of the public are more resistant to the weight of time. Although arousal predicts better than valence or dominance support for the President, levels of arousal are also highly related to polarisation in valence: the higher the heterogeneity in valence reactions, the higher are arousal levels.

The interaction of different emotional dimensions over time, and their relationship to political attitudes, has gone largely unnoticed by survey and poll research, but it has important repercussions for our understanding of how the public think. The analyses above build a case to start using online discussions and Internet-enabled communication as sources of public opinion data. We have shown that online discussions are representative of public opinion trends, even though they are not demographically representative of the population. We have also shown that the emotions identified in written communication can be used as consistent indicators of political attitudes. As we already mentioned above, this approach is not intended as a substitute for other approaches to public opinion or emotions, but as an additional tool to measure what is an elusive and complex dimension of human behaviour. By analysing real-time reactions to political events, and aggregating the emotional content of opinions voluntarily expressed, we can overcome some of the measurement problems associated to survey research; and by analysing large-scale, longitudinal data we can overcome some of the limitations of experimental psychology, mostly the threat of external validity.

Other implications of our research are theoretical. Research on public opinion still misses an individual level mechanism that can explain the aggregated shifts of opinions. Political psychology research has focused on the cognitive effects of emotions, and on how they affect information processing or settle predispositions for action; but it does not offer empirical evidence on large-scale shifts in emotional reactions, or the exact timing when reactions become more permanent and manage to shift the mood of the public. By showing that emotional reactions can predict approval rates we are strengthening the validity of the measure, but also the theoretical explanation we can give to changes in public opinion: these ultimately derive from individuals, and emotions offer a crucial link between what individuals think and what they do. Our findings generate some relevant questions in this respect. We have found that arousal explains, more than valence, support for the President, but it is a pending question whether that is also the case for other expressions of public opinion like, say, support for capital punishment or guns control. The ANEW words might be missing important emotional dimensions that are crucially related to political behaviour, so it is also a pending question whether results would have been different if we had been able to identify words implying anxiety as separate from words implying anger. The arousal dimension mixes both types of emotions. Finally, we also need more research about the decaying rates of emotions as triggers for action, and about whether those rates remain stable over time. Future research should consider how emotional reactions are related to behaviour, like voting, as opposed to just attitudes, and whether their influence wanes with time.

These are all questions that require transcending the traditional ways in which we have been measuring public opinion. In this paper, we have provided a guideline on how to do that, profiting from the opinions that the public voluntarily express in the forum created by online discussions. Ours is a bottom-up approach that does not assume a list of relevant issues about which we want the public to have an opinion, but rather lets the public speak about the issues that most concern them. This approach has a number of advantages: we analyse opinions on a wider range of topics, we
have less response bias, and we obtain richer longitudinal information, involving significantly lower costs in data collection than using sample surveys. Comparing how close the measures of these two approaches are (i.e. the topics about which people discuss voluntarily and the issues about which researchers have been asking them for decades) is an interesting question in itself that requires further investigation: we might find that not all the “non-attitudes” (Converse 1964) are an artefact of survey methods. There are many alternative ways in which we can mine online public opinion to measure trends in general sentiment (i.e. the passions that drive political discourse). This paper has followed one approach, but we need to investigate alternative ways to make emotions operational concepts and find more fine-grained categories of emotional response.

Moving beyond public opinion research, our results have also wider implications for other areas of inquiry. There is an obvious marketing edge in this approach, which is fitted to track public opinion about products and goods, and project market revenues in line with what customers (current or potential) think. Something along the lines has been done by Asur and Huberman (2010); it would be interesting to replicate their analysis with the ANEW lexicon and test if the predictive power of the model changes significantly. There are also implications for public health research: happiness has long been acknowledged as an important component of health, and recent research has found evidence of the contagious nature of emotions and their ability to spread in the population (Fowler and Christakis 2008). Online discussion networks like those we analyse here might also be channelling contagion processes; if so, this would offer a crucial explanation of how public opinion is formed. Some other studies have found that emotions are a crucial mechanism in the dynamics of “viral culture”: awe-inspiring newspaper articles, for instance, are more likely to be among the most e-mailed stories on a given day (Berger and Milkman 2010). If the news that inspire certain emotional reactions are read by more people, then emotions are, again, an important factor to explain the formation of opinions.

This takes us back to our findings: the same emotion-based viral mechanism could be playing a role in the way people select topics from their news sources, topics that they will then bring to the public discussions we track. This agrees with political psychology research on the way emotions can play a heuristic role in how citizens process information. And this, in turn, highlights the most important moral of this paper: that we need to explore further the explanatory power of emotions if we are to distinguish alternative explanations of how public opinion is formed. The analytical strategy we propose does not allow us to make the usual demographic breakdowns (this information is usually absent from digital data), but it sheds light into a fundamental principle of human action, that is, the part of our motivational structure that starts where rationality ends. Emotions have been an elusive target for analysis on a large, societal scale; we can move this line of research further by implementing new methods that pay attention to the opinions that people voluntarily express.

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A Appendix

Figure A.1: Smoothed Time Series Used in the Analyses of Section 4.3.
This figure "Figure_1.png" is available in "png" format from:

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