The Role of Negative Affect in Shaping Populist Support: Converging Global Evidence From The Field

George Ward[1], H. Andrew Schwartz[2], Salvatore Giorgi[3], Jochen Menges[4], and Sandra C. Matz[5]

[1]University of Oxford

[2]Stony Brook University

[3]University of Pennsylvania

[4]University of Zürich

[5]Columbia University

Author Note

Correspondence: George Ward, University of Oxford; george.ward@some.ox.ac.uk. We are very grateful to Gallup, Twitter, and the Victor Pinchuk Foundation for generous access to data. For replication purposes, all code will be made available along with all publicly available data. Data from Gallup is proprietary and cannot be shared publicly, but is available to academic researchers (e.g. through institutional subscriptions) and all code required to replicate the results will be shared. County-level aggregates of negative emotions derived from Twitter data will be made available in the form of aggregated word and topic level features. Due to Twitter's Terms of Service and privacy considerations, we are unable to share individual-level Twitter data (i.e., individual tweets, features per person). *Preregistration* details can be found and reviewed at `https://aspredicted.org/blind.php?x=di7k5u`.

Abstract

Support for populism has risen substantially during the past two decades. We investigate the extent to which the rising electoral demand for populist parties and causes can be explained by negative affect. Globally, negative affect has risen rapidly in recent years and has even been referred to by some as a "blind spot" for politicians and policymakers who have failed to recognize its significance. We use a multi-modal, multi-method empirical approach, using data from a diverse set of geographical and political contexts. Across four studies, we demonstrate that negative affect – measured via self-reported emotions as well as automated text analyses of over 2 billion Tweets – predicts i) individual-level populist attitudes in global survey data (Studies 1a and 1b), ii) longitudinal changes in populist party vote shares at general elections in European countries (Study 2), iii) area-level Brexit voting in the 2016 UK referendum (Study 3) and iv) county-level vote shares for Donald Trump in the 2016 and 2020 US presidential elections (Studies 4a and 4b). We find that negative emotions—such as fear and anger as well as more often overlooked low-arousal negative emotions like depression and sadness—are predictive of populist beliefs as well as voting. We establish a boundary condition by demonstrating that the relationship does not hold for populist politicians who are already in power: Like other incumbents, governing populists do not benefit electorally when their constituents continue to experience negative affect after they have been elected. With negative affect being fertile ground for populist support, our research calls for politicians to alleviate rather than avail themselves of negative affect.

Keywords: negative affect, voting, populism, natural language processing

The Role of Negative Affect in Shaping Populist Support: Converging Global Evidence From The Field

There has been a significant increase in electoral support for populist parties and causes across democracies around the world. The ascendance of populist parties in Europe, the UK's collective decision to leave the European Union, and the rise of Trumpism in the United States have spurred an ever growing body of literature aimed at identifying the factors driving the increased appeal of populism. Much of this discussion has centered around a contest between economic and cultural explanatory factors, with proposed explanations including fiscal austerity and economic hardship (Guriev, 2018; Becker et al., 2017; Fetzer, 2019), globalization and trade exposure (Dorn et al., 2020; Colantone and Stanig, 2018), status threat (Mutz, 2018; Knowles and Tropp, 2018) and cultural backlash (Norris and Inglehart, 2019). Nonetheless, any account of the rise of populism will likely be incomplete without providing a thorough psychological understanding of the demand for political populism (Obschonka et al., 2018; Bakker et al., 2016; Forgas et al., 2021).

Headlines such as the "Trump's Army of Angry White Men" or "Populist Anger Upends Politics on Both Sides of the Atlantic" have become commonplace and reflect the intuition that populism thrives where people experience negative affect (see, e.g., Blow, 2020; Yardley, 2016). However, despite such conjectures, empirical evidence linking negative affect to the rise of populism is relatively scarce – particularly when it comes to assessing impacts on real stakes voting and electoral outcomes at scale. Also, standard predictive models used by polling institutes and reported widely in the media typically omit proximal indicators of behavior such as human feelings (see, e.g., Fair, 1978; Hibbs, 2000), which may go some way in accounting for polling failures in fully capturing the rising levels of populist support in recent elections. In this paper, we investigate the extent to which the increasing experience of negative affect worldwide could contribute to the growing electoral success of populist parties, candidates, and causes.

The Rise of Populism

While populism may be a contested and multifaceted concept, consensus has emerged around the ideational approach to defining it. In this view, populism is comprised of three main tenets: i) antielitism, ii) a Manichean outlook, and iii) people-centrism (Mudde, 2017). First, the mass of virtuous "ordinary" people is typically pitted against corrupt "elites," who are seen as nefariously running society to the detriment of ordinary people. Second, populism is typically a Manichean affair in that it divides society into two irreconcilable and antagonistic groups – the people and the elite – who are essentially seen as forces for good and evil, respectively. Third, populism typically holds that politics should be a pure expression of the "will of the people" (*volonté générale*), with populist actors claiming represent the interests and will of the "common man" more than mainstream politicians.

Populism is a "thin-centered" ideology in that it is not a set of public policies but rather a set of ideas, which can be attached or merged with a variety of other ideologies—such as nationalism, socialism, and conservatism—depending on the situation (Mudde, 2004). Fundamentally, populism is rooted in a strong sense of discontent about the existing political and societal order, which is seen as being designed by and for elites, combined with a belief that things could be made better if things were run by the people (Hawkins et al., 2018). Given the focus of populist political actors on the idea that ordinary people are being betrayed by a corrupt elite, it perennially emphasizes a sense of threat to the people and sees society as being in a state of crisis (Canovan, 2004; Mudde, 2004).

Populism can be distinguished from various other related concepts such authoritarianism, Far Right voting, and antipathy toward immigration. By emphasizing three main aspects, the ideational definition allows for theorizing and empirical analysis that are focused on populism as a clear concept – for example, by using survey scales specifically designed to elicit attitudes on each of the three dimensions (Silva et al., 2018) or by using expert surveys categorizing political parties according to the ideational definition (Rooduijn et al., 2019). In our analyses, we do both: We investigate the links between negative affect and populist attitudes to begin with, but move beyond this to also assess the extent to which changing levels of negative affect are able to predict subsequent populist voting behavior and, ultimately, consequential electoral outcomes at scale.

Global Increases in Negative Affect: A Blind Spot?

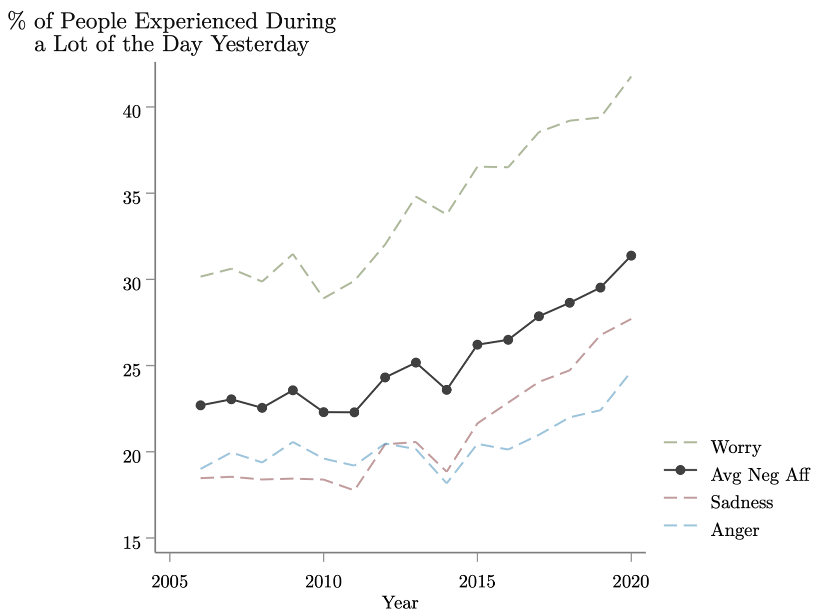
The mood of the nation was once thought of as an unmeasurable variable, meaning that investigating the extent to which emotions might sway behavior and elections at scale was essentially impossible. However, developments in the measurement of affect mean this is no longer the case. Following detailed guidelines laid down by the influential Organisation for Economic Co-operation and Development (OECD), many national statistics agencies around the world have begun to include affective questions in large governmental surveys (Durand, 2018). Equally, polling companies also now regularly measure people's emotional experience in numerous countries around the world on a regular basis. Gallup, for example, surveys many countries around the world to produce their annual *Global Emotions Report* while YouGov now measures Britain's mood on a weekly basis using question on various emotions.[1] Furthermore, advances in natural language processing, using data from platforms such as Twitter and Facebook, mean that real-time impressions of affect are becoming much more possible and prevalent (see, e.g., Schwartz et al., 2013).

[1] See `https://yougov.co.uk/topics/science/trackers/britains-mood-measured-weekly`.

While worldwide levels of life evaluation and positive affect have remained largely stable over the past two decades, a more striking trend can be observed when looking at the experience of negative affect (Helliwell et al., 2019). Survey data from the Gallup World Poll, for example – which collects data from large representative samples from over 150 countries on an annual basis – shows that the experience of negative emotions like anger, worry, and sadness has increased markedly. As can be seen in Figure 1, since this data began to be collected on a global scale in 2006, the worldwide incidence of these negative emotional states has increased by around 38% (Gallup, 2022).

Figure 1

Global rise in negative affect using data from 167 countries worldwide. Source: Gallup World Poll. Nationally representative survey data ($N \approx 1,000$) is collected each year. Worldwide mean per year plotted is weighted by national population. Total $N = 2,494,559$.



Given the sharp rise in negative affect, it is perhaps surprising that the consequences of this are not more widely studied and, in particular, linked to developments in the political sphere. Indeed, the lack of attention that has been paid to the global increase in negative affect has even been referred to as a "blind spot" for politicians, who seem to have missed this large change in the way people feel in their day-to-day lives and possibly failed to recognize its significance (Clifton, 2022). But is this really the case? In this paper, we shed empirical light on this issue, using multiple methods and data sources, by assessing the extent to which the experience of negative affect shapes both populist attitudes as well as voting for populist politicians and causes.

Emotional Bases of Political Behavior

A long history of work has shown that affect, or people's emotional state, can significantly influence their attitudes, decision-making, and behaviors (Gross and Barrett, 2013; Lerner et al., 2015; Schwarz, 1990; Forgas, 2001). While traditional models in political science and economics have focused on rational accounts of political behavior, it is now widely accepted that emotions also play a role in shaping political attitudes and actions (see, e.g., Redlawsk et al., 2017; Marcus et al., 2019, for comprehensive reviews of this growing literature).

A small body of research has investigated the relationship between negative emotions and populist attitudes (see, e.g., Salmela and von Scheve, 2017; Demertzis, 2006; Spruyt et al., 2016). This work has typically focused on the effects of discrete negative emotions such as fear and anger (Marcus, 2021). For instance, Rico et al. (2017) found that anger about the economic situation in Spain is linked to support for populist parties, while Vasilopoulou and Wagner (2017) suggest that anger about Britain's membership of the European Union predicts preferences towards leaving the union. Additionally, Rico et al. (2020) found a connection between anger about the economic crisis and populist attitudinal measures in European countries.

Related research has explored the impact of negative emotions on outcomes associated with, but distinct from, populism, such as authoritarianism, conspiracy thinking, and nativism. Marcus et al. (2019) draw, for example, on affective intelligence theory—which has been very influential in political psychology and sees emotions largely as appraisals that precede and guide how people see, think, and act—to suggest that anger, but not fear, mobilizes support for the authoritarian far-right in France. Similarly, Vasilopoulos et al. (2019) show that anger about terrorist attacks increases support for authoritarianism; despite the authors arguing that fear or anxiety works in the opposite direction, Jost (2019) shows using the same data that fear is in fact positively correlated with authoritarianism. As with populism, the most commonly studied negative emotions in this literature have been anger and fear. However, a key challenge is that people typically experience multiple emotions at any given moment (Abelson et al., 1982; Watson et al., 1988).

Approaches to affect in the political sphere differ in the extent to which they study the effects of discrete emotions or instead provide a more dimensional account that focuses primarily on positive and negative affect more broadly (Brader et al., 2011). We take a more dimensional approach and test the broad hypothesis that negative affect in general raises support for populist candidates and causes. Although we often use indices of negative affect that comprise multiple emotions, we nevertheless also examine discrete emotions to explore potential differences in effects across them in terms of their effects on populist attitudes and voting behavior. In doing so, we follow existing work by looking at both the discrete emotions of fear and anger, but also build on it by also considering further negative emotions like sadness that are typically overlooked. Moreover, we go beyond work that looks at short-lived directed emotions that can be seen as a reaction to a particular political stimulus—for example anger *about* the economy, anxiety *in relation to* terrorism, fear *of* immigration—in order to look more generally at negative affect as a whole.

We use data on negative affect at scale using both survey questions that are now typically collecting in government surveys asking about the emotions people have experienced in, say, the prior day or week as well as using natural language processing approaches that observe people's affective tone. Using these two growing sources of data, which are each increasingly providing policymakers and others with real time impressions of affect, we are able to link such experiences with patterns of voting behavior and electoral outcomes.

Impacts of Negative Affect on the Demand for Populism

The influential *affect-as-information* hypothesis posits that affective states are a source of information that people use to make sense of the world around them (see Martin and Clore, 2013, for a more in-depth discussion of how theoretical work on why affect may influence judgment, information processing, and, ultimately, behavior). At a high level, by discerning what is important to an individual and distinguishing between "positive" and "negative" emotions, affective states can influence people's decisions and behaviors. Negative affect, in particular, functions as an indicator that something is wrong and motivates behavior aimed at resolving the negative emotional state. People experiencing negative affect are more likely to seek courses of action that will repair their emotional state (Schwarz, 1990). In other words, those experiencing negative affect are more likely to be feeling under threat and a desire for (often rapid) change.

How does this relate to the three core aspects of populism? The antielitism and Manichean worldview that are inherent to populism both stress a negative state of the world and a fundamental desire to overhaul the system. They each emphasize threat and, in doing so, cue a desire for change. We thus test the general hypothesis that individuals experiencing a high level of negative affect will be more likely to vote for populist actors, as they offer a chance to effect change and overhaul their negative affective state. This approach is more general than one which highlights specific action tendencies associated with different discrete emotions, such as anger and fear. Indeed, the logic of this theoretical approach applies to a range of negative emotional states, including lower arousal negative emotions like depression and sadness.

This theoretical perspective suggests that increased negative affect among the population is likely to raise support for populist challengers when they are running against mainstream incumbents. However, when populists are running as incumbents, an increase in negative affect is unlikely to help them unless they can find a way to rebrand themselves as anti-establishment outsiders. This is because support for populism is fundamentally rooted in a desire for change, and an incumbent populist does not represent change unless they can successfully reframe themselves as challenging the status quo. To investigate the relationship between negative affect and populist support, we examine multiple political contexts from around the world over multiple time periods. This allows us to observe instances where populists are running as challengers as well as where they are running as incumbents. By doing so, we can more fully investigate the relationship between negative affect and populist support in the contexts where populists are already in power.

The third core aspect of populism is people-centrism, which emphasizes the redemptive power of the people. This aspect of populism is less clearly linked to negative affect than the first two aspects. In fact, one might expect the relationship to work in the opposite direction, as people-centrism is positively valenced in affective terms. Therefore, we do not make any strong predictions about the relationship between negative affect and people-centrism. Nevertheless, using survey questions specifically developed to measure populism, we are able to test for differences the effects of negative affect across each of the three main aspects of populism.

Overview of Current Research

Across six studies, we test the hypothesis that negative affect increases populist support. We take a multi-modal and multi-method approach, employing data from a diverse range of political and geographical contexts. We use both survey and behavioral measures of negative affect, on the one hand, as well as attitudinal survey measures of populism and real-stakes populist voting behavior on the other. In all studies, we report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study.

In Studies 1a and 1b, we use cross-national survey data from over 150 countries worldwide to relate negative affect with populist attitudes beliefs at the individual level. This analysis includes custom survey questions that allow for us to link the experience of various negative emotions to each of the three main dimensions of populism. In Study 2, we go beyond these attitudinal correlations within surveys, and instead examine cross-country longitudinal data. Here we are able to use national-level data on negative affect at scale and over time, gleaned from repeated large-scale international surveys, and link it to subsequent changes in populist party vote shares over time in real-stakes general elections.

Studies 3 and 4 move from self-reported emotions to public expressions of affect in a real-world setting. In these studies, we analyze sentiment expressed in well over two billion Twitter posts using a language-based assessment (Schwartz et al., 2014; Park et al., 2015). In Study 3, we focus on the 2016 Brexit Referendum in the United Kingdom, and examine the extent to which area-level aggregates of negative sentiment are able to predict voting for the Leave campaign. In Study 4a, we use Twitter data from the USA in order to test the extent to which county-level aggregates of negative sentiment are able to predict voting for Donald Trump in the 2016 presidential election. Finally, in Study 4b, we further replicate these analyses using Tweets before the 2020 presidential election, where there was a populist incumbent, and build on them by estimating longitudinal models that examine the change in emotions and vote shares from one election to the next.

Study 1a: Self-Reported Negative Affect and Populist Attitudes

Materials and Methods

We used data from the Gallup World Poll, which is a large cross-national annual survey including data from nationally representative samples. Around 1,000 respondents per country were surveyed per wave. The survey has been conducted annually since 2005. Focusing on individual-level responses, we analyzed survey reports of both i) discrete emotions and ii) political attitudes. In total, this provides us with a large sample of over 1.3 million respondents from over 150 countries worldwide.

Negative affect was measured by asking respondents whether they had experienced a series of negative emotions yesterday, including worry, anger, and sadness. We used an index of negative affect, which is the mean of the three, as well as looking separately at each discrete emotion. For our outcome measures, we focused on eight attitudinal questions in the survey. Each question had a binary response, corresponding either to yes/no or agree/disagree, with a series of statements that are included in full in the appendix.

We estimated logistic regression models and controlled in each model for a rich set of observable characteristics of survey respondents, including age, age^2, dummies for medium and high education (versus low), dummies for marital status, the natural logarithm of household income, and the number of children in the household, as well as a full set of country fixed effects (and year fixed effects where multiple years of data were available). Standard errors were adjusted for clustering on countries. We report exponentiated coefficients (odd ratios) in the main tables.

Results

The outcome variables in columns (1) to (4) of Table 1 constitute measures of populism that do not have a direct reference to right- or left-wing sentiment, and thus can be thought of as approximating "pure" populist attitudes. In each case, negative affect significantly predicted increased populist attitudes and beliefs. The outcome variables in the remaining columns (5-8) constitute measures of populism that incorporate elements of broader ideologies. For example, in column (5) we used a measure referring to business elites, which is likely to be an example of left-wing populism. In the next two columns we used measures of sentiment towards immigrants, which tap into nativist ideologies and likely resonate with right-wing populists. Across all of the models, we found a consistent pattern of results: negative affect increased the likelihood of respondents' reporting populist beliefs and attitudes.

In Table S1 we break down the analysis by individual emotion. We found that all three emotions that we studied – anger, worry, and sadness – had strong and positive associations with populist beliefs and attitudes. The three emotions show substantial inter-correlations, meaning that introducing them into the same equation can be problematic since it may lead to issues of multi-collinearity and potential suppression effects (cf. Jost, 2019). Nevertheless, as Table S2 in the Supplementary Materials shows, all three emotions remained strongly positive and statistically different from zero even when added into a model simultaneously.

Table 1

Negative Affect and Populist Attitudes in Gallup World Poll

	(1) Leaders Represent My Interests (No = 1)	(2) Government Corruption Widespread (Yes = 1)	(3) Gov Not Doing Enough on Corruption (Yes = 1)	(4) Confident in the Media (No = 1)	(5) Businesspeople Are Good Role Models (No = 1)	(6) Immigrants Living in Country (Bad = 1)	(7) Immigrant As Neighbor (Bad = 1)	(8) Leave The EU (Yes = 1)
Negative Affect (z-score)	1.24***	1.16***	1.14***	1.14***	1.14***	1.11***	1.10***	1.27***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)
Observations	93441	1282853	317867	187067	503920	133763	133261	16226
Mean Dep Var	0.49	0.76	0.61	0.45	0.23	0.28	0.25	0.20
Countries	93	156	129	116	151	136	136	17
Log-Likelihood	-60,588.6	-593,701.0	-187,502.4	-118,678.5	-253,093.4	-68,971.3	-64,935.0	-7,559.2

Notes: Odds ratios reported from logistic regression models. Robust standard errors in parentheses, clustered on countries. Country fixed effects included in all models. All models include controls for gender, age, age^2, education, (log) income, marital status, children in household, and year where there are multiple waves of survey data.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Study 1b: Negative Affect and the Three Main Components of Populism

Materials and Methods

Study 1a showed a strong correlation between negative affect and attitudes that we defined as populist. However, a significant drawback is that the attitudinal measures were not specifically designed with the measurement of populism in mind. We thus collected data from large nationally representative samples in 13 countries worldwide. We were able to insert questions on populism and emotions into the Global Happiness and Political Attitudes Survey (GHPAS), fielded by Yalta European Strategy (YES) in early 2019. The survey includes data from Australia, Brazil, Finland, France, Germany, Hungary, India, Italy, South Africa, Turkey, UK, USA, and Ukraine. Around 1,000 respondents per country were surveyed online (see Appendix for more details of the survey). The survey covers a smaller number of countries than the

Table 2

Negative Affect and Populist Voting in Beliefs in Global Survey

	(1) Populism Index	(2) People-Centrism	(3) Anti-Elitism	(4) Manichean
Negative Affect	0.061***	-0.088***	0.050**	0.158***
	(0.017)	(0.014)	(0.021)	(0.014)
Observations	12659	12659	12659	12659
R^2	0.116	0.115	0.122	0.098
Countries	13	13	13	13

Notes: Robust standard errors in parentheses, clustered on countries. Country fixed effects are included in all models. Outcome variable is the populism index developed by Silva et al. (2018), which is z-scored to have a mean of 0 and SD of 1. Controls included for gender, age bands, marital status dummies, number of children, education (BA or more dummy), employment status dummies, and household income quintiles.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Gallup World Poll used in Study 1a; however, we still use large nationally representative samples in each case, and the data cover countries across six continents, whose population in total sums to be around half of the world's population.

The survey included self-reported questions on the experience of negative emotions "yesterday." The five discrete emotions that were surveyed are stress, anger, sadness, worry, and anxiety. These emotions were measured on a 0 to 10 scale from "not at all" to "all the time." In each case, we z-score the variable to have a mean of 0 and standard deviation of 1, in order to aid interpretation. We added into the survey a battery of questions on populism. The questions were developed and tested by Silva et al. (2018) to measure populist beliefs and attitudes according to the ideational definition of populism, with battery of 9 questions including 3 each on people-centrism, anti-elitism, and Manichean outlook.

We estimated OLS regressions that predicted the overall populism scale, which was the mean of all the items, as well as the 3 sub-scales separately. Our main independent variables were self-reported negative emotions, which we included in the equation separately as well as in a negative affect index (which was the mean of the five emotions). In all models, we included a series of country fixed effects and set of demographic controls including gender, age bands, marital status dummies, number of children, education (BA or more dummy), employment status dummies, and household income quintiles. Standard errors were adjusted for clustering on countries.

Results

The outcome variable in column (1) of Table 2 is the overall index of populist attitudes. We found that negative affect was positively correlated with populist attitudes, controlling for a rich set of observables including gender, age, marital status, number of children, education, employment status, and household income. In Table S3, we break the negative affect index out into its constituent parts. Here we found that sadness, fear, and stress were all strongly correlated with populism. Anger, on the other hand, was not significantly related to the overall measure of populist attitudes.

In columns (2) to (4), we break the overall populism index into its three parts. As we hypothesized above, negative affect was positively associated with anti-elitism and Manichean outlook. Although we made no *a priori* prediction on the relationship between negative affect and people-centrism (which was measured here using questions such as the extent to which people agree that "the will of the people should be the highest principle in this country's politics"), we found that people-centrism was actually negatively associated with negative affect.

Study 2: Changes in Country-Level Negative Affect and Changes in Populist Vote Shares at General Elections

In line with much of the existing literature, the analyses of Study 1 were based on self-reported accounts of both affect as well as populism. In the remainder of the paper, we focus on actual behavior in the form of voting. This is important since populist beliefs may not necessarily translate into voting behavior, which is what ultimately determines electoral outcomes.

Materials and Methods

We studied general elections in 24 European countries between 2005 and 2018, and assessed the relationship between country-level negative affect in the Gallup World Poll and subsequent populist party vote shares. The countries included in the analysis were Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Slovakia, Spain, Sweden, United Kingdom.[2]

We coded parties as either "populist" or "mainstream" according to the classification system of *The PopuList* (Rooduijn et al., 2019), which is a large-scale survey of multiple experts in each country on the basis of which parties display the characteristics of populism as defined by the ideational approach.[3] Our main outcome variable, populist vote share, was the collective vote share received by all of the populist parties at each election, using data drawn from the ParlGov Database (Döring and Manow, 2018).

[2] Countries that were part of the Gallup World Poll, but either i) had no populist party (e.g. Portugal) during the period studied or ii) where we only had one matchable election within 12 months of the survey, were not included in the analysis.

[3] See `https://popu-list.org/` for more details of this data collection.

We matched each general election with the closest wave of the Gallup World Poll carried out in that country prior to the election (if there has been a nationally representative survey in that country in the 12 months prior to that election). We focused on the three negative emotions that have been surveyed consistently throughout the period in the Gallup World Poll. The question asks "*Did you experience the following feelings during a lot of the day yesterday? How about anger? How about worry? How about sadness?*" Answers were recorded in a binary response format (yes/no). We coded the national % who experienced each emotion as our measure of negative affect. For a summary index, we z-scored each emotion at the national level, and then calcualted the mean of the three.

We estimated OLS regression models that included country and year fixed effects. That is, we studied negative affect and populist voting as they vary *longitudinally* within countries over time, holding constant any time-invariant third factors (such as national culture, language, climate, history, and so on) as well as continent-wide shocks (such as the financial crisis). Our analysis was thus focused on within-country changes and not differences between countries, i.e. which countries generally experienced more negative affect overall or which were generally most populist – both of which are likely to vary as a result of a wide range of cultural, geographic and other factors. We also included controls for the three main time-varying macroeconomic indicators typically used in the voting literature: GDP, unemployment, and inflation.

Results

In Table 3 we report coefficients from these longitudinal models, using a summary index of negative affect to begin with. A one standard deviation increase in negative affect was associated within countries over time with around a 5.6 percentage point increase in populist party vote share, from a base of around 20%. This corresponds to a sizable association, since a 5.6 percentage point gain is equivalent to over a third of a standard deviation of populist vote shares during the period.

In line with the academic literature and the popular discussion of populism, populist gains were also predicted by factors capturing the strength of the national economy (see Models (2)-(4) of Table 3). Increases in real GDP per capita depressed the populist vote, while rises in the unemployment rate were found to raise it. When including both negative affect and macroeconomic factors in the same model, the association of negative affect with populist vote shares were slightly reduced, but remained statistically robust and substantively significant in magnitude.

In addition to the index of negative affect, we also investigated the relationships between the three discrete emotions and populist vote share separately. As Table S9 in the Supplementary Materials illustrates, the same positive relationship with populist vote share was found for all three emotions. Although the

Table 3

Negative Affect and Populist Voting in Europe

	DV: Populist Vote Share				
	(1)	(2)	(3)	(4)	(5)
Negative Affect (z-score)	5.61**				4.41*
	(2.02)				(2.20)
GDP per capita (log)		-36.11**			-37.91
		(14.74)			(27.26)
Unemployment Rate (%)			0.66*		-0.47
			(0.36)		(0.67)
Inflation Rate (%)				0.95	0.96
				(0.92)	(0.82)
Observations	77	77	77	77	77
Countries	24	24	24	24	24
Country & Year FEs	✓	✓	✓	✓	✓
Within R^2	0.135	0.089	0.050	0.031	0.196
Overall R^2	0.850	0.843	0.836	0.832	0.861

Notes: Robust standard errors in parentheses, clustered on countries. Sample in all models is 77 general elections, in 24 European countries between 2005 and 2018. Country and year fixed effects are included in all models. Outcome variable is the collective vote share received by populist parties at the election, lying between 0 and 100. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

literature focused on survey measures of negative affect and populist attitudes to date has focused on fear and anger, we found that within-country changes in sadness was a more powerful predictor of subsequent changes in populist vote shares in real-stakes elections.

In Study 1 we included all 3 emotions in the equation simultaneously, and found each had a significant association with populist beliefs independently (see Table S2). However, given concerns that these correlated negative emotions may lead to issues of multicollinearity and potential suppression effects (cf. Jost, 2019), we examined variance inflation factors (VIFs) for these three variables and found them to be reassuringly low in that context (in the region of 1 to 1.5). But once the three emotions were aggregated to the country level in this study, introducing all three emotions simultaneously is likely to become much more problematic. For our equation in Study 2 we calculated VIFs in the region of 15 to 25 for the three emotion variables when included together, and thus we did not report results from these regressions. We found similar problems of multicollinearity in Studies 3 and 4, which also used aggregated emotions. As a result, we largely look at negative affect broadly as a dimensional concept or introduce negative emotions individually into voting equations.

Study 3: Expressed Negative Affect and Brexit Voting

Materials and Methods

In this preregistered study, we used natural language processing to examine the correlation between expressed negative affect in Twitter posts and populist voting in the 2016 referendum in the UK (also known as the "Brexit" vote). The campaign to leave the EU was defined by populist themes. Much of the Leave campaign's discourse also focused on the perceived nefarious workings of a Brussels elite, and their allies in the domestic 'liberal elite'.

We analyze Twitter posts in the United Kingdom during 2015, the year prior to the referendum. Unlike in Studies 1 and 2, the sample used here is not representative of the national population at large, but is rather the universe of posts during 2015, with a preregistered set of filters. We first identified the local authority district (LAD) of each tweet, using a combination of tweets' geographic coordinates as well as self-reported location, as described in Schwartz et al. (2013).[4] We included tweets posted in English, limiting the analysis to include users with at least 30 tweets during that year. In total, 372 LADs in Great Britain had at least 100 eligible users. This amounted to data drawn from 62,971,196 tweets from 177,014 users.

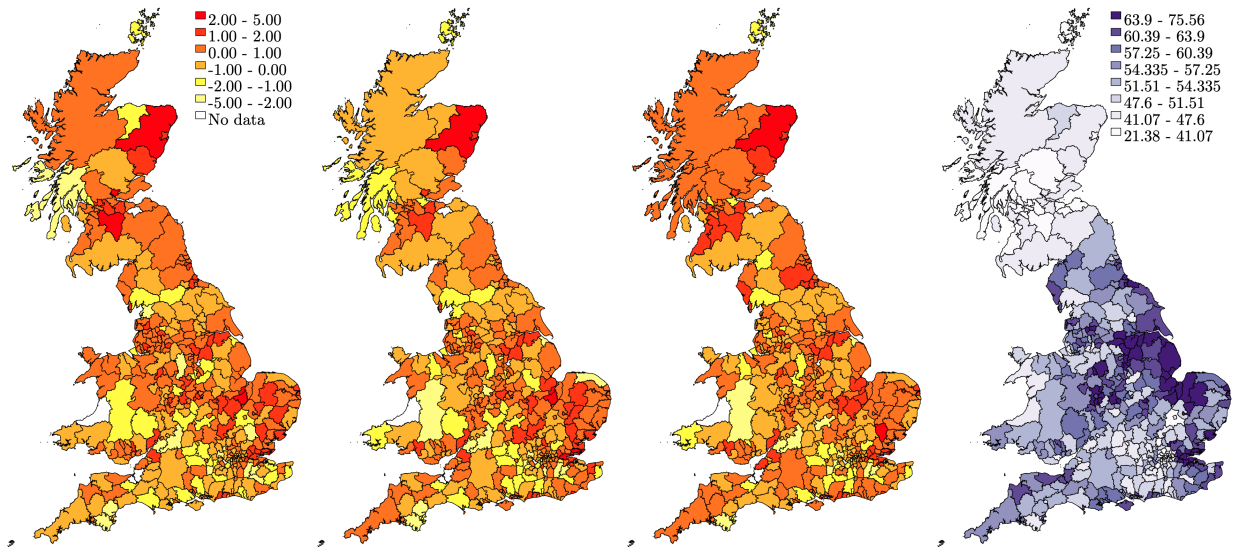
We analyzed word frequencies in order to measure expressed anger, anxiety, and depression at the LAD-level using a language-based assessment. Language-based assessments derive scores from the frequency with which terms are mentioned (Park et al., 2015; Kern et al., 2016). This language-based approach has been used to compare expressed affect with community life satisfaction (Schwartz et al., 2013), health behaviors (Culotta, 2014), heart disease mortality rates (Eichstaedt et al., 2015), and drinking behaviors (Curtis et al., 2018). Linguistic data from these Twitter posts were aggregated in a way that mirrors survey data. We first calculated the mean rate of words or topics (clusters of words) per user, and subsequently used those means to calculate an average across all users in a given LAD (Giorgi et al., 2018). Using these LAD-level average values for each of the linguistic features, we applied a previously validated, language-based assessment to estimated area-level expressed depression, anger, and anxiety (for more details see Schwartz et al., 2014). All models were applied using the Differential Language Analysis ToolKit, a social science language analysis library for Python (Schwartz et al., 2017).

There is considerable spatial variation in the incidence of negative affect across Great Britain, even within relatively fine-grained geographical regions (see Figure 2). We estimated LAD-level weighted least squares (WLS) regression models, where each LAD was weighted by its total number of votes cast in the referendum. We controlled for a rich set of area-level variables, including median income, income inequality,

[4] Votes were counted at the level of the LAD in the referendum, making it the smallest geographical unit to analyze in terms of voting behavior and outcomes.

Figure 2

Spatial Distribution of Negative Affect in Great Britain. Panels (a) to (c) show the spatial distribution of negative affect across the UK in 2015. Panel (d) shows the spatial distribution of the Leave vote in the 2016 referendum. Each emotional variable is z-scored to have a mean of 0 and a standard deviation of 1.



(a) *Anger* (b) *Anxiety* (c) *Depression* (d) *Leave Vote*

unemployment, population density, and migrant stock. Full details of these covariates are provided in the Supplementary Materials.

We further tested the robustness of our findings by examining voting in the 2019 EU Parliamentary Election in the UK. Using the same methodology, we estimated LAD-level measures of negative sentiment using tweets post during the year 2018, and correlated these with the collective vote share of the Brexit Party and the U.K Independence Party (neither of whom were incumbent parties) in May 2019. Finally, we estimated models in which we regressed the change in Leave vote share from 2016 to 2019 on the change in LAD-level negative affect from 2015 to 2018. These longitudinal models take the strength empirical analysis further, since they have the key benefit of netting out all of the unobserved aspects of LADs that are time-invariant such as culture, political history, climate, human and social capital, and so on.

Results

The results of pre-registered multiple regression analyses show that all three affective variables were strongly correlated with the Leave vote across Great Britain, with anger showing the strongest and most robust link (see Table 4). Overall, a one standard deviation increase in anger levels raised the Leave vote by around 3 percentage points (in a referendum that was won 52-48). A one standard deviation increase

Table 4

Negative Affect and Brexit Voting

	DV: Leave Vote Share								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anger	2.86***	3.10***	2.33***						
	(0.58)	(0.48)	(0.39)						
Anxiety				1.89***	1.94***	1.36***			
				(0.59)	(0.47)	(0.38)			
Depression							1.96***	2.10***	1.22***
							(0.59)	(0.49)	(0.39)
Observations	372	372	363	372	372	363	372	372	363
R^2	0.06	0.48	0.70	0.03	0.45	0.68	0.03	0.45	0.68
Region FEs		✓	✓		✓	✓		✓	✓
Full Controls			✓			✓			✓

Notes: Local authority-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Referendum. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variable is the Leave vote share, lying between 0 and 100. Emotional variables are drawn from tweets posted in 2015 (see Methods for further details).

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

in anxiety and depression raised the Leave vote share by around 2 percentage points. These correlations remained robust when comparing districts within narrowly-defined regions (see columns 2, 5 and 8). The inclusion of region effects—such that we are comparing local authorities within the same geographic area—strengthens the relationship both in terms of magnitude and statistical precision. One reason for this is the presence of Scotland in our initial regression analyses. While Scottish local authorities tended to express more negative affect (see Figure 2), Scotland largely voted to remain in the EU. Nevertheless, even when looking solely across the districts within Scotland (see Table S14 in the Supplementary Information), there was a robust relationship between negative affect and the proportion of vote shares for the Leave campaign.

These associations were robust to the inclusion of a set of observable covariates such as prior leave vote (in the 1975 referendum), area-level log income, employment, population density, and EU migrant stock (see columns 3, 6 and 9). These additional regressions are best seen as sensitivity checks, since many of these factors may be causing any variation in negative affect – thus "controlling" for an exhaustive set of LAD characteristics may lead to issues of mis-specification and variance inflation.

The observed associations were not likely to be driven by reverse causality (i.e. the Leave campaign stirring up negative affect) since we measured affect in 2015, prior to the announcement of the referendum in February 2016. Moreover, in additional sensitivity checks, we included a more exhaustive set of covariates such as the proportion of public housing, income inequality, age, trait neuroticism, and EU funds received per capita (see Table S15 in the Supplementary Information). The inclusion of area-level education in Table

S15 brought down the size of the coefficient substantially for both anxiety and depression. Instead, the most robust relationship in the case of the UK analysis was between expressed anger and populist voting, particularly once education was accounted for in the equation.

As can be seen in Table S17, we found—in line with our initial findings—that negative sentiment was strongly predictive of populist voting in the 2019 European Parliament elections (this time using the vote share of the Brexit Party). These results also held when including a powerful lagged dependent variable in the equation, namely the vote share received for leave in the 2016 referendum. In Table S19 we go further than this and present longitudinal models in which we regressed the *change* in leave vote between 2016 and 2019 on the *change* in expressed affect between 2015 and 2018. Here we found consistent evidence that negative affect was strongly associated with populist voting. As above, we found that in the case of the UK, anger was most strongly associated with populist behavior. These longitudinal findings corroborate that our results were not likely to be driven by confounding variation in other key factors, and suggest that negative sentiment—and, in the UK, expressed anger in particular—was strongly predictive of populist voting over and above what is typically considered in the literature. In this instance, we tracked the vote share of the Brexit party, a non-incumbent populist party. Notably, the party was able to pick up the votes of people experiencing negative affect when running against Boris Johnson's incumbent Conservative Party, who in general supported Brexit and has taken populist stances on a number of issues. This provides initial suggestive evidence that the electoral calculus changes for populists once they are in power.

Study 4a: Expressed Negative Affect and Trump Voting in the 2016 Presidential Election

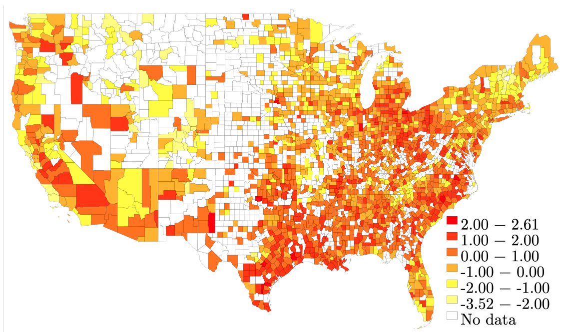
Materials and Methods

We used the same natural language processing approach to examine the correlation between expressed negative affect in Twitter posts and vote shares for Donald Trump in the 2016 US Presidential Election. We analyzed the word frequencies from 1.53 billion Twitter posts across the USA prior to the 2016 presidential election to measure expressed anger, anxiety, and depression at the county level using a language-based assessment. Specifically, we used the County Tweet Lexical Bank (Giorgi et al., 2018) which contains the mean frequencies with which the most common 25,000 terms in US tweets were used between 2009 and 2015 (before the 2016 presidential campaign began) among members of 2,041 US counties. These term frequencies were fed to a language-based assessment for depressive, angry, and anxious language (Schwartz et al., 2014).

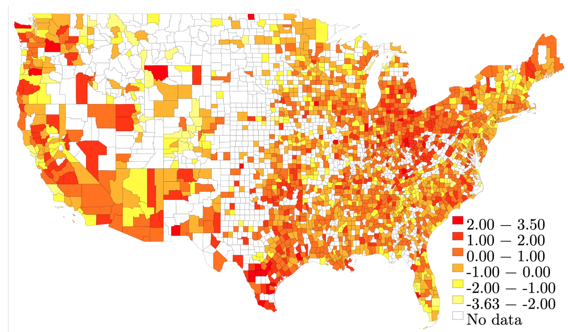
We tested the extent to which county-level aggregates of negative sentiment were able to predict a) the Trump vote share in 2016, b) the electoral swing toward Trump in 2016 from previous elections, and c) the

Figure 3

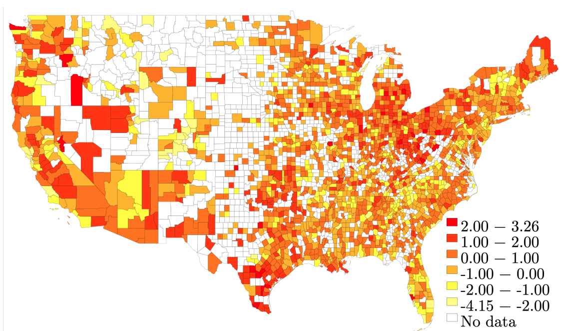
Spatial Distribution of Negative Affect and Voting in the USA. Panels (a) to (c) show the spatial distribution of negative emotions across the USA, 2009-2015. Panel (d) shows the spatial distribution of voting in the 2016 election, compared to baselines – specifically, Δ(Trump Vote - Republican Average 2000-2012). Each emotional variable is z-scored to have a mean of 0 and a standard deviation of 1.



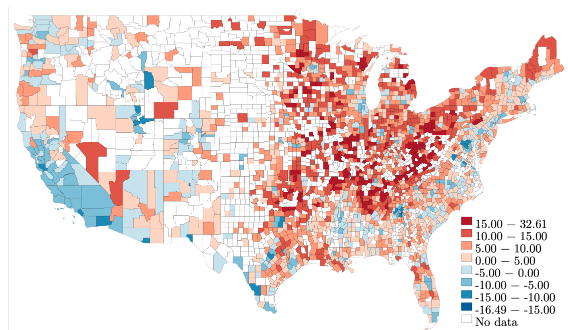
(a) *Anger*



(b) *Anxiety*



(c) *Depression*



(d) *Trump Voting*

Trump vote share in the Republican primary elections. We estimated county-level weighted least squares (WLS) regression models, where each county was weighted by its total number of votes cast in the 2016 Presidential Election. We controlled for a rich set of county-level variables, including income, unemployment, racism, age, race, population density, moral values, and trade exposure. Full details of these covariates are provided in the Supplementary Materials.

Results

Figure 3 shows that there is considerable variation in negative sentiment across counties, even within relatively narrow geographical regions. All three affective states were strongly predictive of Trump voting across the three measures (see Table 5). While much of the popular discussion in the USA focuses on the effects of anger, we found that anxiety and depression were equally, if not more strongly, associated with Trump voting in 2016.

Table 5

Negative Affect and Voting in the USA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A	DV: Trump Vote Share in 2016 Presidential Election								
Anxiety	6.79***	3.74***	4.03***						
	(0.36)	(0.30)	(0.30)						
Anger				3.37***	2.56***	2.59***			
				(0.40)	(0.31)	(0.33)			
Depression							6.95***	3.34***	4.05***
							(0.35)	(0.30)	(0.30)
R^2	0.39	0.72	0.88	0.31	0.71	0.87	0.40	0.72	0.88
Panel B	DV: Δ(Trump - GOP Baseline)								
Anxiety	3.36***	1.76***	1.74***						
	(0.13)	(0.12)	(0.12)						
Anger				2.53***	1.42***	1.16***			
				(0.14)	(0.12)	(0.13)			
Depression							3.64***	1.97***	1.88***
							(0.12)	(0.12)	(0.12)
R^2	0.51	0.72	0.87	0.42	0.70	0.86	0.55	0.72	0.87
Panel C	DV: Trump Vote Share in 2016 Republican Primaries								
Anxiety	3.41***	2.11***	1.62***						
	(0.16)	(0.17)	(0.23)						
Anger				3.22***	1.95***	1.58***			
				(0.17)	(0.18)	(0.24)			
Depression							3.57***	2.27***	1.79***
							(0.16)	(0.17)	(0.23)
R^2	0.88	0.91	0.93	0.88	0.91	0.93	0.89	0.91	0.93
State FEs	✓	✓		✓	✓		✓	✓	
Commuting Zone FEs			✓			✓			✓
Full Controls		✓	✓		✓	✓		✓	✓

Notes: County-level WLS estimates using N=2,030 counties. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Presidential Election. Full controls: log(median household income), unemployment rate, log(population density), racism index, fraction religious, longitude, latitude. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In each case, we z-scored the negative sentiment variables such that they had a mean of 0 and a standard deviation of 1 across the counties we studied. An increase in anxiety of one standard deviation increased the Trump vote share in 2016 by around 7 percentage points (see column (1) of Panel A). This association was not driven by confounding variation in a set of observable county characteristics (such as median household income, unemployment, religiosity, and racism), and remained robust when including a full set of state fixed effects to further reduce the threat of unobserved “third variables” driving the relationship (i.e. when we compare between counties within any given state; see column (2)). Finally, the associations remained stable when including fixed effects for commuting zones (small clusters of counties that make up a local labor market) to provide even tighter restrictions to spatial variation such that we essentially compared between neighboring or near-neighboring counties.

While the absolute proportion of Trump’s vote share is somewhat informative, a comparison with

Republican baselines provides additional confidence in the validity of effects (see Panel B of Table 5). That is, our analyses aimed to move away from predicting which counties are *generally* more Republican,[5] and instead focused on whether negative affect could predict which states swung most concertedly towards Donald Trump in 2016.[6] Examining the relationship between negative affect and the Trump vote swing, we found consistent evidence that angrier, more anxious, and sadder areas were more likely to shift their vote in the direction of Trump compared to the Republican vote share one would historically expect.

Finally, in Panel C of Table 5, we replicated the previous findings by focusing on the Republican primary elections in 2016. In line with the previous results, we show a consistent impact of negative affect on increasing support for Trump's populist candidacy, even when we only focus on votes within the Republican party. This is important since in analyses such as those in Study 2 above it can be difficult to disentangle non-incumbent voting from populist voting. Here we observed a strong relationship between negative sentiment and voting for a populist candidate within an election race where all candidates are ultimately running against the incumbent Democratic Party.

These correlations are unlikely to be driven by reverse causality (i.e. by negative affect stirred up by Donald Trump), since our sentiment measures were collected before Donald Trump entered the political sphere. Moreover, in addition to conditioning on state and commuting zone fixed effects, we provide further evidence that our findings were not driven by confounding variation in an even more exhaustive set of control variables, such as trade exposure, income inequality, racial and age structure of counties, and trait neuroticism (see Table S26 in the Supplementary Information). Again, given that many of these observable variables may themselves have been related to variation in negative affect, these analyses are best thought of as sensitivity checks, because "controlling" for an exhaustive set of county characteristics inevitably runs the risk of leading to mis-specification and variance inflation.

---

[5] A long-running literature examines whether liberals are generally more or less happy than conservatives (e.g. Napier and Jost, 2008). We were interested in this paper whether sentiment can explain the swing toward Trump over and above this.

[6] The importance of distinguishing between those two outcomes is illustrated by median household income. While median household income was positively correlated with the level of the Trump vote share in 2016 (consistent with the typical finding that wealthier areas are usually more Republican), it was negatively correlated with the Trump swing in 2016 (for full reporting of the coefficients from these models, see Tables S22 to S25).

Study 4b: Longitudinal Analysis of Negative Affect and Populist Voting in the USA

Materials and Methods

We replicated our analysis from Study 4a, this time using county-level vote shares at the 2020 election. In order to measure affect, we followed the same logic as the previous study, and used Twitter data from 2019. We examined the cross-sectional relationship between affect and voting in 2020, controlling for a rich set of county-level covariates. And moving beyond this, we also looked at the longitudinal relationship between negative affect and voting. Here we regressed the change in Donald Trump's vote share on the change in county-level negative affect, and also controlled for changes in household income and unemployment.

Table 6

Negative Affect and Trump Voting: Longitudinal Evidence

	Δ Trump Vote Share (2020-2016)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Anger (2019-2015)	-0.59***	-0.44***				
	(0.09)	(0.09)				
Δ Anxiety (2019-2015)			-0.25***	-0.17**		
			(0.09)	(0.09)		
Δ Depression (2019-2015)					-0.38***	-0.31***
					(0.09)	(0.08)
Δ Log Income (2019-2015)		16.19***		15.42***		15.64***
		(1.57)		(1.58)		(1.57)
Δ Unemployment (2019-2015)		-1.20***		-1.34***		-1.32***
		(0.12)		(0.12)		(0.12)
Observations	1344	1344	1344	1344	1344	1344
R^2	0.03	0.18	0.01	0.16	0.01	0.17

Notes: County-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2020 Presidential Election. Affect variables are standardized using their means and SDs in 2016. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Results

In Table 6, we present the findings from our longitudinal analysis. In line with a theoretical approach that stresses the role of negative affect in signaling threat and cuing a desire for change, we found that changes in negative affect were negatively related to changes in the Trump vote share. That is, counties that improved emotionally (i.e. reduced their negative affect) were more likely to support Trump, while counties that got worse emotionally turned against the incumbent. In these "first-difference" regressions, negative affect behaved much like other variables typically used in predicting electoral outcomes in the incumbent voting literature – "positive" changes, like lower unemployment and higher household incomes, increase support for incumbents running again. Ultimately, then, populists who gained power by appealing to sad, angry, and anxious voters seem to face difficulty once they are in power.

Discussion

Our findings add to a small but growing literature on negative emotions and populism (e.g., Rico et al., 2017, 2020; Webster, 2018; Oliver and Rahn, 2016; Salmela and von Scheve, 2017). We draw on affect-as-information theory, which suggests that affective states provide people with a meaningful source of information about the world around them and, in doing so, signal whether a situation is conducive or threatening to an individual's well-being and progress (Schwarz, 1990). We argue that negative affect, at a high level, provokes a desire for change. This is promised in radical form by populist political actors. Across a range of political and geographical contexts, we find strong support for the hypothesis that negative affect shapes populist support, not only in terms of people's beliefs and attitudes but also when it comes to voting in high-stakes elections with significant consequential outcomes.

Theoretical Considerations

Our findings contribute to the theoretical debate seeking to explain the upward trend in populist support in a number of ways. First, while this burgeoning academic literature has sought to explain the rise of populism largely by focusing on a range of economic versus cultural factors, we instead assess a more proximal indicator of behavior. The proposition that negative affect plays a key role in shaping populist support does not stand in contention with these existing explanations, however. Rather, it adds to their explanatory and predictive power by considering affective states as a proximal *psychological pathway* through which these distal factors influence political beliefs – and, ultimately, voting behavior and electoral outcomes (cf. Ward et al., 2021). Indeed, one thing that many of the cultural and economic discourses surrounding populism have in common is that they emphasize discontent. We suggest that while a range of circumstances of people's lives—cultural, economic, or otherwise—may explain why some sections of the electorate experience disproportionate amounts of negative affect, it is these moods and emotions that ultimately funnel into political beliefs and behavior.

Second, we find that various negative emotions, including anger, fear, anxiety, sadness, and depression all predict populist support and voting. Much of the public discourse on negative affect and populism has focused on the discrete emotions of anger and fear. We move this debate forwards by showing that negative emotions beyond anger are strongly predictive of populism. Indeed, it is not only high-activation negative emotions such as anger and anxiety that drive populist support, but also low-activation negative emotions such as depression and sadness that predict people's populist attitudes, beliefs, and behavior.

Third, our approach to affect differs from much of the existing literature on populism (and related concepts), which has focused on discrete emotions specifically tied to various political phenomena, such as fears about the economy, anxiety about immigration, or anger at particular political candidates. Instead, we tested a more general argument about the role of negative affect, broadly understood, on behavior.[7] This is important given the remarkable yet under-discussed rise in the experience of negative affect worldwide over the past decade (Gallup, 2022), which has been called a "blind spot" for politicians who have missed this large change in the way people feel in their day-to-day lives (Clifton, 2022).

Fourth, while much of the existing literature studies a range of related outcomes such as Far Right voting, authoritarianism, and conspiracy thinking (e.g. Jost, 2019; Vasilopoulos et al., 2019; Marcus et al., 2019), the analysis presented in this paper focuses on the electoral demand for a specifically-defined concept: populism. We fielded a survey with a battery of attitudinal questions designed to measure each of the three core tenets of populism and also used electoral data coded according via an expert survey to define populist parties according to the ideational definition.

Fifth, we were able to consider differences in the relationship across the three main tenets of populism. This is important since the theoretical links between negative affect and populism are not straightforward, particularly when it comes to people-centrism. We identified strong theoretical links between the experience of negative affect and antielitism as well as Manichaenism, but we did not hypothesize a link between negative affect and people-centrism. In the empirical analysis, we actually found that negative affect is related to the people-centric aspect of populism in the other direction: higher levels of negative affect decrease people-centric attitudes. Although this requires further theorizing and empirical research, the initial evidence suggests that populism is not simply synonymous with discontent. The mix between i) a largely negative outlook emphasizing crises and betrayal coupled with ii) a more hopeful belief in the power of the general will of the people is, ultimately, what makes populism a set of ideas that go beyond just political grievance. Nevertheless, the data do suggest that although populism may have positive emotional aspects to it, it remains dominated by its negative antielitist and Manichean components when it comes to consequential behavior at the polls, given that negative affect ultimately strongly predicts populist voting and election

[7] This adds to work that takes a dimensional approach on the positive side of affect, which has investigated the links between subjective wellbeing and subsequent incumbent voting patterns, showing that sitting governments tend to struggle to get re-elected when the population has low levels of general happiness (see, e.g., Ward, 2020; Liberini et al., 2017; Ward et al., 2021).

results.[8]

Finally, we considered the role of affect in shaping support for incumbent populists, something that is an ever more common occurrence as populist parties gain power. We find that while populist politicians are able to capitalize on the negative affect of voters, the data suggest that this is no longer true once they are in power. Counties in the USA that deteriorated emotionally were more likely to swing against Trump in 2020 compared to 2016, for example. Having appealed to sad, angry, and anxious voters by promising radical change that would improve the experience of their lives, populist politicians have to deliver if they want to retain these voters. This finding is in line with theoretical accounts that see negative affect, broadly understood, as signaling threat and cuing a desire for change. This provides a potential challenge for theoretical accounts that either emphasize congruence between the negative emotional content of populist discourse and the experience of negative emotions by the population, or that focus on specific action tendencies associated with a particular emotion and populism. The hypothesis that people experiencing higher levels of negative affect will be drawn towards the negative tone of populists, for example, would be expected to hold up regardless of whether that populist actor was already in office or not. Similarly, if populist discourse is tied up with a sense injustice, which is associated with the emotion of anger, we might again expect that to be the case regardless of whether or not the populist was an incumbent.

Limitations and Future Research

We take a multi-modal and multi-method approach that has a number of advantages, but also some potential limitations. First, our empirical approach allowed us to move beyond self-reported populist attitudes to actual voting behavior and consequential election results at scale. This is critical given that there is often a considerable gap between the attitudes people report and the actions they take in the real world (Baumeister et al., 2007), particularly in contexts that can be prone to social desirability biases, such as populist attitudes and voting. Nevertheless, further research may look further into the dynamics of the causal chain in this regard and try to better understand the ways in which negative emotions may lead to populist attitudes and behaviors in potentially different ways – for example, building on work that has shown anger (in response to injustices) is likely to motivate action in particular (cf. Tausch et al., 2011).

Second, we used both emotional experience (measured via self-reports within large, nationally representative samples of a large and varied set of countries) and emotional expression (measured via natural

[8] Populism may vary in terms of the extent to which populist actors emphasize anti-elitist elements versus people-centric ones. In this case, we may expect the extent to which negative affect predicts support to vary somewhat, with negative emotions drawing people to populism more so in instances where populist discourse is weighted heavily toward anti-establishment messages.

language processing of Twitter posts). The use of measures of affect that do not rely on self-reported data (such as those predicted from digital footprints) helps to overcome issues surrounding mis-measurement of emotions through self-reports and also to mitigate the risk of overestimating relationships due to common method bias when relying on survey data in which both predictors and outcomes are asked at the same time (Baumeister et al., 2007; Youyou et al., 2017). Further research using survey data may, rather of using natural language processing techniques, instead look to overcome issues surrounding self-reported emotions using measures of implicit negative affect (Quirin et al., 2009).

Third, our data allowed us to study a wide range of contexts. We go beyond existing empirical evidence (which typically relies on single-country studies, usually in wealthy Western societies) by using data from a diverse range of 150 countries around the world. Nevertheless, further research may seek to investigate possible moderators of the relationship between negative affect and populism related to the cultural, political, and geographic context across these countries. Moreover, while we use samples in Studies 1 and 2 that are representative of each country studied in terms of a range of demographic and socioeconomic characteristics, additional research may investigate potential moderators related to such characteristics.

Fourth, although we were able to use data on multiple negative emotions, the study of discrete emotions is likely better studied in more controlled environments where it is easier to disentangle these typically intercorrelated phenomena. Indeed, our more dimensional approach is not necessarily in contention with work on individual discrete emotions. While our setting was not well suited to studying fine-grained mechanisms and distinguishing between different negative emotions, further research, most likely in laboratory settings, will be useful to more fully understand these processes. One line of research could, for example, look more closely at the ways in which mood may affect information processing style (cf. Forgas, 2007; Harmon-Jones et al., 2013; Bohner and Weinerth, 2001), and in doing so affect how people interpret the news as well as their scrutiny of populist messaging. Equally, further research may investigate more closely differences across discrete emotions, building on work that shown that anger can lead people to rely more heavily on heuristics or pre-conceived ideas, and fear to information-seeking behavior that is focused on finding threats (e.g. MacKuen et al., 2010; Albertson and Gadarian, 2015; Marcus et al., 2000).

A significant limitation of our study is that we rely on observational data, and we are therefore unable to make any strong causal claims. Using observational data in multiple contexts, we are able to show consistent patterns of behavior in real-world, real-stakes elections. However, it is likely that at least some of the effect operates in both directions (see, e.g., Schumacher et al., 2022; Nai, 2018; Widmann, 2021). In a laboratory setting, Seawright (2012) finds that experimentally manipulated anger raises support for "outsider" candidates in hypothetical electoral choices, lending some support to the notion that the types of correlation we observe may be causal. However, further research is required – for example, looking to employ natural field experiments that make use of potentially exogenous shocks to voter mood at scale.

We took a number of steps to ensure the robustness of the (partial) correlations we observe. For example, using data on emotional experience and expression in years or months before each instance of populist voting, we show that these associations are unlikely to be driven by reverse causality. In addition, we control for the potentially confounding effects of a large set of economic and cultural drivers that have previously been linked to populism such as income, unemployment, trade shocks, migrant share, trait neuroticism, and others. The findings are also robust when relying on variation within narrowly defined geographic regions such as commuting zones in the USA and government regions in the UK, further alleviating concerns related to omitted variable bias. Moreover, we showed that our main findings are robust in longitudinal models. This was true both in the case of country-level panel analyses that considered changes in negative affect and subsequent changes populist party vote shares over time in Europe as well as in area-level analyses in the UK and USA that linked changes in affect to changes in voting patterns.

Predictive Utility of Affective Data

While more work is needed to corroborate the causal links between affect and populist voting, our analyses provide useful *predictive* evidence, irrespective of the underlying causal mechanisms (Yarkoni and Westfall, 2017). Regardless of the extent to which the effects are causally determined, the empirical relationships between negative affect and subsequent populist voting may be used for forecasting political behavior and outcomes across geographic regions for which self-reported or publicly expressed sentiment are available. In Table S28, we document the incremental amount of variance in populist outcomes that can be explained over and above the usual predictors used in the literature, such as GDP, unemployment, inflation, and so on. In each case, we found that the addition of affect and sentiment into the equation explains a significant amount of additional variance – in the case of European general elections more than double.

Notably, none of the prominent forecasting models currently deployed to predict election outcomes includes affect as a predictor. A potential reason for this is that affect has traditionally been difficult to measure at scale. However, many countries around the world now include questions on discrete emotions in large national surveys (Krueger and Stone, 2014), and polling companies measure people's emotional experience in numerous countries on a regular basis. Furthermore, our work suggests that predictive models could take advantage of novel real-time measures of population sentiment, such as automated prediction of negative affect and mood on social media platforms such as Twitter and Facebook (e.g. Schwartz et al., 2013). While these estimates may be biased in their own way (e.g. skewing toward younger individuals), our results suggest that they can nevertheless add considerable value when considered in the context of forecasting election outcomes.

Conclusion

Across a range of geographical and political contexts, we establish a clear link between negative affect and the demand for populism. While each of our settings, samples, and methodologies has both advantages and disadvantages, taken together the analyses tell a compelling story of a robust empirical link between negative affect and the demand for political populism.

References

Abelson, R. P., Kinder, D. R., Peters, M. D., and Fiske, S. T. (1982). Affective and semantic components in political person perception. *Journal of personality and social psychology*, 42(4):619.

Albertson, B. and Gadarian, S. K. (2015). *Anxious politics: Democratic citizenship in a threatening world.* Cambridge University Press.

Autor, D., Dorn, D., and Hanson, G. (2018). When work disappears: Manufacturing decline and the falling marriage-market value of young men. *American Economic Review: Insights*, 1(2):161–78.

Bakker, B. N., Rooduijn, M., and Schumacher, G. (2016). The psychological roots of populist voting: Evidence from the united states, the netherlands and germany. *European Journal of Political Research*, 55(2):302–320.

Baumeister, R. F., Vohs, K. D., and Funder, D. C. (2007). Psychology as the science of self-reports and finger movements: Whatever happened to actual behavior? *Perspectives on Psychological Science*, 2(4):396–403.

Becker, S. O., Fetzer, T., and Novy, D. (2017). Who voted for Brexit? A comprehensive district-level analysis. *Economic Policy*, 32(92):601–650.

Blow, C. M. (2020). Trump's army of angry white men. *The New York Times.*

Bohner, G. and Weinerth, T. (2001). Negative affect can increase or decrease message scrutiny: The affect interpretation hypothesis. *Personality and Social Psychology Bulletin*, 27(11):1417–1428.

Brader, T., Marcus, G. E., and Miller, K. L. (2011). Emotion and public opinion. In *The Oxford Handbook of American Public Opinion and the Media.*

Canovan, M. (2004). Populism for political theorists? *Journal of Political ideologies*, 9(3):241–252.

Chetty, R. and Hendren, N. (2018). The impacts of neighborhoods on intergenerational mobility II: County-level estimates. *The Quarterly Journal of Economics*, 133(3):1163–1228.

Clifton, J. (2022). *Blind Spot: The Global Rise of Unhappiness and How Leaders Missed It.* Gallup Press.

Colantone, I. and Stanig, P. (2018). The trade origins of economic nationalism: Import competition and voting behavior in western europe. *American Journal of Political Science*, 62(4):936–953.

Culotta, A. (2014). Estimating county health statistics with Twitter. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*, pages 1335–1344. ACM.

Curtis, B., Giorgi, S., Buffone, A. E., Ungar, L. H., Ashford, R. D., Hemmons, J., Summers, D., Hamilton, C., and Schwartz, H. A. (2018). Can Twitter be used to predict county excessive alcohol consumption rates? *PloS ONE*, 13(4):e0194290.

Demertzis, N. (2006). Emotions and populism. *Emotion,Politics and Society*, pages 103–122.

Döring, H. and Manow, P. (2018). Parliament and government composition database (parlgov). *An infrastructure for empirical information on parties, elections and governments in modern democracies. Version*, 12(10).

Dorn, D., Hanson, G., Majlesi, K., et al. (2020). Importing political polarization? the electoral consequences of rising trade exposure. *American Economic Review*, 110(10):3139–83.

Durand, M. (2018). Countries' experiences with well-being and happiness metrics. In Sachs, J., editor, *Global Happiness Policy Report*, pages 200–245. Global Happiness Council.

Eichstaedt, J. C., Schwartz, H. A., Kern, M. L., Park, G., Labarthe, D. R., Merchant, R. M., Jha, S., Agrawal, M., Dziurzynski, L. A., Sap, M., et al. (2015). Psychological language on Twitter predicts county-level heart disease mortality. *Psychological Science*, 26(2):159–69.

Fair, R. C. (1978). The effect of economic events on votes for president. *Review of Economics and Statistics*, 60:159–73.

Fetzer, T. (2019). Did austerity cause Brexit? *American Economic Review*, 109(11):3849–86.

Forgas, J. P. (2001). *Feeling and thinking: The role of affect in social cognition*. Cambridge University Press.

Forgas, J. P. (2007). When sad is better than happy: Negative affect can improve the quality and effectiveness of persuasive messages and social influence strategies. *Journal of experimental social psychology*, 43(4):513–528.

Forgas, J. P., Crano, W., and Fiedler, K. (2021). The psychology of populism: The tribal threat to liberal democracy. In Forgas, J. P., Crano, W., and Fiedler, K., editors, *The Psychology of Populism*, pages 81–104. Routledge.

Gallup (2022). *Gallup 2022 Global Emotions Report*. https://www.gallup.com/analytics/349280/gallup-global-emotions-report.aspx.

Giorgi, S., PreoŢiuc-Pietro, D., Buffone, A., Rieman, D., Ungar, L., and Schwartz, H. A. (2018). The remarkable benefit of user-level aggregation for lexical-based population-level predictions. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1167–1172. Association for Computational Linguistics.

Gross, J. J. and Barrett, L. F. (2013). The emerging field of affective science. *Emotion*, 13(6):997.

Guriev, S. (2018). Economic drivers of populism. *AEA Papers and Proceedings*, 108(1):200–203.

Harmon-Jones, E., Gable, P. A., and Price, T. F. (2013). Does negative affect always narrow and positive affect always broaden the mind? considering the influence of motivational intensity on cognitive scope. *Current Directions in Psychological Science*, 22(4):301–307.

Hawkins, K. A., Carlin, R. E., Littvay, L., and Kaltwasser, C. R. (2018). *The ideational approach to populism: Concept, theory, and analysis*. Routledge.

Helliwell, J. F., Huang, H., and Wang, S. (2019). Changing world happiness. In Sachs, J., Layard, R., and Helliwell, J. F., editors, *World Happiness Report*. Columbia Earth Institute.

Hibbs, D. A. (2000). Bread and peace voting in US presidential elections. *Public Choice*, 104(1-2):149–180.

Jost, J. T. (2019). Anger and authoritarianism mediate the effects of fear on support for the far right—what vasilopoulos et al.(2019) really found. *Political Psychology*, 40(4):705–711.

Kern, M., Park, G., Eichstaedt, J., Schwartz, H., Sap, M., Smith, L., and Ungar, L. (2016). Gaining insights from social media language: Methodologies and challenges. *Psychological Methods*, 21(4):507–525.

Knowles, E. D. and Tropp, L. R. (2018). The racial and economic context of Trump support: Evidence for threat, identity, and contact effects in the 2016 presidential election. *Social Psychological and Personality Science*, 9(3):275–284.

Krueger, A. B. and Stone, A. A. (2014). Progress in measuring subjective well-being: moving toward national indicators and policy evaluations. *Science*, 346(6205):42–43.

Lerner, J. S., Li, Y., Valdesolo, P., and Kassam, K. S. (2015). Emotion and decision making. *Annual Review of Psychology*, 66(1):799–823.

Liberini, F., Redoano, M., and Proto, E. (2017). Happy voters. *Journal of Public Economics*, 146:41 – 57.

MacKuen, M., Wolak, J., Keele, L., and Marcus, G. E. (2010). Civic engagements: Resolute partisanship or reflective deliberation. *American Journal of Political Science*, 54(2):440–458.

Marcus, G. E. (2021). The rise of populism: The politics of justice, anger, and grievance. In *The Psychology of Populism*, pages 81–104. Routledge.

Marcus, G. E., Neuman, W. R., and MacKuen, M. (2000). *Affective intelligence and political judgment.* University of Chicago Press.

Marcus, G. E., Valentino, N. A., Vasilopoulos, P., and Foucault, M. (2019). Applying the theory of affective intelligence to support for authoritarian policies and parties. *Political Psychology*, 40:109–139.

Martin, L. L. and Clore, G. L. (2013). *Theories of mood and cognition: A user's guidebook.* Psychology Press.

Mudde, C. (2004). The populist zeitgeist. *Government and opposition*, 39(4):541–563.

Mudde, C. (2017). An ideational approach. In Kaltwasser, C. R., Taggart, P., Espejo, P. O., and Ostiguy, P., editors, *The Oxford handbook of populism*, pages 27–47. Oxford University Press Oxford.

Mutz, D. C. (2018). Status threat, not economic hardship, explains the 2016 presidential vote. *Proceedings of the National Academy of Sciences*, 115(19):E4330–E4339.

Nai, A. (2018). Fear and loathing in populist campaigns? Comparing the communication style of populists and non-populists in elections worldwide. *Journal of Political Marketing*, 20(9):1–32.

Napier, J. L. and Jost, J. T. (2008). Why are conservatives happier than liberals? *Psychological Science*, 19(6):565–572.

Norris, P. and Inglehart, R. (2019). *Cultural backlash: Trump, Brexit, and authoritarian populism.* Cambridge University Press.

Obschonka, M., Stuetzer, M., Rentfrow, P. J., Lee, N., Potter, J., and Gosling, S. D. (2018). Fear, populism, and the geopolitical landscape: The "sleeper effect" of neurotic personality traits on regional voting behavior in the 2016 Brexit and Trump elections. *Social Psychological and Personality Science*, 9(3):285–298.

Oliver, J. E. and Rahn, W. M. (2016). Rise of the trumpenvolk: Populism in the 2016 election. *The ANNALS of the American Academy of Political and Social Science*, 667(1):189–206.

Park, G., Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Kosinski, M., Stillwell, D. J., Ungar, L. H., and Seligman, M. E. (2015). Automatic personality assessment through social media language. *Journal of personality and social psychology*, 108(6):934–52.

Posner, J., Russell, J. A., and Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and psychopathology*, 17(3):715–734.

Quirin, M., Kazén, M., and Kuhl, J. (2009). When nonsense sounds happy or helpless: the implicit positive and negative affect test (ipanat). *Journal of personality and social psychology*, 97(3):500.

Redlawsk, D. P., Pierce, D., Arzheimer, K., Evans, J., and Lewis-Beck, M. (2017). Emotions and voting. *Sage handbook of electoral behaviour*, pages 406–432.

Rentfrow, P. J., Jokela, M., and Lamb, M. E. (2015). Regional personality differences in Great Britain. *PLoS ONE*, 10(3):e0122245.

Rico, G., Guinjoan, M., and Anduiza, E. (2017). The emotional underpinnings of populism: How anger and fear affect populist attitudes. *Swiss Political Science Review*, 23(4):444–461.

Rico, G., Guinjoan, M., and Anduiza, E. (2020). Empowered and enraged: Political efficacy, anger and support for populism in europe. *European Journal of Political Research*, 59(4):797–816.

Rooduijn, M., Van Kessel, S., Froio, C., Pirro, A., De Lange, S., Halikiopoulou, D., Lewis, P., Mudde, C., and Taggart, P. (2019). *The PopuList: An Overview of Populist, Far Right, Far Left and Eurosceptic Parties in Europe*. http://www.popu-list.org/.

Salmela, M. and von Scheve, C. (2017). Emotional roots of right-wing political populism. *Social Science Information*, 56(4):567–595.

Schumacher, G., Rooduijn, M., and Bakker, B. N. (2022). Hot populism? affective responses to antiestablishment rhetoric. *Political Psychology*.

Schwartz, H. A., Eichstaedt, J., Kern, M. L., Park, G., Sap, M., Stillwell, D., Kosinski, M., and Ungar, L. (2014). Towards assessing changes in degree of depression through facebook. *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality*, pages 118–125.

Schwartz, H. A., Eichstaedt, J. C., Kern, M. L., Dziurzynski, L., Agrawal, M., Park, G. J., Lakshmikanth, S. K., Jha, S., Seligman, M. E., Ungar, L., et al. (2013). Characterizing geographic variation in well-being using tweets. In *Seventh International AAAI Conference on Weblogs and Social Media (ICWSM 2013)*.

Schwartz, H. A., Giorgi, S., Sap, M., Crutchley, P., Eichstaedt, J. C., and Ungar, L. (2017). Dlatk: Differential language analysis toolkit. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, EMNLP.

Schwarz, N. (1990). Feelings as information: Informational and motivational functions of affective states. In Higgins, E. T. and Sorrentino, R. M., editors, *Handbook of Motivation ad Cognition: Foundations of Social Behaviour, Vol. 2*, pages 527–561. Guilford Press.

Seawright, J. (2012). *Party-system collapse: The roots of crisis in Peru and Venezuela*. Stanford University Press.

Silva, B. C., Andreadis, I., Anduiza, E., Blanuša, N., Corti, Y. M., Delfino, G., Rico, G., Ruth-Lovell, S. P., Spruyt, B., Steenbergen, M., et al. (2018). Public opinion surveys: A new scale. In *The ideational approach to populism*, pages 150–177. Routledge.

Spruyt, B., Keppens, G., and Van Droogenbroeck, F. (2016). Who supports populism and what attracts people to it? *Political Research Quarterly*, 69(2):335–346.

Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using google search data. *Journal of Public Economics*, 118(1):26–40.

Tausch, N., Becker, J. C., Spears, R., Christ, O., Saab, R., Singh, P., and Siddiqui, R. N. (2011). Explaining radical group behavior: Developing emotion and efficacy routes to normative and nonnormative collective action. *Journal of personality and social psychology*, 101(1):129.

Vasilopoulos, P., Marcus, G. E., Valentino, N. A., and Foucault, M. (2019). Fear, anger, and voting for the far right: Evidence from the november 13, 2015 paris terror attacks. *Political Psychology*, 40(4):679–704.

Vasilopoulou, S. and Wagner, M. (2017). Fear, anger and enthusiasm about the european union: Effects of emotional reactions on public preferences towards european integration. *European Union Politics*, 18(3):382–405.

Ward, G. (2020). Happiness and voting: evidence from four decades of elections in europe. *American Journal of Political Science*, 64(3):504–518.

Ward, G., De Neve, J.-E., Ungar, L. H., and Eichstaedt, J. C. (2021). (Un)Happiness and voting in us presidential elections. *Journal of Personality and Social Psychology*, 120(2):370–383.

Watson, D., Clark, L. A., and Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the panas scales. *Journal of personality and social psychology*, 54(6):1063.

Webster, S. W. (2018). Anger and declining trust in government in the american electorate. *Political Behavior*, 40(4):933–964.

Widmann, T. (2021). How emotional are populists really? factors explaining emotional appeals in the communication of political parties. *Political Psychology*, 42(1):163–181.

Yardley, J. (2016). Populist anger upends politics on both sides of the atlantic. *The New York Times*.

Yarkoni, T. and Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, 12(6):1100–1122.

Youyou, W., Stillwell, D., Schwartz, H. A., and Kosinski, M. (2017). Birds of a feather do flock together: Behavior-based personality-assessment method reveals personality similarity among couples and friends. *Psychological science*, 28(3):276–284.

Supplementary Online Materials

SOM: Study 1a

Survey Data is drawn from the Gallup World Poll. We focus on 8 attitudinal questions in the survey. Each question has a binary response, corresponding either to yes/no or agree/disagree. The question wordings are as follows:

- "Do you think that this country should stay in the EU or withdraw from the EU?" (2014; limited number of countries surveyed)
- "Now, I would like to ask you some questions about foreign immigrants - people who have come to live and work in this country from another country. Please tell me whether you, personally, think each of the following is good thing or a bad thing?[1]
  - Immigrants living in [country].
  - Having an immigrant as a neighbor." (2016)
- "Please tell me whether you agree or disagree with the following statements: Leaders in the city or area where you live represent your interests." (2010 only)
- "Is corruption widespread throughout the government in this country, or not?" (2005-2018)
- "Do you think the government of your country is doing enough to fight corruption, or not?" (2008-2011; 2015)
- "In this country, do you have confidence in each of the following, or not? How about quality and integrity of the media?" (2006-2011)

Control Variables included in all models are: age, age^2, dummies for medium and high education (versus low), dummies for marital status, the natural logarithm of household income, and the number of children in the household.

Analysis is carried out using logistic regression models, since each of our outcomes is binary. We report exponentiated coefficients (a.k.a. odd ratios) in the main tables. All models include country fixed effects and, where there are multiple years of data, wave fixed effects. Standard errors are clustered on countries. **Sample** is in total 1,851,354 individuals.

[1] A volunteered response of "depends" was also allowed. We code the variables as equal to 1 if "bad", 0 if "good" or "depends".

Table S1

Negative Emotions and Populist Attitudes

	(1) Leaders Represent My Interests (No = 1)	(2) Government Corruption Widespread (Yes = 1)	(3) Gov Not Doing Enough on Corruption (Yes = 1)	(4) Confident in the Media (No = 1)	(5) Businesspeople Are Good Role Models (No = 1)	(6) Immigrants Living in Country (Bad = 1)	(7) Immigrant As Neighbor (Bad = 1)	(8) Leave The EU (Yes = 1)
Panel A								
Worry Yesterday = 1	1.40***	1.32***	1.26***	1.23***	1.20***	1.15***	1.11***	1.31***
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.09)
Log-Likelihood	-60,755.6	-594,096.5	-187,623.0	-118,800.7	-253,467.9	-69,042.6	-64,996.4	-7,600.4
Panel B								
Anger Yesterday = 1	1.46***	1.29***	1.22***	1.31***	1.27***	1.22***	1.21***	1.74***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.10)
Log-Likelihood	-60,793.6	-589,918.5	-181,606.8	-111,532.3	-253,395.4	-69,019.1	-64,957.8	-7,567.2
Panel C								
Sadness Yesterday = 1	1.45***	1.26***	1.24***	1.22***	1.30***	1.23***	1.21***	1.50***
	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.10)
Log-Likelihood	-60,780.1	-594,871.5	-187,750.7	-118,861.2	-253,296.6	-69,004.2	-64,952.5	-7,587.6
Individuals	93,441	1,282,853	317,867	187,067	503,920	133,763	133,261	16,226
Mean Dep Var	0.49	0.76	0.61	0.45	0.23	0.28	0.25	0.20
Countries	93	156	129	116	151	136	136	17

Notes: Each panel reports results from a separate series of regression models. Dependent variables are shown in the column titles. Odds Ratios are reported from logistic regression models in each case. Robust standard errors are in parentheses, adjusted for clustering on countries. Source: Gallup World Poll. Country fixed effects are included in all models, as well as controls for gender, age, age^2, education dummies, (log) household income, marital status dummies, number of children in household. Year fixed effects also included in models where multiple waves of survey data are available. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S2

Negative Emotions and Populist Attitudes in Gallup World Poll

	All European Countries							UK Only
	(1) Leaders Represent My Interests (No = 1)	(2) Government Corruption Widespread (Yes = 1)	(3) Gov Not Doing Enough on Corruption (Yes = 1)	(4) Confident in the Media (No = 1)	(5) Businesspeople Are Good Role Models (No = 1)	(6) Immigrants Living in Country (Bad = 1)	(7) Immigrant As Neighbor (Bad = 1)	(8) Leave The EU (Yes = 1)
Sadness Yesterday = 1	1.23***	1.08***	1.09***	1.06***	1.19***	1.15***	1.15***	1.26***
	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.08)
Anger Yesterday = 1	1.29***	1.17***	1.13***	1.23***	1.17***	1.14***	1.15***	1.56***
	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.07)
Worry Yesterday = 1	1.23***	1.24***	1.17***	1.15***	1.09***	1.06***	1.02	1.13*
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)
Observations	93441	1274226	307163	175571	503920	133763	133261	16226
Mean Dep Var	0.49	0.76	0.61	0.45	0.23	0.28	0.25	0.20
Countries	93	154	129	103	151	136	136	17
Log-Likelihood	-60,586.9	-588,776.4	-181,361.3	-111,429.7	-253,071.7	-68,965.1	-64,921.7	-7,550.3

Notes: Odds ratios reported from logistic regression models. Robust standard errors in parentheses, clustered on countries. Country fixed effects included in all models. All models include controls for gender, age, age^2, education, (log) income, marital status, children in household, and year where there are multiple waves of survey data.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure S1

Negative Emotions and Opinions across Europe in 2014 on Withdrawing from the EU

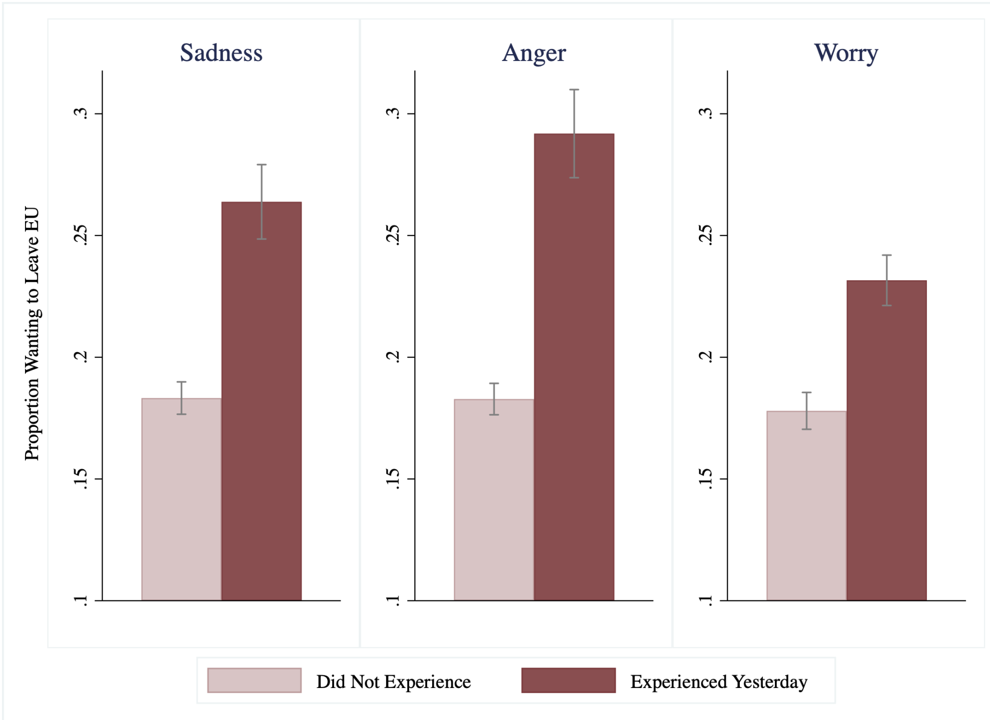
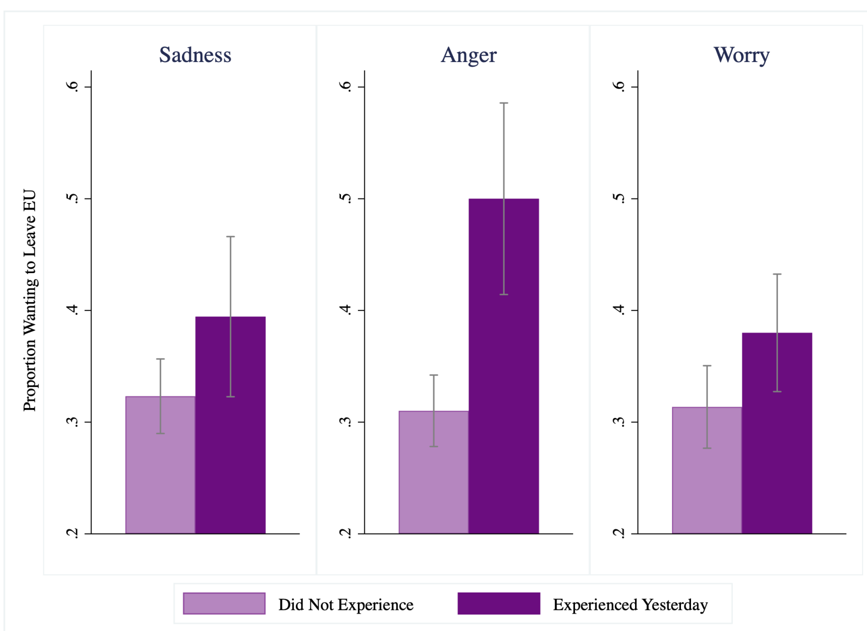


Figure S2

Negative Emotions in the UK and Opinions on Withdrawing from the EU.



Note: Data reported from the 2014 from the Gallup World Poll. 95% confidence intervals shown.

SOM: Study 1b

Data Description

Global Happiness and Political Attitudes Survey. The GHPAS surveys a random sample of respondents in 15 countries, across 6 continents. These 15 countries represent around 52% of the world's population. The countries included are: Australia, Brazil, Finland, France, Germany, Hungary, India, Italy, South Africa, Turkey, UK, USA, Ukraine. Surveys were carried out in May & June 2019. The survey was carried out on behalf of the Victor Pinchuk Foundation, to whom we are grateful for data access.

In each country a sample of around 1,000 was collected, with the exception of Australia (500 respondents). Samples are representative of national populations for all countries, except for India and South Africa. For these two countries, the survey is representative of the population with internet access. Interviews in Hungary were a mixture of face-to-face and online. Russia and Ukraine were telephone and online. Remaining countries were online only.

Populism Measures. Populism is measured using the following questions, to which respondents are asked about the extent they agree/disagree on a 1 to 5 scale. The starred questions are reverse-coded.

People Centrism:

- Politicians should always listen closely to the problems of the people.
- Politicians don't have to spend time among ordinary people to do a good job.*
- The will of the people should be the highest principle in this country's politics.

Anti-elitism:

- The government is pretty much run by a few big interests looking out for themselves.
- Government officials use their power to try to improve people's lives.*
- Quite a few of the people running the government are crooked.

Manichaean outlook:

- You can tell if a person is good or bad if you know their politics.
- The people I disagree with politically are not evil.*
- The people I disagree with politically are just misinformed.

Emotions. Negative Emotions were measured using the following set of questions:

The following questions ask about how you felt yesterday on a scale from 0 to 10. Zero means you did not experience the feeling "at all" yesterday while 10 means you experienced the feeling "all the time" yesterday. I will now read you a list of ways you might have felt yesterday.

- *Sad*
- *Worried*
- *Angry*
- *Anxious*
- *Stressed*

Extra Results

Table S3

Negative Emotions and Populist Beliefs in Global Survey

	Populism Index Total (z-score)				
	(1)	(2)	(3)	(4)	(5)
Sadness	0.038**				
	(0.015)				
Worry		0.070***			
		(0.016)			
Anger			0.028		
			(0.019)		
Anxiety				0.057***	
				(0.017)	
Stress					0.060***
					(0.016)
Observations	12659	12659	12659	12659	12659
R^2	0.114	0.117	0.113	0.116	0.116
Countries	13	13	13	13	13

Notes: Robust standard errors in parentheses, clustered on countries. Country fixed effects are included in all models. Outcome variable is the populism index developed by Silva et al. (2018), which is z-scored to have a mean of 0 and SD of 1. Controls included for gender, age bands, marital status dummies, number of children, education (BA or more dummy), employment status dummies, and household income quintiles. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S4

Negative Emotions and People-Centrism

	People-Centrism (z-score)				
	(1)	(2)	(3)	(4)	(5)
Sadness	-0.094***				
	(0.014)				
Worry		-0.042***			
		(0.010)			
Anger			-0.114***		
			(0.012)		
Anxiety				-0.072***	
				(0.019)	
Stress					-0.049***
					(0.011)
Observations	12659	12659	12659	12659	12659
R^2	0.116	0.110	0.120	0.113	0.110
Countries	13	13	13	13	13

Notes: Robust standard errors in parentheses, clustered on countries. Country fixed effects are included in all models. Outcome variable is the populism sub-index noted above, developed by Silva et al. (2018), which is z-scored to have a mean of 0 and SD of 1. Controls included for gender, age bands, marital status dummies, number of children, education (BA or more dummy), employment status dummies, and household income quintiles. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S5

Negative Emotions and Anti-Elitism

	Anti-Elitism (z-score)				
	(1)	(2)	(3)	(4)	(5)
Sadness	0.028				
	(0.019)				
Worry		0.062***			
		(0.020)			
Anger			0.021		
			(0.022)		
Anxiety				0.048**	
				(0.019)	
Stress					0.050**
					(0.017)
Observations	12659	12659	12659	12659	12659
R^2	0.120	0.123	0.120	0.121	0.122
Countries	13	13	13	13	13

Notes: Robust standard errors in parentheses, clustered on countries. Country fixed effects are included in all models. Outcome variable is the populism sub-index noted above, developed by Silva et al. (2018), which is z-scored to have a mean of 0 and SD of 1. Controls included for gender, age bands, marital status dummies, number of children, education (BA or more dummy), employment status dummies, and household income quintiles. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S6

Negative Emotions and Manichean Outlook

	Manichean Outlook (z-score)				
	(1)	(2)	(3)	(4)	(5)
Sadness	0.143***				
	(0.014)				
Worry		0.116***			
		(0.015)			
Anger			0.152***		
			(0.017)		
Anxiety				0.134***	
				(0.016)	
Stress					0.116***
					(0.013)
Observations	12659	12659	12659	12659	12659
R^2	0.095	0.088	0.097	0.092	0.088
Countries	13	13	13	13	13

Notes: Robust standard errors in parentheses, clustered on countries. Country fixed effects are included in all models. Outcome variable is the populism sub-index noted above, developed by Silva et al. (2018), which is z-scored to have a mean of 0 and SD of 1. Controls included for gender, age bands, marital status dummies, number of children, education (BA or more dummy), employment status dummies, and household income quintiles. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

SOM: Study 2

Election Data is drawn from the ParlGov Database (Döring and Manow, 2018). We include national parliamentary elections only, and code parties as either populist or non-populist, according to the classification system of *The PopuList* (Rooduijn et al., 2019). The parties were classified through a large-scale survey of multiple experts in each country on the basis of which parties display the characteristics of populism as defined by the ideational approach, i.e. the extent to which parties endorse ideas i) that society is divided into two antagonistic groups, the (pure) "people" versus the (corrupt) "elite," and ii) that politics ought to be be a pure expression of the "will of the people" (*volonté générale*).[2] Populist vote share is the collective vote share received by all of the populist parties at each election.

Negative Affect data is drawn from the Gallup World Poll, which is a multi-wave cross-national survey that began in 2005. Representative random samples of around 1,000 respondents are drawn in each country for each wave. We match each election with the closest wave prior to the election, if there has been a survey in that country in the 12 months prior to that election. Different emotions have been asked about in different waves; we focus on the three negative emotions that have been surveyed consistently throughout the period in the Gallup World Poll. The question asks "*Did you experience the following feelings during a lot of the day yesterday? How about anger? How about worry? How about sadness?*" Answers are yes/no. We code the national % who experienced each emotion. For our summary index, we z-score each emotion at the national level, and then take the mean of the three.

Macroeconomic Data is drawn from the World Bank Development Indicators (WDI), and supplemented where missing using data from the IMF's World Economic Outlook (WEO) database. For elections that take place in the first six months of the year, we take the annual value from the previous year, and for elections in the second six months of the year we take the election-year's value. GDP is per capita in 2011 PPP international dollars. Unemployment and inflation rates are percentages.

Analysis is carried out using OLS regressions that adjust for country and year fixed effects. Standard errors are adjusted for clustering on countries. Two-sided tests are reported throughout the paper. **Countries Included** are: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Slovakia, Spain, Sweden, United Kingdom. European countries that are part of the Gallup World Poll, but either i) have no populist party (e.g. Portugal) or ii) where we only have one matchable election within 12 months of the survey, are not included in the analysis.

Table S7

Descriptive Statistics: European Elections

Variable	Obs	Mean	Std. Dev.	Min	Max
Populist Vote Share	77	19.98	15.94	0	64.72
Worry Yesterday	77	.35	.09	.22	.58
Sadness Yesterday	77	.19	.05	.1	.36
Anger Yesterday	77	.17	.06	.06	.35
log GDP per Capita	77	10.42	.38	9.67	11.48
Unemployment Rate	77	9.26	5.13	2.74	26.49
Inflation Rate	77	1.86	2.29	-2.1	12.69

[2] See `https://popu-list.org/` for more details.

Table S8

Correlation Matrix: European Elections

		1	2	3	4	5	6	7
1	Populist Vote Share	1.00						
2	Worry Yesterday	0.15	1.00					
3	Sadness Yesterday	0.25	0.68	1.00				
4	Anger Yesterday	0.19	0.28	0.44	1.00			
5	GDP per Capita (ln)	-0.40	-0.37	-0.43	-0.26	1.00		
6	Unemployment Rate	0.25	0.62	0.49	0.42	-0.48	1.00	
7	Inflation Rate	-0.07	-0.27	-0.08	-0.01	-0.01	-0.34	1.00

Table S9

Negative Emotions and Populist Vote Shares in Europe

	Populist Vote Share						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Worry (z-score)		5.05^{**}	2.10				
		(2.34)	(2.65)				
Sadness (z-score)				7.30^{***}	6.28^{**}		
				(2.38)	(2.74)		
Anger (z-score)						3.78^{*}	2.46
						(1.91)	(1.52)
GDP per capita (log)	-40.48		-39.52		-31.54		-41.64
	(28.17)		(27.81)		(27.53)		(28.38)
Unemployment Rate (%)	0.03		-0.17		-0.44		-0.23
	(0.68)		(0.75)		(0.60)		(0.69)
Inflation Rate (%)	1.30		1.11		0.83		1.24
	(0.91)		(1.00)		(0.77)		(0.86)
Observations	77	77	77	77	77	77	77
Countries	24	24	24	24	24	24	24
Country & Year FEs	✓	✓	✓	✓	✓	✓	✓
Within R^2	0.145	0.074	0.152	0.210	0.253	0.054	0.162
Overall R^2	0.852	0.840	0.853	0.863	0.871	0.836	0.855

Notes: Robust standard errors in parentheses, clustered on countries. Sample if 77 general elections in 24 European countries 2005 and 2018. Country and year fixed effects included in all models. Outcome variable is the collective vote share received by populist parties at the election, lying between 0 and 100.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

SOM: Study 3

Preregistration details for Study 3 can be found and reviewed at `https://aspredicted.org/blind.php?x=di7k5u`.

Negative Emotions Data is drawn from Twitter in the same manner as in the USA (see SOM Study 4, below, for a more detailed discussion). We identify the *local authority district* (LAD) of each tweet, and include tweets in English posted in 2015, limiting the analysis to include users with at least 30 tweets during that year. In total, 372 LADs in Great Britain had at least 100 eligible users.[3] This amounts to data drawn from 62,971,196 tweets from 177,014 users.[4] We applied the same language-based assessment as in Study 4 with counties, in order to estimate LAD-level depression, anger, and anxiety.

Electoral Data from the EU Referendum in the UK on the 23rd June 2016 is at the LAD-level, the geographical unit at which the votes were counted. We code the percentage of voters in each LAD voting to leave the European Union (as opposed to remain).

Covariates. Demographic data on age, migrant stock, population density and housing are taken from the 2011 U.K Census. Median Pay (and inequality, which is the inter-quartile range) is taken from the 2015 Annual Survey of Hours and Earnings. Unemployment rate is drawn from the 2015 UK Labour Force Survey. Trait neuroticism is drawn from (Rentfrow et al., 2015). Additional covariates are drawn from (Becker et al., 2017).

Analysis is carried out at the LAD-level using WLS regression models, where each LAD is weighted by the total number of votes cast in the Referendum.

Table S10

Descriptive Statistics: Brexit

Variable	Obs	Mean	Std. Dev.	Min	Max
Leave Vote Share	380	53.14	10.42	21.38	75.56
Anger	372	0	1	-3.58	2.31
Anxiety	372	0	1	-3.69	3.36
Depression	372	0	1	-4.93	3.53
Unemployment Rate	377	5.26	2.11	1.6	12.1
log Household Income	380	2.59	.15	1.8	3.16
log Population Density	373	1.73	1.49	-2.3	4.93
1975 Leave Vote Share	380	.31	.05	.23	.58
EU Migrant Stock	380	.01	.01	0	.12
UKIP+BP Vote (2019 EU Election)	380	37.66	12.05	7.03	64.11

[3] Shetland and Na h-Eileanan an Iar are omitted from the maps, since there is insufficient Twitter data.

[4] For the analysis of the 2019 EU parliamentary election, we use 49,940,962 tweets posted in 2018 from 162,536 users. Using the same threshold of 100 users, we are able to observe 332 LADs.

Table S11

Correlation Matrix: Brexit Vote (N=363)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	2016 Leave Vote Share	1.00								
2	Anger (2015)	0.28	1.00							
3	Anxiety (2015)	0.20	0.87	1.00						
4	Depression (2015)	0.20	0.82	0.87	1.00					
5	Unemployment Rate	0.12	0.24	0.16	0.16	1.00				
6	log Household Income	-0.55	-0.26	-0.18	-0.21	-0.22	1.00			
7	log Population Density	-0.16	0.14	0.13	0.07	0.26	0.24	1.00		
8	1975 Leave Vote Share	-0.23	0.22	0.15	0.19	0.30	-0.04	0.08	1.00	
9	EU Migrant Stock	-0.55	-0.21	-0.13	-0.19	-0.10	0.56	0.38	-0.18	1.00
10	UKIP+BP Vote (2019)	0.93	0.18	0.14	0.14	-0.00	-0.42	-0.24	-0.37	-0.45

Table S12

Autocorrelation of Negative Emotions in Great Britain (N=339)

		(1)	(2)	(3)	(4)	(5)	(6)
1	Depression (2015)	1.00					
2	Anger (2015)	0.80	1.00				
3	Anxiety (2015)	0.86	0.86	1.00			
4	Depression (2018)	0.68	0.70	0.68	1.00		
5	Anger (2018)	0.63	0.77	0.67	0.88	1.00	
6	Anxiety (2018)	0.59	0.72	0.68	0.86	0.88	1.00

Table S13

Full Reporting of Table 4. Negative Emotions and Brexit

	DV: Leave Vote Share								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anger	2.86***	3.10***	2.33***						
	(0.58)	(0.48)	(0.39)						
Anxiety				1.89***	1.94***	1.36***			
				(0.59)	(0.47)	(0.38)			
Depression							1.96***	2.10***	1.22***
							(0.59)	(0.49)	(0.39)
Unemployment			0.44			0.50			0.54
			(0.39)			(0.40)			(0.40)
Median Pay (ln)			-3.46***			-3.71***			-3.68***
			(0.53)			(0.54)			(0.55)
Population Density (ln)			-2.61***			-2.36***			-2.23***
			(0.47)			(0.48)			(0.48)
Leave Vote Share (1975)			1.14*			1.18*			1.12*
			(0.65)			(0.67)			(0.67)
EU Migrant Share			-4.35***			-4.52***			-4.54***
			(0.48)			(0.49)			(0.49)
Observations	372	372	363	372	372	363	372	372	363
R^2	0.06	0.48	0.70	0.03	0.45	0.68	0.03	0.45	0.68
Region FEs		✓	✓		✓	✓		✓	✓

Notes: Local authority-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Referendum. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variable is the Leave vote share, lying between 0 and 100. Emotional variables are drawn from tweets posted in 2015 (see Methods for further details).

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S14

2016 Referendum: Robustness to Omission/Inclusion of Scotland

	No Scotland			Scotland Only		
	(1)	(2)	(3)	(4)	(5)	(6)
Anger	2.65***			2.85***		
	(0.44)			(0.88)		
Anxiety		1.53***			2.89***	
		(0.42)			(0.80)	
Depression			1.27***			2.50**
			(0.44)			(0.88)
Unemployment	0.26	0.36	0.39	1.34	1.88	1.75
	(0.41)	(0.42)	(0.42)	(1.22)	(1.20)	(1.31)
Median Pay (ln)	-3.09***	-3.43***	-3.46***	-7.88***	-7.52***	-7.40***
	(0.56)	(0.58)	(0.59)	(2.11)	(1.99)	(2.16)
Population Density (ln)	-2.35***	-2.09***	-1.94***	-2.33**	-2.50**	-2.11*
	(0.51)	(0.53)	(0.53)	(1.02)	(0.98)	(1.06)
Leave Vote Share (1975)	0.81	0.81	0.80	1.08	1.21	0.67
	(0.73)	(0.76)	(0.76)	(1.18)	(1.12)	(1.24)
EU Migrant Share	-4.33***	-4.47***	-4.47***	5.38*	4.80*	4.10
	(0.48)	(0.49)	(0.50)	(2.78)	(2.59)	(2.79)
Observations	335	335	335	28	28	28
R^2	0.66	0.64	0.63	0.74	0.76	0.72
Region FEs	✓	✓	✓			

Notes: Local authority-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Referendum. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variables is the Leave vote share, lying between 0 and 100. Region effects are omitted in columns (4) to (6) since Scotland is one region in the data.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S15

2016 Referendum: Robustness to Extensive Set of Controls

	Leave Vote Share					
	(1)	(2)	(3)	(4)	(5)	(6)
Anger	1.85***	0.78**				
	(0.40)	(0.32)				
Anxiety			0.90**	0.21		
			(0.39)	(0.30)		
Depression					1.02**	0.27
					(0.40)	(0.32)
Unemployment	1.36***	-0.02	1.46***	-0.01	1.47***	-0.01
	(0.42)	(0.35)	(0.43)	(0.35)	(0.43)	(0.35)
Median Pay (ln)	-1.72***	2.17***	-1.99***	2.19***	-1.98***	2.19***
	(0.54)	(0.52)	(0.55)	(0.52)	(0.55)	(0.52)
Population Density (ln)	1.00	0.07	1.28*	0.19	1.32**	0.20
	(0.65)	(0.51)	(0.66)	(0.52)	(0.66)	(0.52)
Leave Vote Share (1975)	0.92	-0.73	1.14*	-0.67	1.14*	-0.67
	(0.66)	(0.54)	(0.68)	(0.54)	(0.68)	(0.54)
EU Migrant Share	-4.06***	-0.41	-4.23***	-0.35	-4.20***	-0.35
	(0.63)	(0.56)	(0.65)	(0.57)	(0.65)	(0.57)
Non-EU Migrant Share	-3.22***	-4.10***	-3.40***	-4.26***	-3.44***	-4.26***
	(0.77)	(0.61)	(0.80)	(0.62)	(0.79)	(0.62)
EU Migrant Growth	1.53**	0.71	1.64**	0.75	1.60**	0.74
	(0.68)	(0.54)	(0.70)	(0.54)	(0.70)	(0.54)
Non-EU Migrant Growth	0.47	1.23***	0.39	1.24***	0.51	1.26***
	(0.54)	(0.43)	(0.55)	(0.43)	(0.55)	(0.43)
Public Employment	-1.22**	-0.99**	-1.28**	-0.99**	-1.30**	-1.00**
	(0.49)	(0.39)	(0.50)	(0.39)	(0.50)	(0.39)
EU Funds per Capita	-1.83***	-1.77***	-1.92***	-1.81***	-1.86***	-1.80***
	(0.50)	(0.40)	(0.52)	(0.40)	(0.52)	(0.40)
Fraction 60+	2.82***	1.25**	2.78***	1.18**	2.76***	1.18**
	(0.68)	(0.55)	(0.70)	(0.55)	(0.70)	(0.55)
Council Housing	-0.61	-1.98***	-0.59	-2.03***	-0.70	-2.05***
	(0.48)	(0.39)	(0.49)	(0.39)	(0.49)	(0.39)
Trait Neuroticism	0.76*	-0.16	0.79*	-0.17	0.75	-0.18
	(0.45)	(0.36)	(0.46)	(0.36)	(0.46)	(0.36)
Income Growth	0.01	-0.96***	-0.07	-1.03***	-0.06	-1.03***
	(0.41)	(0.33)	(0.42)	(0.33)	(0.42)	(0.33)
Fraction Low Education		9.04***		9.36***		9.34***
		(0.67)		(0.66)		(0.66)
Observations	312	312	312	312	312	312
R^2	0.69	0.81	0.67	0.81	0.68	0.81

Notes: Local authority-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Referendum. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variables is the Leave vote share, lying between 0 and 100. Trait neuroticism data is drawn from Rentfrow et al. (2015), based on a large dataset collected as part the "BBC Big Personality Test". Additional variables used but not described in main methods section are drawn from Becker et al. (2017).

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S16

2019 European Parliamentary Elections

	Brexit Party + UKIP Vote Share								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anger	1.80***	2.34***	0.52**						
	(0.57)	(0.50)	(0.22)						
Anxiety				1.57***	1.96***	0.36*			
				(0.55)	(0.47)	(0.21)			
Depression							1.53***	1.84***	0.65***
							(0.55)	(0.47)	(0.20)
Unemployment		-0.41	-0.83***		-0.31	-0.81***		-0.29	-0.81***
		(0.49)	(0.21)		(0.49)	(0.21)		(0.49)	(0.21)
Median Pay (ln)		-1.92***	1.83***		-1.92***	1.84***		-1.88***	1.90***
		(0.66)	(0.30)		(0.67)	(0.31)		(0.67)	(0.30)
Population Density (ln)		-3.77***	-1.05***		-3.70***	-1.01***		-3.62***	-1.06***
		(0.55)	(0.25)		(0.56)	(0.25)		(0.56)	(0.25)
Leave Vote Share (1975)		0.45	-0.40		0.54	-0.38		0.39	-0.44
		(0.78)	(0.34)		(0.78)	(0.34)		(0.79)	(0.33)
EU Migrant Share		-3.60***	0.71***		-3.62***	0.73***		-3.66***	0.71***
		(0.54)	(0.26)		(0.55)	(0.26)		(0.55)	(0.26)
2016 Referendum Vote			10.74***			10.79***			10.75***
			(0.29)			(0.29)			(0.28)
Observations	332	332	332	332	332	332	332	332	332
R^2	0.55	0.70	0.94	0.55	0.70	0.94	0.55	0.69	0.94
Region FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Local authority-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2019 EP election. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variables is the combined vote share of the Brexit Party and UK Independence Party, lying between 0 and 100.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S17

2019 European Parliamentary Elections: Omission/Inclusion of Scotland

	No Scotland			Scotland Only		
	(1)	(2)	(3)	(4)	(5)	(6)
Anger	2.51***			1.31**		
	(0.55)			(0.49)		
Anxiety		2.17***			1.10***	
		(0.54)			(0.37)	
Depression			2.07***			0.86*
			(0.54)			(0.46)
Unemployment	-0.49	-0.41	-0.42	0.33	0.50	0.66
	(0.53)	(0.53)	(0.53)	(0.65)	(0.64)	(0.74)
Median Pay (ln)	-1.96***	-1.96***	-1.91***	-2.74**	-2.59**	-2.20*
	(0.72)	(0.72)	(0.73)	(1.15)	(1.11)	(1.20)
Population Density (ln)	-4.06***	-4.02***	-3.92***	-2.14***	-2.12***	-2.22***
	(0.64)	(0.65)	(0.65)	(0.56)	(0.54)	(0.61)
Leave Vote Share (1975)	0.76	0.83	0.74	0.07	0.18	-0.13
	(0.91)	(0.92)	(0.92)	(0.58)	(0.57)	(0.62)
EU Migrant Share	-3.59***	-3.59***	-3.64***	2.47	2.43	2.25
	(0.58)	(0.58)	(0.59)	(1.48)	(1.44)	(1.59)
Observations	302	302	302	30	30	30
R^2	0.63	0.63	0.62	0.73	0.74	0.69
Region FEs	✓	✓	✓			

Notes: Local authority-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2019 EP election. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variables is the combined vote share of the Brexit Party and UK Independence Party, lying between 0 and 100. Region effects are omitted in columns (4) to (6) since Scotland is one region in the data.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S18

2019 European Parliamentary Elections: Additional Controls

	Brexit Party + UKIP Vote					
	(1)	(2)	(3)	(4)	(5)	(6)
Anger	0.35**	0.36**				
	(0.17)	(0.17)				
Anxiety			0.25	0.26		
			(0.17)	(0.17)		
Depression					0.42***	0.44***
					(0.16)	(0.16)
Unemployment	-0.17	-0.11	-0.15	-0.09	-0.19	-0.12
	(0.18)	(0.19)	(0.18)	(0.19)	(0.18)	(0.19)
Median Pay (ln)	0.89***	0.67**	0.88***	0.67**	0.95***	0.72**
	(0.29)	(0.33)	(0.29)	(0.34)	(0.29)	(0.33)
Population Density (ln)	0.16	0.20	0.18	0.23	0.17	0.21
	(0.26)	(0.26)	(0.26)	(0.27)	(0.26)	(0.26)
Leave Vote Share (1975)	0.18	0.25	0.18	0.24	0.15	0.23
	(0.30)	(0.31)	(0.30)	(0.31)	(0.30)	(0.31)
EU Migrant Share	1.49***	1.37***	1.50***	1.38***	1.49***	1.35***
	(0.25)	(0.27)	(0.25)	(0.27)	(0.25)	(0.27)
Non-EU Migrant Share	-2.11***	-1.99***	-2.13***	-2.02***	-2.09***	-1.96***
	(0.33)	(0.34)	(0.33)	(0.34)	(0.33)	(0.34)
EU Migrant Growth	0.27	0.29	0.29	0.30	0.25	0.27
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
Non-EU Migrant Growth	-1.61***	-1.67***	-1.62***	-1.68***	-1.57***	-1.64***
	(0.20)	(0.21)	(0.20)	(0.21)	(0.20)	(0.21)
Public Employment	0.23	0.24	0.19	0.21	0.21	0.23
	(0.21)	(0.21)	(0.21)	(0.21)	(0.20)	(0.20)
EU Funds per Capita	-0.50**	-0.47**	-0.49**	-0.46**	-0.49**	-0.46**
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
Fraction 60+	1.09***	1.13***	1.06***	1.11***	1.11***	1.16***
	(0.29)	(0.29)	(0.29)	(0.29)	(0.28)	(0.29)
Council Housing	0.38*	0.49**	0.39**	0.50**	0.39**	0.51**
	(0.19)	(0.21)	(0.20)	(0.22)	(0.19)	(0.21)
Trait Neuroticism	-0.13	-0.11	-0.16	-0.14	-0.14	-0.12
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
Income Growth	-0.17	-0.10	-0.17	-0.11	-0.17	-0.10
	(0.16)	(0.17)	(0.16)	(0.17)	(0.16)	(0.16)
2016 Referendum Vote	9.68***	9.93***	9.71***	9.95***	9.70***	9.96***
	(0.26)	(0.32)	(0.26)	(0.32)	(0.25)	(0.32)
Fraction Low Education		-0.58		-0.54		-0.62
		(0.45)		(0.45)		(0.45)
Observations	280	280	280	280	280	280
R^2	0.97	0.97	0.97	0.97	0.97	0.97

Notes: Local authority-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2019 EP election. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variables is the combined vote share of the Brexit Party and UK Independence Party, lying between 0 and 100.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S19

Longitudinal Models for UK Leave Voting

	Δ Leave Vote (2019 EuroParl - 2016 Referendum)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Anger	0.08***	0.08***				
	(0.03)	(0.03)				
Δ Anxiety			0.01	0.03		
			(0.02)	(0.02)		
Δ Depression					0.04*	0.06**
					(0.02)	(0.02)
Observations	330	330	330	330	330	330
R^2	0.38	0.55	0.36	0.54	0.36	0.54
Region FEs		✓		✓		✓

Notes: Local authority-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2019 EP election. The three emotion independent variables are z-scored such that they have a mean of 0 and an SD of 1 within each year, and the difference is then taken between the two years. Outcome variable is the difference between the z-score of the 2019 leave vote in the European Parliament elections and the z-score of the 2016 Brexit referendum vote. Baseline controls from Table S13 are included in all models. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

SOM: Study 4

Negative Emotions Data was taken from Twitter using the County Tweet Lexical Bank (Giorgi et al., 2018).[5] The lexical bank contains an aggregation of 1.53 billion US tweets posted between 2009 and 2015, from 6.06 million users. These tweets were mapped to counties using a combination of tweets' geographic coordinates as well as self-reported location, as described in (Schwartz et al., 2013). After filtering non-English tweets, the data was further limited to include only those from users with at least 30 total tweets over the period, in order to ensure reasonable measurement precision per person (see Kern et al., 2016). Finally, analyses were restricted to counties with at least 100 eligible users, leaving us with 1.53bn tweets covering 2,041 counties across the USA. Alaska is dropped from the analysis, since election results are not reported by county, leaving a final sample of 2,030 counties.

Linguistic data from these Twitter posts were aggregated in a way that mirrors survey data. We first calculated the mean rate of words or topics (clusters of words) per user, and subsequently used those means to calculate an average across all users in a given county (Giorgi et al., 2018). Using these county-level average values for each of the linguistic features, we applied a previously validated, language-based assessment to estimate county-level expressed depression, anger, and anxiety (for more details see Schwartz et al., 2014). While only the emotion of anger is a direct replication of the results from Studies 1 and 2, the emotions of anxiety and depression are closely related to those of stress and sadness. According to the emotion circumplex model (Posner et al., 2005), the emotion of anxiety is akin to stress in that both emotions are unpleasant and activating. Similarly, the emotion of depression is closely related to sadness, with both emotions being associated with unpleasantness and deactivation. Studying stress and depression allowed us to draw on previously published and validated prediction models (for more details see Schwartz et al., 2014). All models were applied using the Differential Language Analysis ToolKit, a social science language analysis library for Python (Schwartz et al., 2017).

For the 2020 replication study, we follow the same logic and use Twitter data from 2019. We begin with a 10% random sample of Twitter, which we then map to counties. We take users with at least 30 county-mapped tweets. We consider only counties with at least 100 users. This gives us a total 1344 counties in 2019.

Election Data is drawn from the Dave Leip Atlas of U.S. Presidential Elections. All data are at the U.S. county-level. The 2016 vote share is the Republican two-party vote share (i.e. omitting any votes for parties that are not Republican or Democrat). The Trump swing is the Δ between the 2016 Republican vote share and the mean Republican vote share at the 2000, 2004, 2008 and 2012 presidential elections. For the 2020 replication, we take the 2020 Trump two-party vote share, as well as the change from 2016 to 2020.

Covariates. Racism index is drawn from estimates calculated using Google search data by (Stephens-Davidowitz, 2014). Data on age and racial profile of each county, as well as population density, is drawn from the American Community Survey (5 year estimates - 2012-2016). Religosity and inequality (gini coefficient) is taken from (Chetty and Hendren, 2018). Longitude and latitude taken from the Census U.S. Gazetteer Files. Median Household income is the 2015 value from U.S. Census Bureau's Small Area Income and Poverty Estimate (SAIPE) program. Income growth is the percentage change in median income from 2012 to 2016. Unemployment rate is drawn from the Bureau of Labor Statistics. Trait neuroticism is drawn from (Obschonka et al., 2018). Trade exposure is the change in import penetration from China between 2000-2014 (Autor et al., 2018). Moral values is the relative importance of universalist vs communal moral values as used by (**?**).

Analysis is carried out at the county-level using WLS regression models, where each county is weighted by its total number of votes cast in the 2016 Presidential Election.

[5] We make the data available at `https://github.com/wwbp/county_tweet_lexical_bank`.

Table S20
Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Trump 2016 Vote Share	2030	62.63	15.84	4.3	92.26
Trump Vote Share (2016 - Avg 2000-12)	2030	5.7	7.19	-16.49	32.61
Trump Primaries Vote Share	1916	44.93	15.1	0	89.97
Anxiety	2030	0	1	-3.63	3.5
Anger	2030	0	1	-3.52	2.61
Depression	2030	0	1	-4.15	3.26
Median HH Income	2030	51576.79	13781.86	22045	134609
Unemployment Rate	2030	5.26	1.66	1.93	22.59
Population Density (ln)	2029	4.54	1.33	.36	11.11
Racism Index	1968	63.04	17.11	25.68	154.51
Fraction Religious	2029	.51	.16	.13	1.65

Table S21
Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Trump Vote Share 2016	1.00					
(2)	Trump Vote (2016 - GOP Avg.)	0.68	1.00				
(3)	Trump Vote in Primaries	-0.07	0.09	1.00			
(4)	Anger	0.21	0.26	0.04	1.00		
(5)	Anxiety	0.32	0.42	0.10	0.84	1.00	
(6)	Depression	0.29	0.44	0.13	0.77	0.94	1.00

Table S22

Negative Emotions and the 2016 Election

	Trump Vote Share in 2016								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anxiety	6.80***	3.74***	4.03***						
	(0.36)	(0.30)	(0.30)						
Anger				3.37***	2.56***	2.59***			
				(0.40)	(0.31)	(0.33)			
Depression							6.95***	3.34***	4.05***
							(0.35)	(0.30)	(0.30)
Household Income (ln)		2.61***	5.53***		2.64***	5.56***		2.58***	5.72***
		(0.33)	(0.41)		(0.34)	(0.43)		(0.34)	(0.41)
Unemployment		-2.15***	-1.33**		-1.85***	-0.88		-2.11***	-1.23**
		(0.44)	(0.61)		(0.46)	(0.64)		(0.45)	(0.61)
Population Density (ln)		-10.70***	-9.54***		-11.48***	-10.64***		-10.65***	-9.37***
		(0.24)	(0.31)		(0.23)	(0.31)		(0.24)	(0.32)
Racism Index		2.40***	0.19		2.46***	0.22		2.52***	0.25
		(0.42)	(0.74)		(0.43)	(0.77)		(0.43)	(0.74)
% Relgious		1.81***	0.13		1.96***	0.16		2.05***	0.40
		(0.37)	(0.39)		(0.38)	(0.41)		(0.38)	(0.40)
Latitude		0.21	-7.01**		-0.29	-7.94**		-0.36	-7.83**
		(0.96)	(3.45)		(0.98)	(3.59)		(0.97)	(3.46)
Longitude		4.41**	4.17		3.82*	-1.35		4.80**	0.74
		(1.91)	(5.73)		(1.95)	(5.98)		(1.92)	(5.74)
Observations	2030	1968	1968	2030	1968	1968	2030	1968	1968
R^2	0.39	0.72	0.88	0.31	0.71	0.87	0.40	0.72	0.88
State FEs	✓	✓		✓	✓		✓	✓	
Commuting Zone FEs			✓			✓			✓

Notes: County-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Presidential Election. Emotional variables are z-scored to have a mean of 0 and a standard deviation of 1.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S23

Negative Affect and the 2016 Election

	Trump Vote Share in 2016			Trump Vote Swing			Trump Vote 2016 Primaries		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Negative Affect (z-score)	5.86***	3.29***	3.66***	3.24***	1.75***	1.64***	3.46***	2.16***	1.71***
	(0.36)	(0.30)	(0.31)	(0.13)	(0.12)	(0.12)	(0.16)	(0.17)	(0.23)
Household Income (ln)		2.64***	5.67***		-1.12***	-0.93***		-0.32*	-0.48
		(0.34)	(0.42)		(0.13)	(0.17)		(0.19)	(0.31)
Unemployment		-2.16***	-1.31**		-0.24	0.65**		1.46***	1.84***
		(0.45)	(0.62)		(0.18)	(0.25)		(0.25)	(0.45)
Population Density (ln)		-10.94***	-9.80***		-2.91***	-3.12***		-1.39***	-2.76***
		(0.24)	(0.31)		(0.09)	(0.13)		(0.13)	(0.23)
Racism Index		2.45***	0.17		1.09***	0.41		0.51**	1.55***
		(0.43)	(0.75)		(0.17)	(0.31)		(0.24)	(0.54)
% Relgious		1.95***	0.25		0.74***	0.44***		0.20	-0.72**
		(0.38)	(0.40)		(0.15)	(0.16)		(0.21)	(0.29)
Latitude		-0.08	-7.44**		1.18***	-1.20		-1.98***	-11.98***
		(0.97)	(3.49)		(0.38)	(1.42)		(0.54)	(2.55)
Longitude		4.22**	0.65		0.58	-5.58**		7.69***	15.00***
		(1.92)	(5.80)		(0.75)	(2.36)		(1.08)	(4.25)
Observations	2030	1968	1968	2030	1968	1968	1916	1855	1855
R^2	0.37	0.72	0.87	0.50	0.72	0.86	0.88	0.91	0.93
State FEs	✓	✓		✓	✓		✓	✓	
Commuting Zone FEs			✓			✓			✓

Notes: County-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Presidential Election. Emotional variables are z-scored to have a mean of 0 and a standard deviation of 1.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S24

Negative Emotions and the Trump Swing

	Δ(Trump 2016 - GOP Avg. 2000-12)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anxiety	3.36***	1.76***	1.74***						
	(0.13)	(0.12)	(0.12)						
Anger				2.53***	1.42***	1.16***			
				(0.14)	(0.12)	(0.13)			
Depression							3.64***	1.97***	1.88***
							(0.12)	(0.12)	(0.12)
Household Income (ln)		-1.15***	-1.01***		-1.11***	-0.98***		-1.14***	-0.90***
		(0.13)	(0.17)		(0.14)	(0.18)		(0.13)	(0.17)
Unemployment		-0.13	0.67***		-0.10	0.84***		-0.30*	0.65***
		(0.17)	(0.25)		(0.18)	(0.26)		(0.17)	(0.25)
Population Density (ln)		-2.84***	-3.04***		-3.20***	-3.50***		-2.71***	-2.90***
		(0.09)	(0.13)		(0.09)	(0.13)		(0.09)	(0.13)
Racism Index		1.07***	0.43		1.09***	0.43		1.12***	0.44
		(0.17)	(0.30)		(0.17)	(0.32)		(0.16)	(0.30)
% Relgious		0.68***	0.38**		0.75***	0.40**		0.80***	0.51***
		(0.15)	(0.16)		(0.15)	(0.17)		(0.15)	(0.16)
Latitude		1.25***	-1.04		1.08***	-1.42		1.07***	-1.35
		(0.38)	(1.41)		(0.39)	(1.47)		(0.37)	(1.39)
Longitude		0.71	-4.04*		0.34	-6.47***		0.88	-5.56**
		(0.75)	(2.34)		(0.77)	(2.45)		(0.74)	(2.32)
Observations	2030	1968	1968	2030	1968	1968	2030	1968	1968
R^2	0.51	0.72	0.87	0.43	0.70	0.86	0.55	0.72	0.87
State FEs	✓	✓		✓	✓		✓	✓	
Commuting Zone FEs			✓			✓			✓

Notes: County-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Presidential Election. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S25

Negative Emotions and Trump Voting in the 2016 Primaries

	Trump Vote Share in 2016 Republican Primaries								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anxiety	3.41***	2.11***	1.62***						
	(0.16)	(0.17)	(0.23)						
Anger				3.22***	1.95***	1.58***			
				(0.17)	(0.18)	(0.24)			
Depression							3.58***	2.27***	1.79***
							(0.16)	(0.17)	(0.23)
Household Income (ln)		-0.37*	-0.58*		-0.29	-0.45		-0.37*	-0.49
		(0.19)	(0.31)		(0.19)	(0.31)		(0.19)	(0.31)
Unemployment		1.62***	1.95***		1.53***	1.84***		1.46***	1.91***
		(0.25)	(0.45)		(0.26)	(0.46)		(0.25)	(0.45)
Population Density (ln)		-1.31***	-2.76***		-1.74***	-3.06***		-1.17***	-2.61***
		(0.14)	(0.23)		(0.13)	(0.22)		(0.14)	(0.24)
Racism Index		0.49**	1.59***		0.51**	1.52***		0.55**	1.60***
		(0.24)	(0.54)		(0.24)	(0.54)		(0.24)	(0.54)
% Relgious		0.12	-0.78***		0.21	-0.73**		0.27	-0.65**
		(0.21)	(0.29)		(0.21)	(0.29)		(0.21)	(0.29)
Latitude		-1.89***	-11.92***		-2.04***	-12.09***		-2.13***	-12.14***
		(0.54)	(2.55)		(0.55)	(2.56)		(0.54)	(2.54)
Longitude		7.88***	16.54***		7.27***	13.58***		8.08***	15.01***
		(1.08)	(4.26)		(1.09)	(4.28)		(1.07)	(4.24)
Observations	1916	1855	1855	1916	1855	1855	1916	1855	1855
R^2	0.88	0.91	0.93	0.88	0.91	0.93	0.89	0.91	0.93
State FEs	✓	✓		✓	✓		✓	✓	
Commuting Zone FEs			✓			✓			✓

Notes: County-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Presidential Election. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S26

Robustness to Extensive Set of Controls

	Trump 2016 Vote Share			Δ(Trump 2016 - GOP Avg)			Trump in GOP Primaries		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anxiety	0.30			0.44***			0.72***		
	(0.26)			(0.11)			(0.19)		
Anger		0.99***			0.79***			1.07***	
		(0.27)			(0.11)			(0.19)	
Depression			-0.19			0.67***			0.83***
			(0.26)			(0.11)			(0.19)
Household Income (ln)	2.09***	2.01***	2.19***	-0.08	-0.10	-0.10	0.40	0.40	0.40
	(0.36)	(0.35)	(0.36)	(0.15)	(0.15)	(0.15)	(0.26)	(0.25)	(0.25)
Unemployment	-0.50	-0.72**	-0.37	0.09	-0.03	-0.01	1.62***	1.48***	1.54***
	(0.35)	(0.35)	(0.35)	(0.15)	(0.15)	(0.15)	(0.25)	(0.25)	(0.25)
Population Density (ln)	-2.43***	-2.47***	-2.42***	-0.79***	-0.81***	-0.77***	1.26***	1.24***	1.30***
	(0.29)	(0.28)	(0.29)	(0.12)	(0.12)	(0.12)	(0.21)	(0.21)	(0.21)
Racism Index	1.44***	1.38***	1.45***	0.86***	0.82***	0.87***	0.34	0.29	0.36
	(0.32)	(0.32)	(0.32)	(0.14)	(0.13)	(0.14)	(0.23)	(0.23)	(0.23)
% Relgious	0.17	0.20	0.14	-0.05	-0.04	-0.01	-0.13	-0.12	-0.08
	(0.30)	(0.30)	(0.30)	(0.13)	(0.12)	(0.13)	(0.21)	(0.21)	(0.21)
Latitude	1.10	1.26*	1.01	1.02***	1.11***	1.02***	-2.15***	-2.06***	-2.18***
	(0.75)	(0.75)	(0.75)	(0.32)	(0.32)	(0.32)	(0.54)	(0.53)	(0.53)
Longitude	3.62**	3.62**	3.48**	0.24	0.19	0.35	6.98***	6.88***	7.08***
	(1.45)	(1.45)	(1.46)	(0.62)	(0.61)	(0.62)	(1.03)	(1.03)	(1.03)
% 65+	0.84***	0.87***	0.83***	1.48***	1.50***	1.48***	1.62***	1.64***	1.61***
	(0.23)	(0.23)	(0.23)	(0.10)	(0.10)	(0.10)	(0.16)	(0.16)	(0.16)
% White	9.19***	9.43***	9.22***	1.20***	1.40***	1.20***	0.83***	1.12***	0.86***
	(0.32)	(0.33)	(0.32)	(0.14)	(0.14)	(0.14)	(0.23)	(0.23)	(0.23)
Inequality	-1.77***	-1.70***	-1.82***	-0.44***	-0.40***	-0.40***	-1.60***	-1.55***	-1.55***
	(0.22)	(0.22)	(0.22)	(0.09)	(0.09)	(0.09)	(0.16)	(0.15)	(0.16)
Tade Exposure	-0.24	-0.15	-0.29	0.18*	0.23**	0.20*	-0.45**	-0.39**	-0.45**
	(0.24)	(0.24)	(0.24)	(0.10)	(0.10)	(0.10)	(0.17)	(0.17)	(0.17)
Income Growth	-0.74***	-0.64***	-0.80***	0.27***	0.32***	0.28***	0.13	0.19	0.12
	(0.23)	(0.23)	(0.23)	(0.10)	(0.10)	(0.10)	(0.16)	(0.16)	(0.16)
Trait Neuroticism	-0.08	-0.11	-0.01	1.52***	1.52***	1.47***	0.02	0.04	-0.03
	(0.38)	(0.38)	(0.38)	(0.16)	(0.16)	(0.16)	(0.27)	(0.27)	(0.27)
Moral Values (Univ vs. Comm)	-3.53***	-3.38***	-3.59***	-0.40***	-0.31**	-0.39***	-0.30	-0.19	-0.31
	(0.29)	(0.29)	(0.29)	(0.12)	(0.12)	(0.12)	(0.21)	(0.21)	(0.21)
% Some College +	-5.17***	-4.81***	-5.47***	-2.65***	-2.50***	-2.55***	-3.02***	-2.90***	-3.01***
	(0.42)	(0.41)	(0.41)	(0.18)	(0.17)	(0.17)	(0.30)	(0.29)	(0.30)
Observations	1769	1769	1769	1769	1769	1769	1666	1666	1666
R^2	0.86	0.86	0.86	0.84	0.84	0.84	0.93	0.93	0.93

Notes: County-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2016 Presidential Election, and include State FEs. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variables are vote shares, lying between 0 and 100.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table S27

Negative Affect and Trump Voting in 2020: Cross-Sectional Evidence

	Trump Vote Share in 2020								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Anger (2019)	3.82	5.69***	1.09***						
	(2.38)	(1.63)	(0.31)						
Anxiety (2019)				-5.95**	2.55	4.89***			
				(2.54)	(1.79)	(0.31)			
Depression (2019)							2.08	3.21**	0.33
							(1.91)	(1.31)	(0.25)
Household Income (2019)		1.41***	-0.69***		1.29***	-0.60***		1.38***	-0.72***
		(0.40)	(0.08)		(0.40)	(0.07)		(0.40)	(0.08)
Unemployment (2019)		-0.29	0.47***		-0.36	0.35***		-0.24	0.47***
		(0.47)	(0.09)		(0.47)	(0.08)		(0.47)	(0.09)
Population Density (ln)		-11.11***	-0.14*		-11.12***	-0.20***		-11.08***	-0.12
		(0.29)	(0.08)		(0.29)	(0.07)		(0.29)	(0.08)
Racism Index		2.43***	0.01		2.51***	0.07		2.44***	0.02
		(0.52)	(0.10)		(0.52)	(0.09)		(0.52)	(0.10)
% Relgious		2.06***	0.44***		2.07***	0.32***		2.09***	0.45***
		(0.45)	(0.09)		(0.45)	(0.08)		(0.45)	(0.09)
Latitude		-2.02*	-1.74***		-1.71	-1.54***		-2.02*	-1.72***
		(1.18)	(0.23)		(1.18)	(0.21)		(1.19)	(0.23)
Longitude		6.15**	-1.04**		6.65***	-0.67		6.26**	-1.01**
		(2.54)	(0.49)		(2.55)	(0.45)		(2.55)	(0.49)
Trump Vote Share (2016)			0.92***			0.92***			0.92***
			(0.01)			(0.00)			(0.01)
Observations	1343	1303	1303	1343	1303	1303	1343	1303	1303
R^2	0.28	0.68	0.99	0.28	0.68	0.99	0.28	0.68	0.99

Notes: County-level WLS estimates. Robust standard errors in parentheses. All regression models are weighted by the total number of votes case in the 2020 Presidential Election, and include State FEs. All independent variables are z-scored to have a mean of 0 and a standard deviation of 1. Outcome variables are vote shares, lying between 0 and 100. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Ablation Analysis: Additional Variance Explained by Emotions

Table S28

R^2 Values from Populism Prediction Models

Outcome Variable	R^2 with Controls Only	R^2 with Controls + Emotions	Absolute Difference	% Difference	N
Study 3					
Populist Party Vote Share	0.073	0.161	0.088	120.55%	77
Study 4					
Trump Vote Share	0.577	0.617	0.040	6.93%	1968
Trump Swing	0.519	0.588	0.069	13.29%	1968
Trump Primaries	0.287	0.347	0.060	20.91%	1855
Study 5					
Leave Vote Share	0.424	0.484	0.060	14.15%	363

Notes: Adjusted within-R^2 values are reported. In study 2, this is the adjusted within-R^2 from regressions that include country and year fixed effects. In study 4 this is the adjusted within-R^2 from regressions that include state effects. In Study 3 this is the adjusted within-R^2 from regressions that include region effects. The initial "controls" included in Study 2 are GDP per capita (ln), unemployment rate, and inflation rate. In Study 4 these are household income (ln), unemployment, population density (ln), racism index, % religious, latitude. and longitude. In study 4 these are median pay (ln), unemployment, population density (ln), leave vote share in 1975, and EU migrant share.