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1. Introduction

Many commentators and scholars have argued that anger drives political choices and behavior in the US. For example, in his book *American Rage*, political scientist Steven W. Webster writes that “anger is a powerful and all-present force in shaping patterns of political behavior and public opinion” (p. xiii). Turning more specifically to the rise of populism, economist Dani Rodrik describes populist backlash in terms of giving “voice to the anger of the excluded” (Project Syndicate, March 9, 2016). In this paper, we test the hypothesis that anger affects the populist vote share across US counties in the 2016 electoral cycle. We find contrasted results: the incidence of anger is positively related with the vote share of populist candidates, but its effect weakens once we control for other dimensions of well-being and negative emotions. Our results indicate that a general sense of malaise and gloom, rather than anger *per se*, drives the rise in populism.

The hypothesis that anger might influence the populist vote share is rooted in psychology, where the significant role emotions play in shaping human behavior has long been acknowledged. The psychology literature provides a detailed account of the unique characteristics of anger. Individuals in a state of anger have a sense of control, the impression that they can take action to change the state of the world, and a sense of certainty that such action will achieve the desired and justified goal. Individuals in a state of anger are also quick to assign blame for their woes to specific individuals or groups. Other negative emotions, such as sadness or fear, do not share these characteristics (Lerner and Tiedens, 2006).

These observations raise the possibility that anger might affect political decisions. Anger as an emotion may be particularly conducive to voting for populist candidates. Indeed, blaming elites for the woes of “the people” is part of the very definition of populism. Acting to limit the reach and power of elites is a central part of the agenda of populist movements. It is natural, then, to hypothesize that anger has been a trigger of populist voting. Conversely, populist politicians have every incentive to fan the flames of anger.

Our main empirical exercise consists of assessing the effect of anger on populism, as measured by Trump’s vote shares in the 2016 primary and general elections, Sanders’ vote share in the 2016 primary election, as well as the difference between Trump’s vote share in the 2016 general election and Romney’s vote share in the 2012 election. In our specification, we control for a wide range of putative determinants of the populist vote share that may also correlate with anger, such as the decline in the manufacturing employment share, the degree of urbanization, the unemployment rate, and income. The proper interpretation of our estimated effect, then, is the impact of anger after partialling out these other factors. We document a positive effect of anger, aggregated at the county level, on these vote shares.

However, this effect is sensitive to controlling for indicators of well-being, as well as other negative emotions, despite the fact that anger and these other indicators are conceptually and empirically quite distinct from each other. This makes it hard to ascribe a lot of explanatory power to anger *per se*. Instead, we find that negative emotions and negative life evaluation *in general* are associated with a higher populist vote share. The bottom line of our findings is as follows: on the one hand, our results are consistent with a role for emotions and life satisfaction as determinants of voting for populists, in ways that are consistent with the

psychology literature on the role of emotions in decision making. On the other hand, our findings can also be read as critical of a more specific hypothesis implied by the psychology literature, assigning a role to generalized anger as a distinct emotion affecting populism.

2. Anger and Other Emotions

2.1. The Literature on Anger and Other Emotions

How might anger relate to voting behavior? In a sweeping survey of the psychology literature on the effect of anger on judgment and decision-making, Lerner and Tiedens (2006, Table 1, p. 121) draw out several lessons that are relevant for our study of the political economy of anger.¹ They summarize how anger affects behavior in ways distinct from other emotions. First, anger affects the attribution of causality and responsibility in a way that leads angry individuals to blame others.² Second, anger affects evaluations of members of the outgroup in a negative direction: angry individuals are less likely to trust members of an outgroup, more likely to have negative perceptions of them and to take action against them. Third, angry people are more willing to take risky decisions, as they hold more optimistic beliefs about the outcome of these actions. Fourth, anger builds on itself: being in an angry state raises the persuasiveness of anger-inducing arguments, and raises the perceived likelihood of further angering events. Fifth, anger activates heuristic processes: a greater propensity for stereotyping and a lower attention to the details of an argument. The reader will recognize several of these effects of anger as characteristics of populist platforms: the tendency to blame elites and outsiders, the sense that a populist candidate would have better control over policy outcomes, the strategic use of angry emotions to stir more anger among the electorate, and the frequent use of sweeping stereotypes among populist politicians and voters.

It is important to distinguish anger that arises from a specific source and is directed at a particular target, from generalized anger that may stem from a multiplicity of sources. Anger can arise from a wide range of situations, yet it can influence people's decisions and behaviors in contexts unrelated to its initial trigger. Indeed, the psychology literature emphasizes that generalized anger, regardless of its source and target, affects one's cognitive state and behavior (Lerner and Tiedens, 2006). This is in contrast to anger directed at specific targets. For instance, it stands to reason that a person angry at a politician is likely to vote against them (Rudolph, 2021). Instead, in this paper we focus on measures of anger as a general emotional state, rather than anger directed at a specific target. We test the hypothesis that generalized anger, rather than anger directed specifically at political opponents, drives populism.

¹The psychology literature on the role of emotions in shaping human behavior has spilled over into other social sciences. Examples include Lerner, Small and Lowenstein (2004); Rotemberg (2005); Di Tella and Dubra (2014); Gneezy and Imas (2014); and Castagnetti, Proto and Sofianos (2023).

²Busby, Gubler and Hawkins (2019) explore the role of blame in populist rhetoric. Using an experimental approach, they show that framing issues in terms of dispositional attribution (i.e. blaming the actions of individuals) rather than situational attribution (i.e. blaming a situation) prompts individuals to adopt populist attitudes and makes them more likely to express support for Donald Trump in the 2016 presidential election.

It is also important to note that, in many respects, anger is conceptually distinct from other emotions. Lerner and Tiedens (2006, page 117) state that: “negative events that are blamed on situational forces foster a sense of sadness rather than anger. Negative events accompanied by the belief that oneself is responsible give way to feelings of guilt and shame rather than anger (...). And, when people feel uncertain or lack confidence about the cause of negative events, they are likely to feel fear and anxiety rather than anger.” These observations open up the possibility that anger, as distinct from other negative emotions, affects the propensity to vote for populist candidates, our main hypothesis.

An emerging literature studies the role of anger in motivating voter behavior. Salient examples include Marcus (2000), Weber (2012), Banks (2014), Passarelli and Tabellini (2017), Marx (2019), Fisk et al. (2019), Phoenix (2019), Rudolph (2021), Rhodes-Purdy, Navarre and Utych (2021). Part of this literature has explored the role of anger as a determinant of voting for populist candidates, though with data and methods that differ from ours. Without being exhaustive, Bernecker et al. (2019) find that areas with more angry tweets tended to vote more for Donald Trump; Gutierrez et al. (2019) show that anger served to mobilize Hispanic voters during the 2016 election; Magni (2017) and Rico, Guinjoan and Anduiza (2017) study how anger about the economic crisis increases support for populist parties; Altomonte, Gennaro and Passarelli (2019) argue that negative collective emotions help explain voting for UKIP in the 2010 and 2015 elections; Marcus et al. (2019) and Vasilopoulos et al. (2019) show that after the 2015 Paris terror attack, individuals who reacted angrily voted more for the populist Front National, while those who became fearful were less likely to vote for the Front National; and in a wide-ranging book, Webster (2020) looks at the role of anger in US politics. What sets our work apart from these contributions is the use of high-frequency data on generalized anger to systematically analyze the political effects of cross-county variation in anger (and other emotions) across the entire US.

Finally, focusing on other emotions, Ward et al. (2020) study the effect of unhappiness on voting, with a focus on the 2016 presidential election. Like us, they use data from the Gallup Daily poll, but they do not use any data on anger. They find that subjective well-being is negatively correlated with the Trump vote share (for a related result, see also Herrin et al., 2018).

2.2. Data on Anger and Other Emotions

Our main source of data is the Gallup Daily poll, with over 3.5 million observations spanning January 2008 to January 2017. Since 2008, Gallup interviews daily a repeated cross-section of about 1,000 individuals. The main variable of interest in this study is the question on anger: “Did you experience the following feelings during a lot of the day yesterday: [anger]?” This question was asked of all respondents from 1/2/2008 to 12/31/2012, was asked to half of the sample from 1/3/2013 to 12/29/2013, and then again to half of the sample from 2/16/2016 to 1/4/2017 ($N = 2,101,352$).³ After that, the Gallup Daily poll stopped asking the question on anger. Unfortunately, there is no overlap between the time period during which the questions on both anger and on Trump favorability were asked, precluding an individual-level analysis of the relationship between anger and political preferences.

³See Gallup, Inc. (2017) for details.

In 2008, about 12.05% of respondents reported that they experienced angry feelings for a lot of the previous day. This proportion rose slightly to 12.48% by 2016. The Gallup Daily poll also provides other measures of well-being and of negative and positive emotions (life satisfaction today, expected life satisfaction in 5 years, sadness, stress, worry, happiness, enjoyment, and smile or laughter).⁴

For our county-level regressions, we also need economic, social and political data at the county level: election vote shares are from uselectionatlas.org; demographic and economic variables are from the Census Bureau, CDC, and the Bureau of Labor Statistics; inequality data are from the Economic Policy Institute; and social capital data are from Rupasingha, Goetz and Freshwater (2006). Tables A1 and A2 report summary statistics for the data used in this paper.

2.3. Descriptive Patterns on Anger and Other Emotions

We begin by assessing whether anger is distinct from other emotions and measures of subjective well-being captured in the Gallup Daily data. Using the individual-level data, we examine the simple relationship between anger, other negative emotions (worry, sadness, stress), positive emotions (enjoyment, smile or laugh, and happiness) and subjective well-being. Table I presents simple bivariate frequency tables for these variables. We find that negative emotions do not always coincide (Panel A). For example, 21.2% of the sample experienced worry for a lot of the previous day, but not anger (this is about three quarters of the sample of those who were worried), while 4.10% of the sample experienced anger but not worry (about one third of the sample of angry people). We also find that positive and negative emotions sometimes coexist. For instance, 9.1% of the sample reported being both angry and happy (that is about 3/4 of the people who report having been angry). In other words, the questions on positive and negative emotions seem to capture distinct dimensions of individuals' emotional states. This opens up the possibility of separately identifying the effects of anger on political economy outcomes.

Turning to subjective well-being, Table I Panel B reveals that, while there is a general tendency for individuals who are angry to report low levels of life satisfaction relative to those who are not, the relationship is not very tight. For instance, on a 0-10 Cantril scale of life satisfaction today, almost half of the respondents who report having been angry also record scores of 7 or more on life satisfaction. Here too, therefore, one cannot argue that anger and life satisfaction are just two sides of the same coin.

Figure 1 shows that there is substantial spatial variation in the intensity of anger, averaged at the county-level. Counties at the 90th percentile have an average anger level of 15.2% and counties at the 10th percentile have an anger level of 7.5%. Thus, anger is not simply randomly distributed across individuals. The three most angry counties in the US (when requiring at least 100 observations to compute average anger) are McDowell County (WV), Buchanan County (VA) and Harlan County (KY). These counties are all located closeby in an area of the Appalachians and are among the poorest in the US. The least angry counties are Emmet

⁴It also provides individual-level demographic information, which we use in individual-level regressions on the determinants of anger.

County (IA), Kane County (UT) and Cottonwood County (MN). These also tend to be rural counties, but are economically better off than the most angry counties.

Table I – Anger, Other Emotions and Life Satisfaction

Panel A – Other Emotions – Cross-Frequencies

	Experience Anger Yesterday: 0	Experience Anger Yesterday: 1
Experience Worry Yesterday: 0	66.77	4.10
Experience Worry Yesterday: 1	21.18	7.95
Experience Sadness Yesterday: 0	77.09	6.25
Experience Sadness Yesterday: 1	10.86	5.80
Experience Stress Yesterday: 0	60.78	3.07
Experience Stress Yesterday: 1	27.17	8.98
Experienced Happiness Yesterday: 0	8.31	2.95
Experienced Happiness Yesterday: 1	79.64	9.10
Smile or Laugh: 0	13.50	4.36
Smile or Laugh: 1	74.45	7.69
Experienced Enjoyment Yesterday: 0	10.25	3.93
Experienced Enjoyment Yesterday: 1	77.70	8.12

Based on samples of 2,098,613 observations (worry), 2,097,202 (sadness), 2,098,484 (stress), 2,094,767 (happiness), 2,086,465 (smile/laugh), from January 2008 to January 2017.

Panel B – Life Satisfaction – Cross-Frequencies

	Anger=0	Anger=1
0	0.482	0.286
1	0.435	0.219
2	0.815	0.371
3	1.876	0.691
4	3.360	0.978
5	11.085	2.145
6	9.255	1.526
7	18.395	2.343
8	23.937	2.142
9	9.526	0.677
10	8.795	0.660

Life satisfaction is a Cantril Ladder, ranging from 0 to 10

Based on a sample of 2,040,278 observations from 01-02-2008 to 01-04-2017

Panels A, B and C of Figure A1 display time variation in the average share of individuals experiencing anger across the United States, respectively by day, month and year, for all sampled individuals. At no frequency does the data exhibit any significant trends. In fact, average anger remains quite stable around 12%. Variation is obviously more pronounced at the daily level than at the monthly level, with daily anger levels ranging roughly from 6% to

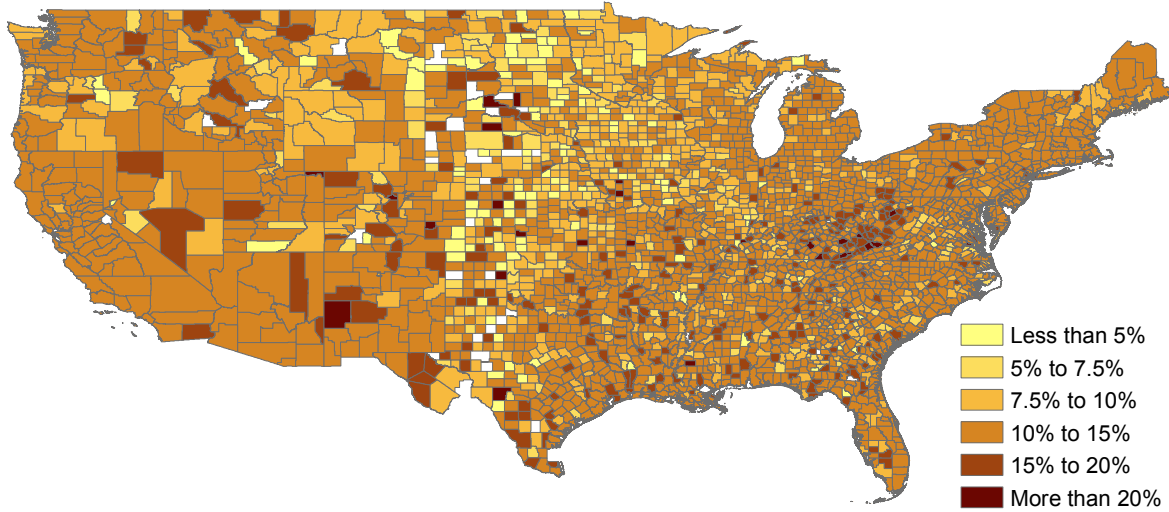


Figure 1: Anger by County: Share of Population

22%. Monthly anger ranges from 11% to 13.5% while annual anger is more tightly contained between 11.8% and 12.5%.

2.4. Persistence of Anger across Counties

How persistent are those spatial patterns over time? To assess the degree of temporal autocorrelation of anger across counties, we create a panel of anger at a two-year frequency. We focus on the period 2008-2013 since there is a gap after that. We also condition on there being enough data available per county to meaningfully calculate average county anger (we require 20, 50 or 200 observations per county over each two-year period). We then regress average county anger on its lag. We can include county fixed effects or not. With county fixed-effects, persistence implies a negative coefficient on lagged anger (reversion to the county-mean) while without county fixed effects, persistence implies a positive coefficient. The results in Appendix Table A3, are consistent with the patterns expected if anger is persistent: in column 3, without county fixed effects, we find a coefficient of 0.18 on lagged anger, implying some degree of persistence; in column 7, with county fixed effects, we estimate a coefficient of -0.47 on lagged anger, implying reversion to the county mean. These coefficients rise in magnitude when requiring that anger be averaged over a greater number of observations per county. Persistence is also stronger when averaging anger over longer periods.

These results provide some basis for averaging anger over as long a period as possible when exploring the determinants and consequences of anger, in order to limit the incidence of sampling variation, short run fluctuations, and measurement error. They also suggest that there is a tendency for some locations to display persistently high or low levels of anger. Many have emphasized the transient nature of anger at the individual level, but there is also a persistent component to anger, possibly related to both underlying county and individual characteristics.

2.5. Determinants of Anger

To validate our measures of anger, we check whether anger is related to a set of observables at the individual and at the county levels. To our knowledge, the data that we rely on here has not been widely used, so it is important to begin by understanding the drivers and correlates of our specific measure of anger. This also informs our choice of control variables when studying the effects of anger on vote shares. These results are shown and further discussed in Appendices A1 and A2. We find that variation in anger, both across individuals and counties, is meaningfully correlated with specific social and demographic characteristics. For instance, we find that angry people tend to be male, have low levels of education and income, and to be located at the extremes of the ideological spectrum (though not at the extremes of the political partisanship spectrum).⁵ We also find that anger is more pronounced in denser, urban places. Finally, anger levels seem to respond in the short run to specific events, like election results and school shootings.

3. Does Anger Drive Populism?

We focus on electoral results from recent elections, coinciding with the period during which daily anger data was gathered (i.e. we focus on elections in the 2008-2016 interval). Our emphasis is on explaining voting for Donald Trump and Bernie Sanders. Our regression takes the following generic form:

$$V = \alpha + \beta Anger + W'\Theta + \varepsilon \quad (1)$$

where V is the political outcome of interest (county presidential vote share in 2012 and 2016, excess of Trump 2016 over Romney 2012, primary vote share for Sanders and Trump) and W are county-level controls (all the county-level determinants of anger detailed in Appendix A1 plus partisanship shares).

In estimating equation (1) using least squares, our identification assumption is that anger is exogenous to electoral outcomes, conditional on the extensive set of controls included in matrix W . Consequently, the proper interpretation of β in equation (1) is as the effect of anger while controlling for the variables in W . Many of these variables, as discussed in Appendix A1, are themselves determinants of anger, and also potential determinants of populist voting. Specifically, in all regressions we control for a set of 17 variables that measure social capital, poverty, inequality, unemployment, racial diversity, the proportion of foreign born, change in manufacturing employment, median income, density, education, the shares of Democrats, Independents and Republicans, average commute time, and the share of people using public transit for commuting. In addition, we also account for state fixed effects and include dummies for different county categories of urbanicity. Therefore, β identifies the effect of anger not originating from these variables. Instead, it captures the effect of both idiosyncratic shocks to anger and unobserved factors unrelated to our outcome of interest. The critical identifying assumption is that, once we include our exhaustive set of controls, the remaining variation in anger is uncorrelated with ε .

A possible threat to identification is reverse causality: as mentioned in the introduction,

⁵Barber and Pope (2019) document the imperfect correlation between ideology and partisanship.

populist candidates have every incentive to fan the flames of anger. We address this concern in four ways. First, we take care to measure anger before the election, ruling out the possibility that the outcome of the election causally affects our measure of anger.⁶ Second, one of our main specifications uses the difference between Trump’s 2016 and Romney’s 2012 general election vote shares as the dependent variable. Given that Trump’s nomination as the Republican candidate was largely unexpected in the years leading up to 2016, this variable can be viewed as an unexpected shock to populist voting, making it unlikely to causally affect anger averaged over the *previous* eight years. Third, the *future shock* to populist vote share, as measured by the differences between Trump’s 2016 and Romney’s 2012 vote shares, is even less likely to be anticipated once we account for the extensive set of controls and fixed effects included in all our regressions. For example, populist sentiment may be trending up in locations with declining manufacturing employment, partly explaining both anger and the Trump minus Romney vote share. However, in all regressions we control for the change in the manufacturing employment share. Fourth, we control for the shares of Republicans, Independents and Democrats in all specifications, which means that the effect we estimate is properly interpreted as the effect of generalized anger on populist *deviations* from counties’ baseline political orientation (i.e. *shocks* to the degree of populism).

3.1. Anger and the Trump Vote Share

Table II reports estimation results where the dependent variables are Trump’s vote share in the 2016 primaries, Sanders’ vote share in the 2016 primaries, Trump’s vote share in the 2016 general election, and the difference between Trump’s 2016 general election vote share and that of Mitt Romney in 2012. We chose these variables to capture preferences for populist candidates on the right and on the left - Donald Trump and Bernie Sanders. The primary vote shares and the difference between Trump and Romney’s 2016 vote shares are particularly pointed measures of support for populism *per se*. In contrast, the Trump vote share in the general election likely includes many voters who associate with the Republican Party more than with the specific candidate, and may thus be a more noisy measure of support for populism.

We find that anger, averaged across counties using all available data between January 2, 2008 and the day of each election, positively affects voting for populists for all four dependent variables. For example, a 10 percentage point increase in the share of a county’s population that reports experiencing anger is associated with a 1.18 percentage point increase in Trump’s county-level vote share in the 2016 primary, and a 1.67 percentage point increase in Sanders’ 2016 primary vote share. The corresponding effects for Trump’s 2016 Presidential election is 2.44 percentage points, and 0.66 percentage points for the vote share difference between Trump and Romney. We note that these effects remain even after controlling for a wide range of correlates of anger that could act as confounding variables. These variables themselves tend to enter the regression with the expected signs.

Our approach based on county level average anger does not allow us to conclude that

⁶We average anger at the county level over different time spans. The start date is always January 2, 2008, but the end date varies: November 8, 2016 for the 2016 presidential election; February 1, 2016 for the 2016 primary elections; November 6, 2012 for the 2012 presidential election.

Table II – Anger and the Trump Vote Share, county-level (Dependent Variable as in Second Row)

	(1)	(2)	(3)	(4)
	2016 Trump Primary vote share	2016 Sanders Primary vote share	2016 Trump Election Vote Share	Trump 2016 minus Romney 2012
Anger (avg. up to Feb. 2016)	10.704** (4.489) [0.018]	17.948*** (5.749) [0.030]		
Anger (avg. up to Nov. 2016)			24.256*** (6.467) [0.043]	6.195** (2.555) [0.029]
Income Inequality	-0.061 (0.257) [-0.002]	-0.747*** (0.288) [-0.027]	-0.728** (0.297) [-0.027]	-1.016*** (0.125) [-0.100]
Share of Democrats	-3.297 (4.718) [-0.018]	15.649** (6.168) [0.084]	-53.671*** (7.030) [-0.298]	1.587 (2.542) [0.023]
Share of Republicans	-5.671 (4.634) [-0.031]	25.330*** (6.093) [0.135]	45.962*** (7.140) [0.253]	-11.610*** (2.459) [-0.170]
Share of Independents	13.169* (7.501) [0.019]	36.222*** (9.446) [0.051]	44.102*** (10.479) [0.064]	28.019*** (4.241) [0.107]
Social Capital	-1.344*** (0.232) [-0.079]	-1.356*** (0.279) [-0.077]	-1.715*** (0.267) [-0.113]	-0.357*** (0.118) [-0.063]
Racial Fractionalization	-2.908** (1.443) [-0.035]	33.400*** (1.849) [0.398]	17.181*** (2.514) [0.211]	2.038*** (0.708) [0.066]
Log Percent Foreign Born	-0.844** (0.356) [-0.040]	4.353*** (0.445) [0.205]	-1.053** (0.505) [-0.051]	-1.246*** (0.175) [-0.160]
Log Population Density	-0.648*** (0.203) [-0.059]	0.182 (0.252) [0.016]	-0.702*** (0.264) [-0.066]	-0.782*** (0.112) [-0.196]
Log Effective Population Density	-0.263 (0.302) [-0.016]	-1.085*** (0.386) [-0.065]	-1.874*** (0.413) [-0.116]	-0.108 (0.162) [-0.018]
Commute Time	0.109*** (0.038) [0.035]	-0.070 (0.047) [-0.022]	-0.112** (0.048) [-0.038]	0.056*** (0.020) [0.050]
Public Transit	0.085 (0.063) [0.017]	-0.166*** (0.048) [-0.034]	0.202*** (0.060) [0.042]	0.006 (0.029) [0.003]
Homeownership rate	0.858*** (0.282) [0.052]	-1.348*** (0.312) [-0.082]	0.896** (0.362) [0.056]	0.403*** (0.132) [0.067]
Log Median household income	-15.412*** (1.586) [-0.236]	5.610*** (1.805) [0.087]	-10.156*** (1.847) [-0.161]	-9.000*** (0.828) [-0.378]
% High School or more	-0.641** (0.271) [-0.039]	2.147*** (0.307) [0.132]	-1.898*** (0.358) [-0.121]	-0.571*** (0.155) [-0.096]
Percent Below Poverty	-1.738*** (0.345) [-0.106]	1.428*** (0.438) [0.087]	-3.887*** (0.454) [-0.246]	-1.495*** (0.215) [-0.250]
Percent Unemployed	2.004*** (0.475) [0.088]	-2.503*** (0.309) [-0.110]	-1.146*** (0.416) [-0.053]	0.347 (0.222) [0.042]
Change in manuf. empl., 2000-2015	0.266** (0.113) [0.016]	-0.090 (0.143) [-0.006]	-0.091 (0.123) [-0.006]	-0.023 (0.062) [-0.004]
Observations	2,419	2,394	2,581	2,581
Adjusted R2	0.894	0.852	0.833	0.767

Note: Robust standard errors in parentheses (*p<0.1; **p<0.05; ***p<0.01); standardized beta coefficients in brackets. All specifications include state fixed effects and dummies for urban/rural categories (large fringe metro, medium metro, micropolitan, noncore and small metro).

angry individuals vote for populist candidates (due to the ecological fallacy problem). The limitations of our data preclude an analysis of preferences for Trump at the individual level, because Gallup ceased to ask the anger question when they began asking about Trump’s favorability in early 2017. We do, however, have overlap between President Obama’s favorability rating and anger at the individual level. In Appendix A3, we find that anger at the county level is negatively associated with both Obama’s vote share in 2012 and the average county-level Obama approval rating (averaged over the 2008-2016 period). At the individual level, angry respondents tend to report being less favorable toward Obama. The lack of a reversal in the sign of the coefficient on anger when moving from county- to individual-level data suggests that the effect of anger at the county level is not driven by an ecological fallacy. However, this does not rule out the possibility that a reversal could occur in the Trump case.

3.2. Anger, Other Emotions, and Trump

A concern with the above regressions is that they do not allow a separate assessment of the effect of anger and of other emotions and mental states. To address this concern, we augment the regression with three variables, either entered individually or jointly. These three variables capture negative emotions (the average of stress, worry and sadness), positive emotions (the average of happiness, smile or laugh, and enjoyment), and life satisfaction today, as measured on a Cantril ladder running from 0 to 10.⁷ Panels A, B, C and D of Table III display the results respectively for each dependent variable. We find that the effect of anger is sensitive to the inclusion of these additional variables in all cases.

One consistent finding across dependent variables is that adding life satisfaction to the specification renders the coefficient on anger insignificant, and in other cases the inclusion of positive or negative emotions has the same effect. Life satisfaction itself enters with a consistently negative coefficient, significant at the 1% level in three of the four cases. In line with Ward et al. (2020), we find that higher levels of negative emotions tend to increase vote shares for Trump, while higher levels of positive emotions reduce them. In sum, the pattern of correlations between anger and other emotions or life evaluation implies that we cannot ascribe a strong predictive role to anger *per se*.

4. Conclusion

Observers who argue that anger and resentment fuel the rise of populism are partly correct. In the 2016 US presidential election, more angry counties voted in greater proportions for Trump, and these counties also saw larger gains for Trump compared to Romney’s vote share four years earlier. More angry counties also displayed a stronger preference for populist candidates on both the right and the left during the 2016 presidential primaries. However, once we control for other negative emotions and life satisfaction, anger no longer acts as a separate channel in driving the populist vote share. Instead, a more complex and multi-faceted sense of malaise is at the origin of the rise in populism.

⁷In constructing these variables, we follow the approach in Ward et al. (2020).

Table III – Anger and the Trump Vote Share, Controlling for Other Emotions and Life Evaluation

	(1)	(2)	(3)	(4)
Panel A: Dependent Variable: 2016 Trump Primary Vote Share				
Anger (avg. up to Feb. 2016)	3.475 (4.659) [0.006]	3.705 (4.523) [0.006]	4.435 (4.551) [0.008]	-0.448 (4.650) [-0.001]
Negative Affect	18.015*** (4.340) [0.042]			4.805 (4.889) [0.011]
Positive Affect		-33.383*** (5.330) [-0.058]		-24.220*** (5.998) [-0.042]
Life Evaluation			-3.949*** (0.729) [-0.053]	-2.612*** (0.761) [-0.035]
Adjusted R ²	0.895	0.896	0.895	0.897
Panel B: Dependent Variable: 2016 Sanders Primary Vote Share				
Anger (avg. up to Feb. 2016)	8.017 (5.965) [0.014]	19.213*** (5.941) [0.032]	15.786*** (5.977) [0.027]	9.197 (6.081) [0.016]
Negative Affect	24.223*** (5.079) [0.055]			31.127*** (5.978) [0.071]
Positive Affect		6.078 (7.011) [0.011]		24.653*** (8.038) [0.043]
Life Evaluation			-1.306 (0.933) [-0.018]	-0.679 (0.986) [-0.009]
Adjusted R ²	0.854	0.852	0.852	0.854
Panel C: Dependent Variable: 2016 Trump Election Vote Share				
Anger (avg. up to Nov. 2016)	4.377 (6.642) [0.008]	16.289** (6.517) [0.029]	8.009 (6.322) [0.014]	-2.222 (6.544) [-0.004]
Negative Affect	48.163*** (5.669) [0.117]			32.604*** (6.303) [0.079]
Positive Affect		-35.917*** (7.534) [-0.065]		2.504 (8.074) [0.005]
Life Evaluation			-10.173*** (0.898) [-0.143]	-8.501*** (0.954) [-0.120]
Adjusted R ²	0.840	0.835	0.844	0.846
Panel D: Dependent Variable: Trump 2016 minus Romney 2012				
Anger (avg. up to Nov. 2016)	6.779** (2.898) [0.032]	4.507* (2.596) [0.021]	0.160 (2.477) [0.001]	3.132 (2.739) [0.015]
Negative Affect	-1.415 (2.516) [-0.009]			-10.522*** (2.986) [-0.068]
Positive Affect		-7.613** (2.967) [-0.037]		-2.938 (3.413) [-0.014]
Life Evaluation			-3.779*** (0.366) [-0.141]	-4.230*** (0.406) [-0.158]
Adjusted R ²	0.767	0.768	0.778	0.779

Note: Robust standard errors in parentheses (*p<0.1; **p<0.05; ***p<0.01); standardized beta coefficients in brackets. All specifications include state fixed effects, dummies for urban/rural categories (large fringe metro, medium metro, micropolitan, noncore and small metro) and all the control variables displayed in Table 2. Regressions in Panel A are run on a sample of 2,419 counties. Regressions in Panel B are run on a sample of 2,394 counties. Regressions in Panels C and D are run on a sample of 2,581 counties.

The finding that anger *per se* is not predictive of the populist vote share is unlikely to be driven by anger being hard to distinguish from other negative sentiments. Both empirically and conceptually, anger is distinct from other emotions. In the data, the correlation between being angry and experiencing other negative emotions is not that high. For example, many people who feel worried do not feel angry, and vice versa. In the psychology literature, different negative emotions display different characteristics that are relevant for voting behavior. In contrast to fear, shame or sadness, anger tends to be directed at a particular individual or group, and hence acts as a call to action against that specific target. While this makes anger a particularly likely driver of the populist vote share, we find instead that populist candidates have stronger appeal in locations where there is a general sense of gloom.

In sum, our results provide a mixed perspective on the role of emotions as a determinant of voting behavior, as implied by the psychology literature. On the one hand, our findings support the notion that emotions influence voting behavior, consistent with the idea that emotions play a role in decision making. On the other hand, our results also offer a critique of the psychology literature that portrays anger as a distinct emotion affecting people's cognitive states in ways that promote voting for populist candidates.

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