Does Anger Drive Populism?*

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Abstract

We study whether anger fuels the rise of populism. Anger as an emotion tends to act as a call to action against individuals or groups that are blamed for negative situations, making it conducive to voting for populist politicians. Using a unique dataset tracking emotions for a large sample of respondents from 2008 to 2017, we explore the relationship between anger and the populist vote share across U.S. counties. More angry counties displayed stronger preferences for populist candidates during the 2016 presidential primaries and elections. However, once we control for other negative emotions and life satisfaction, anger no longer operates as a separate channel in driving the populist vote share. Instead, our results indicate that a more complex sense of malaise and gloom, rather than anger *per se*, drives the rise in populism.

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1 Introduction

Many commentators have suggested that anger is a driving force in the rise of populism.[1] In this paper, we study the effect of anger on electoral outcomes in the United States. In particular, we test whether anger is related to Donald Trump's vote share at the county level. We use data from the Gallup Daily poll, tracking the emotional state of a large sample of respondents, with broad geographic and demographic coverage. We find contrasted results: the incidence of anger is positively related with the vote share of populist candidates, but it ceases to predict the populist vote share once we consider other dimensions of well-being and negative emotions. Hence, low subjective well-being and negative emotions in general drive populism, rather than anger in particular. This comes as a surprise in light of the growing discourse linking "American rage" and populism (Webster, 2020).

Psychologists have long recognized the power of emotions in shaping human behavior. The psychology literature provides detailed analyses of the characteristics and specificities 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, a sense of certainty that such action will actually achieve the desired goal, and that this goal is justified. Individuals in a state of anger are also quick to assign blame for their woes to a person or group of persons. 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, the main hypothesis we seek to test in this paper. 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. Anger as an emotion might be particularly conducive to voting for populist politicians, and conversely populist politicians have every incentive to fan the flames of anger. It is natural, then, to hypothesize that anger has been a trigger of populist voting.

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. 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 generalized anger *per se*. Instead, we find that negative emotions and negative life evaluation *in general* are associated with a higher populist vote share. Our results therefore indicate that a complex sense of malaise and gloom, rather than anger *per se*, may drive the rise in 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

[1] In an opinion piece, economist Dani Rodrik describes populist backlash in terms of giving "voice to the anger of the excluded" (*Project Syndicate*, March 9, 2016). In an interview with the Washington Post, political scientist Kathy Cramer describes Trump voters as feeling resentment about not being heard and understood (*Washington Post*, November 8, 2016). Echoing this view, author David van Reybrouck argues that the anger of voiceless citizens drives the rise of populism in Europe and the United States (*Politico*, November 2, 2016).

out several lessons that are relevant for our study of the political economy of anger.[2] 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.[3] Second, anger affects evaluations and attitudes 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 members of outgroups 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.[4] 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 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.

There is an emerging literature on the role of anger in motivating voter attitudes and behavior. Salient examples along this tradition include Marcus (2000), Weber (2012), Marx (2019), Rudolph (2021), Fisk et al. (2019), Passarelli and Tabellini (2017), Rhodes-Purdy, Navarre and Utych (2021), among others. With few exceptions, this literature has not studied the role of anger as a determinant of voting for populist candidates. Five exceptions stand out, but all of them do so in contexts or with data that are very different from ours, and none of them examine the effect of anger as distinct from other emotions: Bernecker et al. (2019) use Twitter data to examine regional variation in the emotional content of tweets, and find that areas with more angry tweets tended to vote in larger proportions in favor of Donald Trump; Guttierez et al. (2019) look at anger felt by Hispanic voters during the 2016 election, showing that anger served to mobilize and politically motivate these voters; Altomonte, Gennaro and Passarelli (2019) argue that negative collective emotions help explain voting for UKIP in the 2010 and 2015 elections; Vasilopoulos et al. (2019) show that after the 2015 Paris

[2] The psychology literature on anger and more generally on the role of emotions in shaping human behavior has led other social sciences to incorporate a consideration of emotions as determinants of other types of behavior: Lerner, Small and Lowenstein (2004) analyze the effect of negative emotions on the endowment effect in economic transactions. Rotemberg (2005) studies the macroeconomic effects of customer anger at price increases. Di Tella and Dubra (2014) argue that the welfare gain from regulating monopoly power can be larger than conventionally thought if regulation mitigates consumer anger at firms enjoying market power. Gneezy and Imas (2014) study how strategically angering one's opponent can generate benefits in competition. Finally, Castagnetti, Proto and Sofianos (2023) use lab experiments to argue that anger (but not sadess) can impair strategic thinking in the context of bargaining and cooperation games.

[3] Busby, 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 rather than Hillary Clinton in the 2016 Presidential election.

[4] Anger potentially arises from a wide range of sources (sitting in traffic, having domestic disagreements, hearing upsetting news, etc.), but can change people's decisions and behaviors in contexts that have little to do with its initial trigger. This is in contrast to anger directed at specific targets. For instance, it stands to reason that a person angry at a politician would tend to vote against that politician. Instead, we focus here on measures of anger as a general emotional state, rather than anger directed at a specific target. For an analysis of the effect of anger directed at the federal government on the propensity to support Donald Trump, using Pew data, see Rudolph (2021).

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, but he does not use high-frequency data on generalized anger or examine its effect on Trump's vote share, as we do.

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. They find that subjective well-being is negatively correlated with the Trump vote share (for a related result, see also Herrin et al., 2018). Their data and empirical approach share several characteristics with ours, but they do not focus on the role of anger. Their regressions control for measures of negative and positive affect, not including anger. Measures of subjective well-being, negative affect and positive affect are entered separately in the regressions. In our empirical analysis, we include controls for these variables either jointly or separately, alongside our measure of anger - the main focus of this study.[5]

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 ($N = 2,101,352$).[6] 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. According to the Gallup Daily poll, in 2008 about 12.05% of respondents in any given day reported that they experienced angry feelings for a lot of the previous day, and this proportion rose slightly to 12.48% by 2016, when that data source stops. In addition to the anger question, 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).[7]

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, respectively for the county-level and for the individual-level datasets.

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 1 presents simple bivariate

[5] Their measure of negative affect captures whether the respondent experienced stress, worry and sadness the previous day, while their measure of positive affect captures whether respondents experienced happiness, enjoyment and laughter (Ward et al., 2020, p.3). We follow their approach when computing the corresponding variables.

[6] See Gallup, Inc. (2017) for details.

[7] It also provides individual-level demographic information on the interviewees, such as gender, age, political partisanship, ideological predilection and income. We will use these in individual-level regressions on the determinants of anger.

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 for a lot of the previous day (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, while also suggesting that other positive and negative emotions will need to be controlled for.

Turning to subjective well-being, Table 1 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 the previous day 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 the geographic patterns in the intensity of anger, averaged at the county-level using all the available data on anger. There is significant spatial variation in the level of anger. With the exception of the Rust Belt, the middle of the country tends to display a lower average level of anger. In terms of magnitudes, the differences are large. Counties at the 90^{th} percentile have an average anger level of 15.2% and counties at the 10^{th} percentile have an anger level of 7.5%. This implies that anger is not simply randomly distributed across individuals. Instead, there is a significant amount of spatial heterogeneity that begs to be explained. 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 (the first two are adjacent to each other) and are among the poorest in the US. The least angry counties are Emmet 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.

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 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? We can assess the degree of temporal autocorrelation of anger across counties. To do so, we create a panel of anger at a two-year frequency. We focus on the period 2008-2013 since there is a gap after this time window and before the anger question is asked again in 2016. We also condition on there being enough data available per county in each two-year period 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 are presented in Appendix Table A3, and are consistent with the patterns expected if anger was persistent. For instance, 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. For example, when requiring at least 200 observations per county, the coefficient on lagged anger rises in magnitude to 0.36 (without fixed effects) and to -0.55 (with fixed effects). Persistence is also stronger when averaging anger over longer periods (three-years versus two-years). This is what we would expect if: 1) requiring more data per county results in more accurate estimates of county mean anger, and 2) averaging over longer periods also reduces sampling variation across counties and has the effect of smoothing out short run fluctuations in anger.

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 exists a persistent spatial pattern in anger, namely there is a tendency for some locations to display 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 in the political economy literature, 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).[8] 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:

$$V = \alpha + \beta Anger + W'\Theta + \varepsilon \tag{1}$$

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. We believe this is a reasonable approach: we take care to measure anger before the election, ruling out the possibility that the outcome of the election causally affected our measure of anger (reverse causality).[9] The remaining identification concern is omitted variables bias, which we account for by

[8] The idea that ideology and partisanship are only imperfectly related is explored in depth in Barber and Pope (2019).

[9] Indeed, depending upon the outcome variable under consideration, we compute average anger at the county level over different timespans. The starting date is always January 2, 2008, but the ending date varies. Specifically, when the dependent variable pertains to the 2016 presidential election, the endpoint is November 8, 2016. When the dependent variable pertains to the 2016 primary election, the endpoint is February 1, 2016. And when we analyze results from the 2012 presidential election, we average anger until November 6, 2012. Thus, we never include data that pertain to the post-election period.

entering an exhaustive set of county-level observables corresponding to the determinants of anger explored in Appendix A1: in all specifications, we control for a set of 17 variables meant to capture the various factors that the literature has identified as correlates of preferences for Trump and other populist candidates: social capital, poverty, inequality, unemployment, racial diversity, the proportion of foreign born, change in manufacturing employment, median income, various measures of density, education, the shares of Democrats, Independents and Republicans, average commute time, and the share of people using public transit for commuting. We also include state fixed-effects and dummies for various county categories of urbanicity.

3.1 Anger and the Trump Vote Share

Table 2 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 salient 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 elections, 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 (column 1), 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 (columns 2 and 3). 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. For instance, for all three dependent variables, social capital enters negatively (Giuliano and Wacziarg, 2019), and so does county median income.

Our approach based on county level average anger does not allow us to conclude that angry individuals vote for populist candidates (due to the ecological fallacy problem). It is possible that non-angry voters in counties with high levels of anger were the ones who voted for Trump. 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, allowing us to compare the effect of anger at the county level on county-level vote shares, to that of anger at the individual level on Obama's favorability rating. We conduct this analysis 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 (where Obama approval is averaged using all available data over the 2008-2016 period). At the individual level, respondents who report having been angry the day before also 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 finding does not directly 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, respectively, 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.[10] Panels A, B, C and D of Table 3 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 consistently 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 U.S. 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, our results indicate that a more complex and multi-faceted sense of malaise is at the origin of the rise in populism.

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. Future research should aim to investigate how emotions drive preferences for populist politicians using individual-level data, when they become available.

[10] In choosing these definitions, we follow Ward et al. (2020).

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Table 1 – 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
Life Satisfaction Today (1-10 Scale)	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

Table 2 – 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).

Table 3 – 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 R2	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 R2	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.

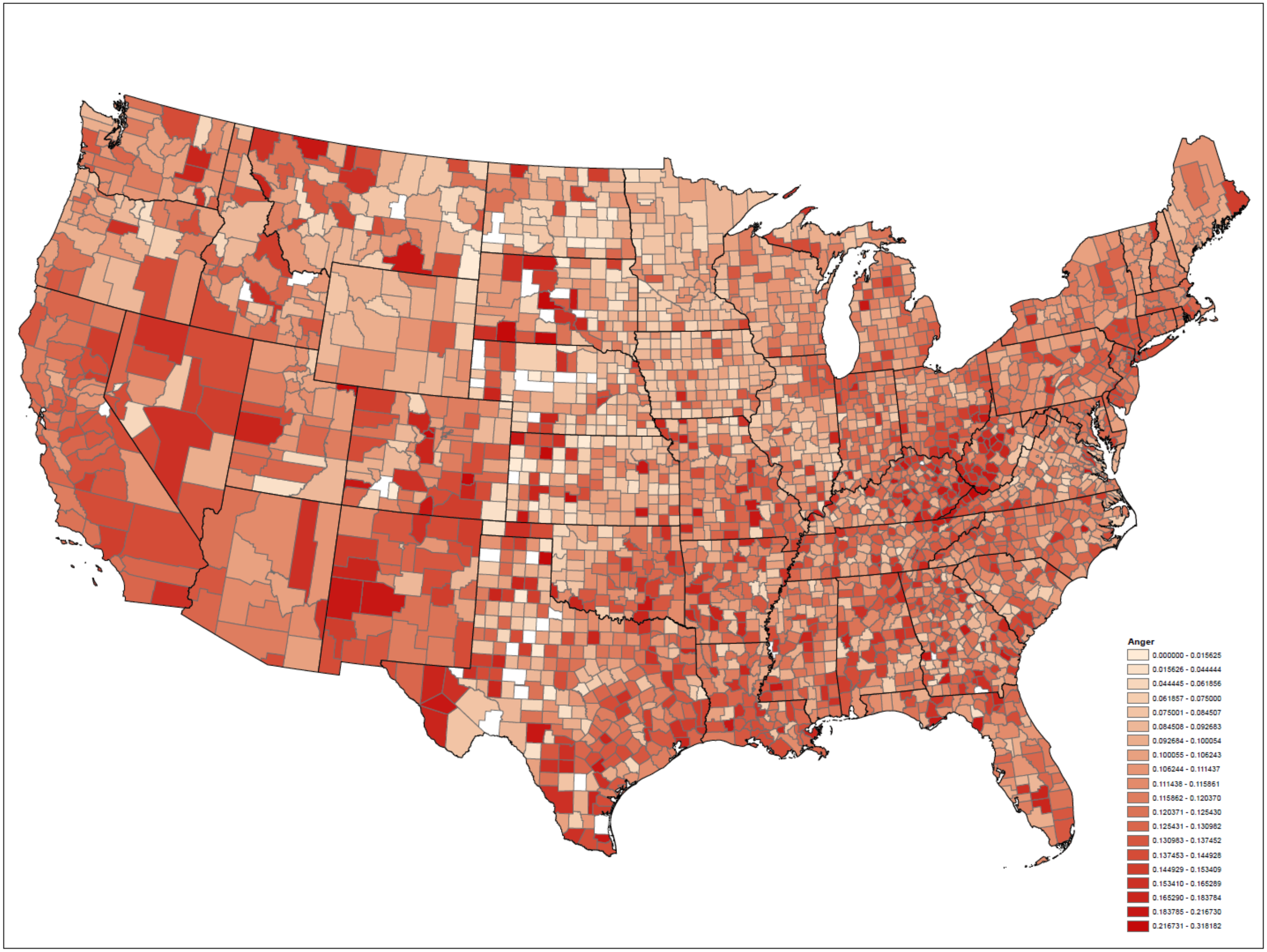


Figure 1 County Map of Anger, averaged over January 2008 – January 2017

Online Appendix

A1. County-Level Correlates of Anger

To explore the correlates of anger across counties, we regress anger on county-level variables:

$$y = \alpha + W'\Theta + \varepsilon$$

where y is mean anger at the county level, averaged over 1/2/2008 to 1/4/2017 and W is a vector of county-level variables. We include a comprehensive set of potential county determinants of anger, ranging from social capital and degree of urbanization, to unemployment, poverty, homeownership, manufacturing employment, and the share of foreign born.

Table A4 shows the results, based on a sample of $2,581$ counties that have any anger data. Column (1) includes a full set of state dummies, while column (2) does not include state fixed effects. Counties with a higher unemployment rate and higher population density display greater levels of anger, whereas counties with higher levels of social capital and a larger share of high school graduates or more have lower levels of anger. The overall adjusted R^2 is 0.196 when not including state-level dummies; it increases to 0.218 when controlling for state fixed effects. These results help validate that the geographic variation in anger follows certain predictable patterns.

A2. Individual-Level Correlates of Anger

Another way to confirm that survey-based measures of anger capture meaningful variation in this emotion is to examine its correlates at the individual level. Next, we regress anger on individual-level variables and county variables:

$$y = \alpha + X'\Gamma + W'\Theta + \varepsilon$$

where y is the individual's response to anger question on a given day, X is a vector of individual-level variables, observed within the Gallup daily poll, and W is a vector of county-level variables.

Table A5 reports our findings.[11] Focusing on demographics, individuals tend to be more angry when young, male or Hispanic, and less angry when married or Asian. For both income and education, we find negative anger gradients: the higher someone's income or education levels, the lower the likelihood that they are angry. Many of the results obtained at the county-level carry over here, after controlling for individual-level observables. For example, individuals are more angry in counties that are denser, have longer commuting times, and have higher unemployment rates. Table A5 also reports the magnitudes of these various effects, as captured by the standardized β coefficients. The largest effect comes from age, with a standardized β of -10.3%. Education and income are also quantitatively important.

Turning to political affiliation and ideology, we document interesting anger gradients, displayed graphically in Figures A2 through A4. The partisan gradient is hump-shaped, whereas the ideological gradient is U-shaped. Republicans and Democrats are less likely to be angry than Independents. This may come as a slight surprise given current perceptions of partisan animosity. We do see a pattern more in line with conventional priors when turning to ideology rather than party affiliation: both the very liberal and the very conservative are more angry than moderates, with the most liberal being significantly more angry than the most conservative. These patterns hold for the full sample as well as for each year of available data. They also hold in a regression sense when controlling for other individual and county characteristics (Table A5).

[11] The sample consists of $1,890,067$ observations in columns 1 and 3, and $1,022,462$ in columns 2 and 4. The latter only include data from 2008 to 2013 because of joint data availability on ideology and anger.

Overall, the regression results shown in Table A5 further validate that there are identifiable drivers of anger, at both the individual and county levels. Some of these drivers are time-invariant so they help explain the spatial persistence of anger documented in Section 2.4.[12]

A3. County-Level and Individual-Level Regressions for Obama Approval

The proper interpretation of this paper's main empirical results is that they identify the effect (or lack thereof) of average anger at the county level on electoral outcomes. They do not imply that angry people themselves act in a certain way when it comes to elections (the "ecological fallacy problem"). For instance, it could be that non-angry people in counties with higher levels of anger are the ones who voted for Trump. The lack of individual-level data on both voting behavior (for the 2016 election) and emotions hinders a convincing resolution of this issue. However, the Gallup daily poll on which we rely does ask respondents whether they hold favorable views of the sitting president. Unfortunately for our purposes, Gallup stopped asking the question on anger when Donald Trump came into office, so we do not have the ability to assess whether angry individuals had a tendency to hold more favorable views of Trump. We do, however, have data on both favorability and anger for virtually all of Barack Obama's two terms in office, so we can test if results at the individual level mirror those found at the county level.

Table A6 presents the results. The first column uses data at the county level. The dependent variable is Obama's vote share in the 2012 general election, and the main regressor of interest is anger averaged at the county level over the period from January 2008 to November 2012. We continue to control for the same county-level variables as in the main text. We see that anger at the county level is negatively associated with the county-level vote share obtained by Obama. Column 2 is also at the county level, but the dependent variable is now the county-level average approval rating of Obama. Here, both the dependent variable and the main regressor (anger at the county-level) are averaged over the full sample period (January 2008 - January 2017). We find the same effect sign: county-level anger is negatively related with Obama average approval. Finally in column 3 we exploit data at the individual level, i.e. column 3 consists of a regression of Obama approval on anger at the individual level. We find that Obama approval is lower among angry people, even after controlling for the large set of individual and county-level observables also included in Table A5. Comparing results across columns, we see that there is no sign reversal when moving from county to individual level regressions. Thus, county-level results for the Obama vote share and Obama approval are unlikely to be attributable to an ecological fallacy problem: the reason why counties with more angry respondents voted in smaller proportions for Obama is plausibly due to angry voters themselves being less likely to vote for Obama.

Appendix References

Pinto, S., P. Bencsik, T. Cluluun, C. Graham (2019), "Presidential Elections, Divided Politics, and Happiness in the US", *HCEO Working Paper* 2019-015, University of Chicago.

Sharkey, P. and Y. Shen (2021), "The Effect of Mass Shootings on Daily Emotions is Limited by Time, Geographic Proximity, and Political Affiliation", *PNAS* 118(23): e2100846118.

[12] To further validate the anger measure, we looked at the effect of big events on anger. For instance, we found that mass shootings lead to spikes in anger, the effect decays as you move away from the affected location, and it lasts for only a few days after the event, in particular in the case of the Sandy Hook shooting (for more on the anger-inducing effects of mass shootings, with similar findings, see Sharkey and Shen, 2021). We also examined the effect of presidential election outcomes on angers of co-partisans of the winner and loser. We found that presidential election outcomes affect individual anger asymmetrically: those with the same party ID as the loser tend to become more angry after the election, but those aligned with the winning party do not tend to become less angry. The effect of electoral outcomes on subsequent anger dies out after a week or so (for more on the effects of elections on emotions and well-being, see Pinto et al., 2019). These results are available upon request.

Table A1 – Summary Statistics for the County-Level Variables

	Obs.	Mean	Standard Deviation	Minimum	Maximum
Anger (county mean, 2008-2017)	3140	0.113	0.035	0	0.500
Anger (avg. up to Nov. 2016)	3139	0.113	0.035	0	0.500
Anger (avg. up to Feb. 2016)	3136	0.113	0.037	0	0.500
Anger (avg. up to Nov. 2012)	3136	0.112	0.039	0	0.500
Positive Affect	3143	0.853	0.037	0	1
Negative Affect	3143	0.269	0.045	0	0.524
Life Evaluation	3143	6.960	0.256	4.857	8.833
Life evaluation in 5 years	3143	7.299	0.375	0	9.667
Income Inequality	3138	1.663	0.592	-0.051	5.025
Share of Democrats	3137	0.324	0.092	0.030	1
Share of Republicans	3138	0.411	0.093	0.067	1
Share of Independents	3093	0.081	0.025	0.009	0.250
Social Capital	3105	-0.003	1.223	-3.562	8.074
Racial Fractionalization	3195	0.692	0.186	0.229	1
Log Population Density	3195	3.873	1.636	0	11.149
Public Transit	3141	0.902	3.066	0	60.700
Log Effective Population Density	3225	5.517	1.003	0.016	10.028
Commute Time	3195	22.989	5.459	4.400	44.200
Homeownership rate	3195	0	1	-8.960	2.703
Median household income	3195	46.061	11.914	19.986	122.238
Percent High School Grad. or Higher	3195	0	1	-5.758	2.093
Percent Below Poverty	3195	0	1	-2.437	5.657
Percent Unemployed	3219	0	1	-1.589	8.041
Change in manuf. empl., 2000-2015	2602	0	1	-0.953	23.846
Large Central Metro	3149	0.022	0.145	0	1
Large Fringe Metro	3149	0.117	0.321	0	1
Medium Metro	3149	0.118	0.323	0	1
Small Metro	3149	0.114	0.317	0	1
Micropolitan	3149	0.204	0.403	0	1
Noncore	3149	0.426	0.495	0	1

Table A2 - Summary Statistics for the Individual-Level Variables

	Obs.	Mean	Standard Deviation	Minimum	Maximum
Anger	2,101,352	0.12	0.33	0	1
Female	2,101,348	0.51	0.50	0	1
Male	2,101,348	0.49	0.50	0	1
Less than High School	2,101,338	0.06	0.23	0	1
High School/Vocational	2,101,338	0.27	0.44	0	1
Any College	2,101,338	0.47	0.50	0	1
Postgraduate	2,101,338	0.20	0.40	0	1
White	2,035,584	0.81	0.39	0	1
Black	2,035,584	0.08	0.26	0	1
Hispanic	2,035,584	0.07	0.26	0	1
Asian	2,035,584	0.02	0.13	0	1
Other	2,035,584	0.03	0.16	0	1
Income < 23,999 USD	2,014,834	0.18	0.38	0	1
Income 24,000 to 59,999 USD	2,014,834	0.30	0.46	0	1
Income > 60,000 USD	2,014,834	0.35	0.48	0	1
Single/Never Married	2,101,351	0.17	0.37	0	1
Married/Partnership	2,101,351	0.58	0.49	0	1
Previously Married	2,101,351	0.24	0.43	0	1
Republican	2,101,352	0.27	0.44	0	1
Lean Republican	2,101,352	0.11	0.32	0	1
Independent	2,101,352	0.08	0.27	0	1
Lean Democrat	2,101,352	0.11	0.32	0	1
Democrat	2,101,352	0.29	0.45	0	1
Very conservative	1,135,580	0.09	0.29	0	1
Conservative	1,135,580	0.34	0.48	0	1
Moderate	1,135,580	0.34	0.47	0	1
Liberal	1,135,580	0.17	0.38	0	1
Very Liberal	1,135,580	0.05	0.22	0	1

Table A3 – Assessing the Time Persistence of Anger, Averaged at the County Level
Dependent Variable: County-level Anger, averaged over 2-year periods, 2008-2013.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lagged Anger	0.046***	0.120***	0.182***	0.363***	-0.416***	-0.449***	-0.473***	-0.553***
	(0.014)	(0.015)	(0.018)	(0.028)	(0.017)	(0.018)	(0.024)	(0.039)
Observations	6,243	4,908	3,196	1,148	6,243	4,908	3,196	1,148
R^2	0.002	0.013	0.031	0.128	0.640	0.660	0.665	0.746
Adjusted R^2	0.002	0.013	0.030	0.127	0.277	0.321	0.331	0.491
County Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Sample restriction (# of obs)[a]	None	20	50	200	None	20	50	200

Note: Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.
a. The sample restriction refers to the number of individual observations on anger (used to compute average county anger) required for a county to be included in the sample.
The panel consists of three two-year periods: 2008-2009, 2010-2011, 2012-2013.

Table A4 – County-level Determinants of Anger
(Dependent Variable: Average County Anger, 1/2/2008 to 1/4/2017)

	(1)	(2)
Income Inequality	0.065 (0.111) [0.014]	0.184* (0.105) [0.039]
Share of Democrats	1.003 (2.506) [0.031]	3.033 (2.363) [0.095]
Share of Republicans	0.474 (2.515) [0.015]	1.861 (2.426) [0.058]
Share of Independents	8.941** (4.528) [0.073]	7.525* (4.005) [0.061]
Social Capital	-0.548*** (0.101) [-0.205]	-0.751*** (0.083) [-0.281]
Racial Fractionalization	-0.707 (0.535) [-0.049]	-0.026 (0.447) [-0.002]
Log Percent Foreign Born	-0.251* (0.150) [-0.069]	-0.135 (0.123) [-0.037]
Log Population Density	0.195** (0.080) [0.105]	0.063 (0.056) [0.034]
Log Effective Population Density	-0.148 (0.143) [-0.052]	-0.004 (0.120) [-0.001]
Commute Time	0.034* (0.018) [0.064]	0.052*** (0.017) [0.100]
Public Transit	0.039*** (0.015) [0.045]	0.039*** (0.015) [0.046]
Homeownership rate	-0.102 (0.105) [-0.036]	-0.158* (0.089) [-0.056]
Log Median household income	0.170 (0.692) [0.015]	-0.027 (0.605) [-0.002]
Percent High School Graduate or Higher	-0.207* (0.117) [-0.075]	-0.174* (0.101) [-0.063]
Percent Below Poverty	0.163 (0.153) [0.058]	0.063 (0.145) [0.023]
Percent Unemployed	0.313*** (0.121) [0.081]	0.355*** (0.101) [0.092]
Change in manufacturing employment, 2000-2015	-0.042 (0.047) [-0.016]	-0.072 (0.048) [-0.027]
Adjusted R^2	0.218	0.196
State Fixed Effects	Yes	No

Note: Robust standard errors in parentheses (*p<0.1; **p<0.05; ***p<0.01); standardized beta coefficients in brackets. All specifications are estimated on a sample of 2,581 counties and include an intercept and dummies for urban/rural categories (large fringe metro, medium metro, micropolitan, noncore and small metro).

Table A5 - Individual and County-level Determinants of Anger
(Dependent variable: Individual-level Anger; Linear Probability Model)

	(1)	(2)	(3)	(4)
Party: Democrat	-0.019*** (0.001) [-0.026]	-0.021*** (0.001) [-0.031]	-0.019*** (0.001) [-0.026]	-0.021*** (0.001) [-0.031]
Party: Lean Democrat	-0.011*** (0.001) [-0.011]	-0.009*** (0.002) [-0.010]	-0.011*** (0.001) [-0.011]	-0.009*** (0.002) [-0.010]
Party: Lean Republican	-0.010*** (0.001) [-0.010]	-0.006*** (0.002) [-0.006]	-0.010*** (0.001) [-0.010]	-0.006*** (0.002) [-0.006]
Party: Republican	-0.024*** (0.001) [-0.033]	-0.022*** (0.001) [-0.031]	-0.024*** (0.001) [-0.033]	-0.021*** (0.001) [-0.031]
Party: Refused	-0.014*** (0.001) [-0.015]	-0.009*** (0.003) [-0.004]	-0.014*** (0.001) [-0.015]	-0.009*** (0.003) [-0.004]
Ideology: Liberal		0.012*** (0.001) [0.015]		0.012*** (0.001) [0.015]
Ideology: Very Liberal		0.035*** (0.002) [0.024]		0.035*** (0.002) [0.024]
Ideology: Conservative		-0.001 (0.001) [-0.001]		-0.001 (0.001) [-0.002]
Ideology: Very conservative		0.018*** (0.001) [0.016]		0.018*** (0.001) [0.016]
Gender: Male	0.010*** (0.0005) [0.016]	0.011*** (0.001) [0.017]	0.010*** (0.0005) [0.016]	0.011*** (0.001) [0.017]
Age	-0.002*** (0.00002) [-0.103]	-0.002*** (0.00002) [-0.103]	-0.002*** (0.00002) [-0.103]	-0.002*** (0.00002) [-0.102]
Race: Black	-0.001 (0.001) [-0.001]	0.001 (0.001) [0.0005]	-0.001 (0.001) [-0.001]	0.001 (0.001) [0.001]
Race: Hispanic	0.007*** (0.001) [0.005]	0.011*** (0.002) [0.008]	0.007*** (0.001) [0.005]	0.011*** (0.002) [0.008]
Race: Other	0.029*** (0.002) [0.014]	0.025*** (0.002) [0.012]	0.029*** (0.002) [0.014]	0.025*** (0.002) [0.012]
Race: Asian	-0.023*** (0.002) [-0.009]	-0.017*** (0.003) [-0.007]	-0.023*** (0.002) [-0.009]	-0.017*** (0.003) [-0.007]

	(1)	(2)	(3)	(4)
Income: 60,000 USD and over	-0.058*** (0.001) [-0.085]	-0.055*** (0.001) [-0.083]	-0.058*** (0.001) [-0.085]	-0.055*** (0.001) [-0.082]
Income: 24,000 USD to 59,999 USD	-0.042*** (0.001) [-0.059]	-0.040*** (0.001) [-0.058]	-0.042*** (0.001) [-0.059]	-0.041*** (0.001) [-0.058]
Income: DK or Refused	-0.052*** (0.001) [-0.058]	-0.049*** (0.001) [-0.053]	-0.052*** (0.001) [-0.058]	-0.049*** (0.001) [-0.053]
Marital: Married/Partnership	0.005*** (0.001) [0.008]	0.007*** (0.001) [0.011]	0.005*** (0.001) [0.007]	0.007*** (0.001) [0.010]
Marital: Previously Married	0.009*** (0.001) [0.012]	0.011*** (0.001) [0.014]	0.009*** (0.001) [0.012]	0.011*** (0.001) [0.014]
Marital: DK/Refused	0.037*** (0.005) [0.005]	0.031*** (0.008) [0.004]	0.036*** (0.005) [0.005]	0.031*** (0.008) [0.004]
Education: Any College	-0.028*** (0.001) [-0.043]	-0.027*** (0.002) [-0.042]	-0.028*** (0.001) [-0.043]	-0.027*** (0.002) [-0.042]
Education: HS/Vocational	-0.025*** (0.001) [-0.033]	-0.023*** (0.002) [-0.032]	-0.025*** (0.001) [-0.033]	-0.023*** (0.002) [-0.031]
Education: Postgrad	-0.035*** (0.001) [-0.043]	-0.036*** (0.002) [-0.044]	-0.035*** (0.001) [-0.043]	-0.035*** (0.002) [-0.044]
Education: DK/Refused	-0.004 (0.004) [-0.001]	-0.002 (0.006) [-0.0003]	-0.004 (0.004) [-0.001]	-0.001 (0.006) [-0.0003]
State Fixed Effects	Yes	Yes	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,890,067	1,022,462	1,890,067	1,022,462
Adjusted R2	0.018	0.019	0.018	0.018

Note: Robust standard errors in parentheses (*p<0.1; **p<0.05; ***p<0.01); standardized beta coefficients in brackets.
The sample includes all available individual-level observations from the Gallup Daily poll for which the anger question was asked. The time coverage is 1/2/2008 to 1/4/2017, with an interruption between 12/30/2013 and 2/15/2016.
In addition to the displayed individual-level determinants, the specification also controls for the following county-level variables: Public Transit; Income Inequality; Share of Democrats; Share of Republicans; Share of Independents; Social Capital; Racial Fractionalization; Large fringe metro dummy; Medium metro dummy; Micropolitan dummy; Noncore dummy; Small metro dummy; Log Percent Foreign Born; Log Population Density; Log Effective Population Density; Commute Time; Homeownership rate; Log Median household income; Percent High School Graduate or Higher; Percent Below Poverty; Percent Unemployed; Change in manufacturing employment, 2000-2015.

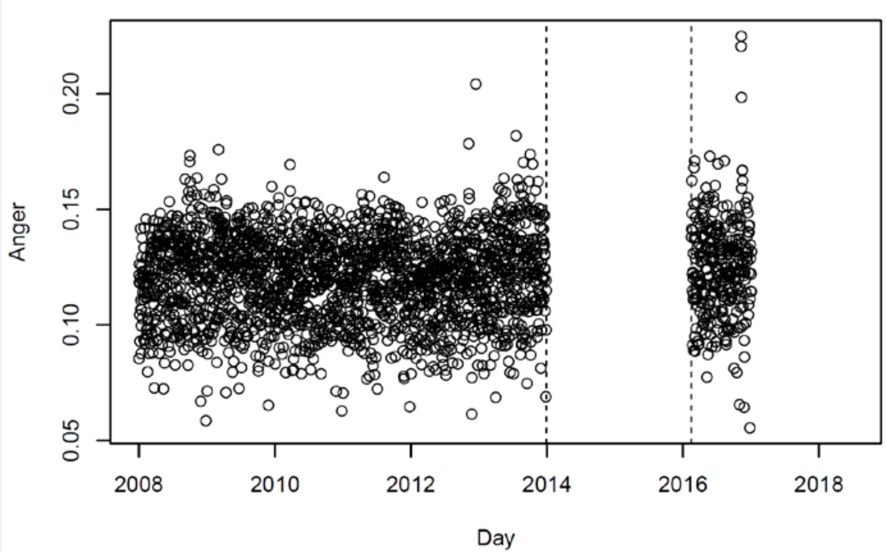
Table A6 – Anger and the Support for Barack Obama

	(1)	(2)	(3)
Dependent Variable:	**Obama 2012 General Election Vote share at the county level**	**Obama approval (from Gallup Daily) averaged at the county level over 2008-2017**	**Obama Approval (individual level, 0/1 variable)**
Anger (avg. up to Nov. 2012)	-13.645** (5.994) [-0.028]		
Anger (county mean, 2008-2017)		-0.243*** (0.053) [-0.058]	
Anger (individual answer, 0/1 variable)			-0.041*** (0.001) [-0.027]
Observations	2,572	2,581	631,798
Adjusted R^2	0.804	0.807	0.511

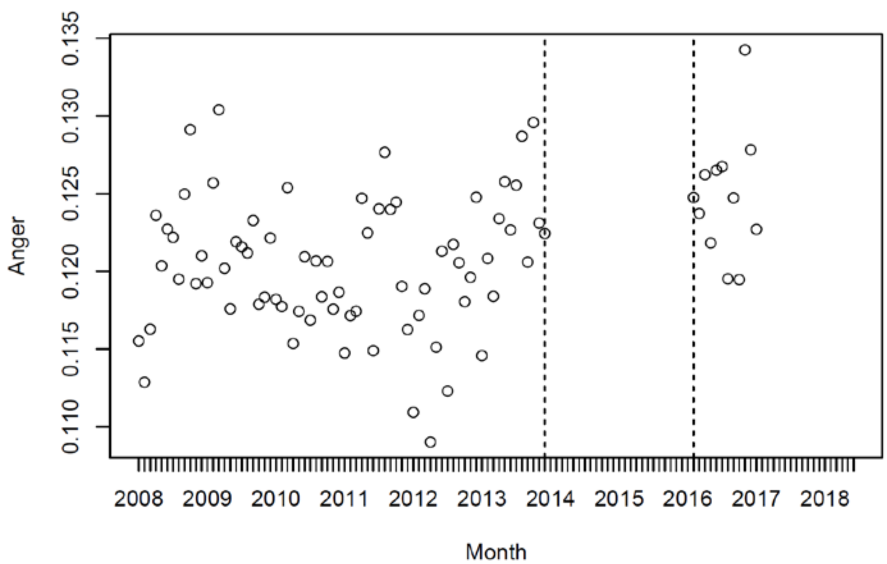
Note: Robust standard errors in parentheses (*p<0.1; **p<0.05; ***p<0.01); standardized beta coefficients in brackets.
Column 1: The specification includes state fixed effects as well as the following controls: Income Inequality; Share of Democrats; Share of Republicans; Share of Independents; Social Capital; Racial Fractionalization; Large fringe metro; Medium metro; Micropolitan; Noncore; Small metro; Log Percent Foreign Born; Log Population Density; Log Effective Population Density; Homeownership rate; Log Median Household Income; Percent High School Graduate or Higher; Percent Below Poverty; Percent Unemployed; Change in Manufacturing Employment, 2000-2015, Commute Time, Public Transit;
Column 2 contains state fixed effects and all county-level controls in Panel A.
Column 3 contains state fixed effects and the same county-level controls as Panel B. Additionally, Panel C includes the following individual-level controls: age and dummies for: Male; Race: Black; Race: Hispanic; Race: Other; Race: Asian; Party: Lean Republican; Party: Lean Democrat; Party: Republican; Party: Refused; Party: Democrat; dummy for Income > 60,000 USD; dummy for income 24,000 USD to 59,999 USD; Dummy for Income Don’t know or refused; Marital: Married/Partnership; Marital: Previously Married; Marital: don’t know or refused; Education: Any College; Education: High School/Vocational; Education: Postgrad; Education: DK/Refused.

Figure A1. Average Anger by Time Period

Panel A – Frequency: Day



Panel B – Frequency: Month



Panel C – Frequency: Year

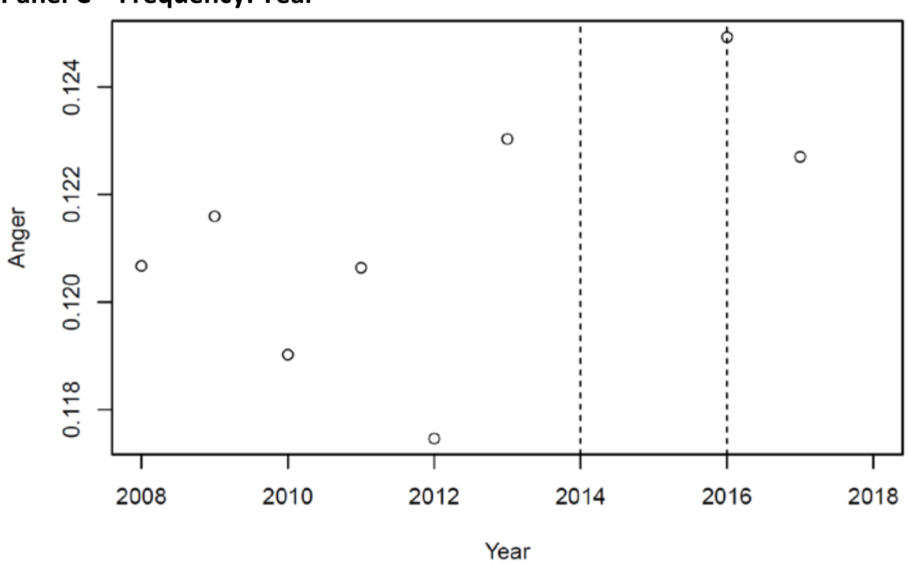


Figure A2 – Mean Anger by Ideology and Year

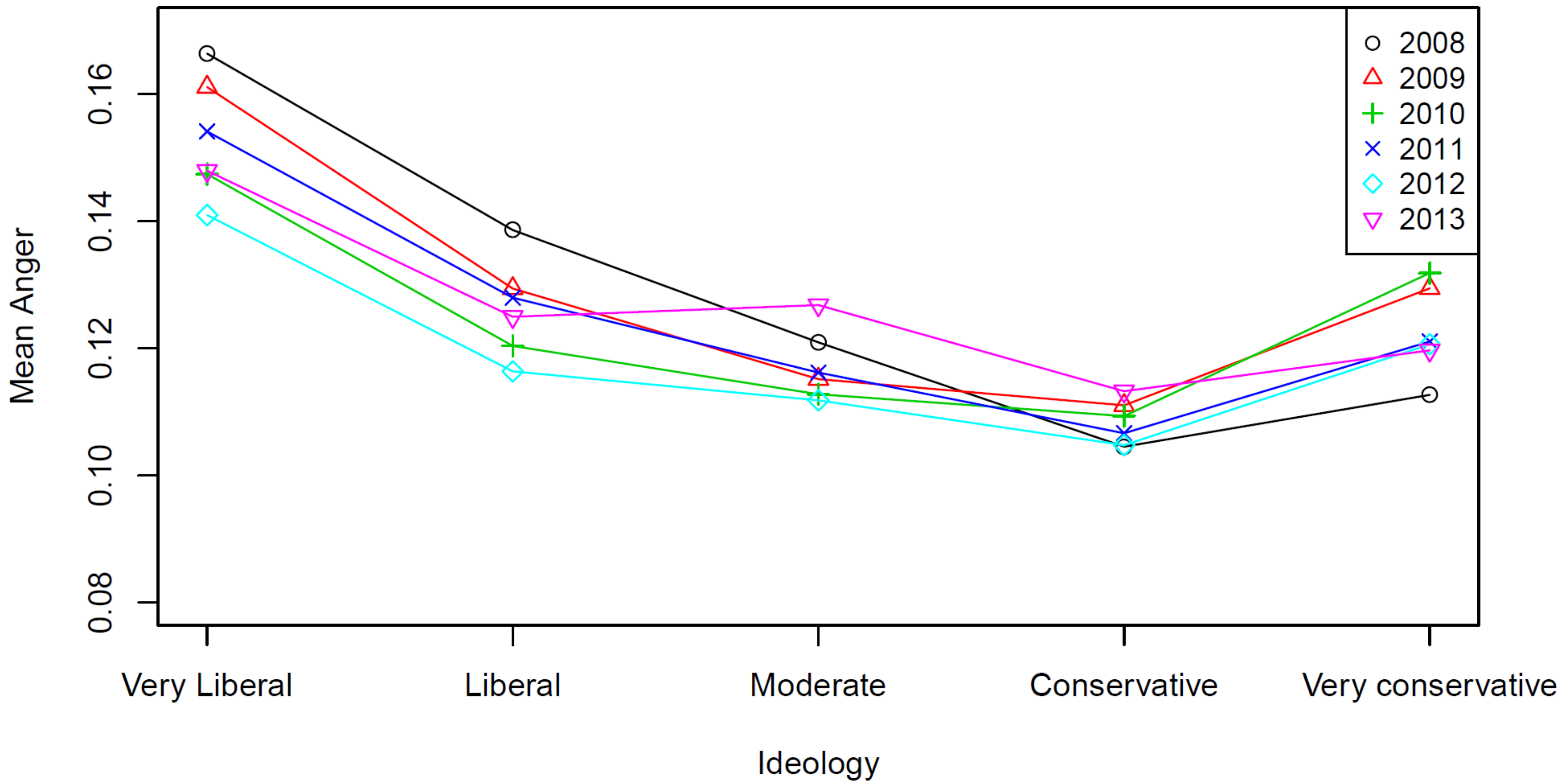


Figure A3 – Mean Anger by Party and Year

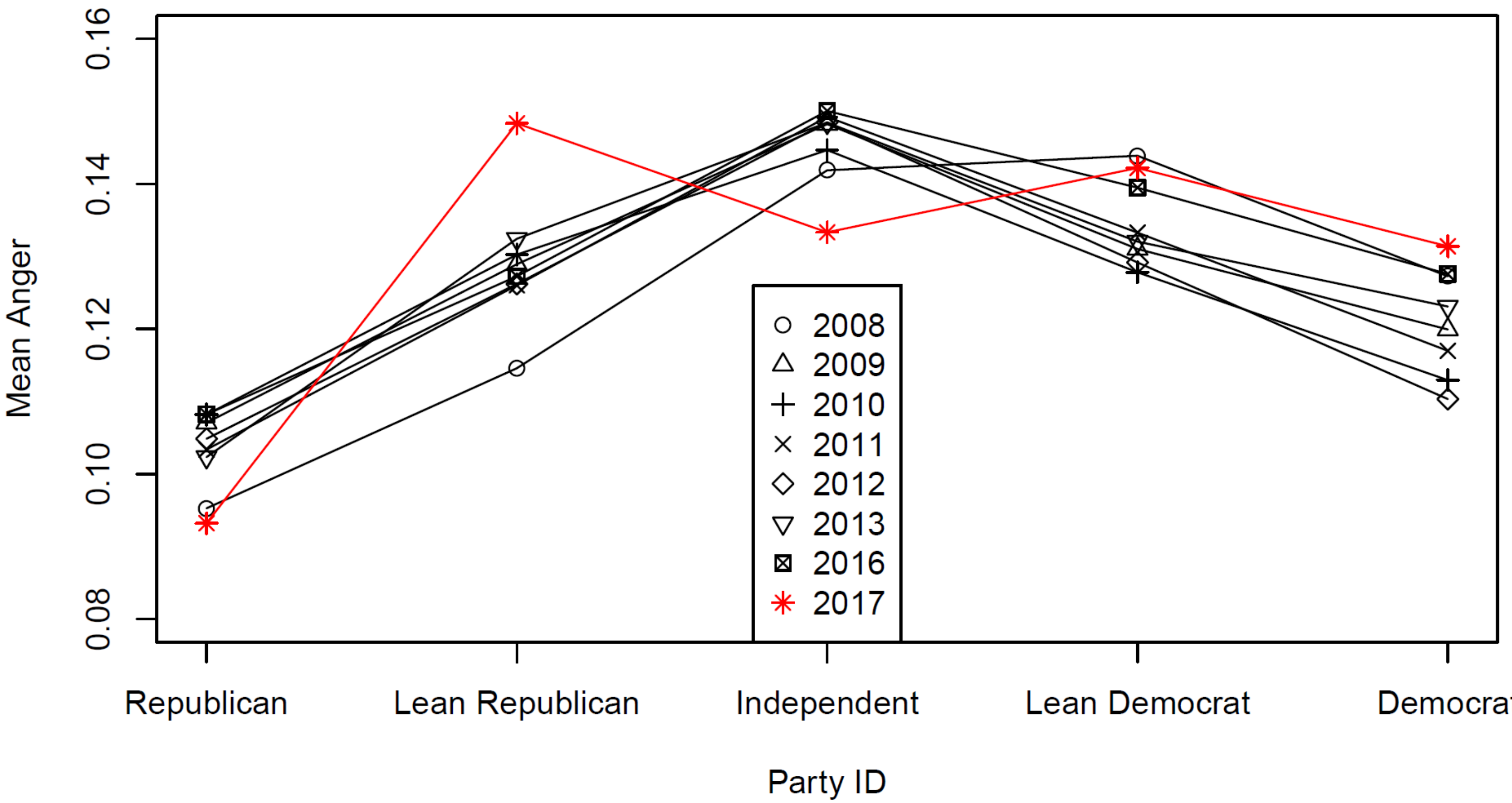


Figure A4 – Percent Angry by Party and Ideology