Geographically aggregated psychological traits from linguistic analysis of Twitter data predict U.S. voter realignment since 2016

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Abstract

The 2016 U.S. Presidential election heralded the beginning of a political realignment in American politics. A key question for understanding this realignment is whether the Republican party's shift towards right-wing populism was driven by Donald Trump's candidacy, versus Trump's political success being driven by dynamics in the electorate that predated his political rise. To address this question, we examined a corpus of Twitter posts written between July 2009 and February 2015, aggregated by U.S. county. The geographic distribution of psychological traits (personality, empathy, and moral foundations) was estimated by applying to the aggregated Twitter data lexica quantifying how strongly individual words predict psychological traits. The aggregate personality measures were then used to predict Donald Trump's vote share in 2016, 2020, and 2024, as compared to Mitt Romney's 2012 vote share, while controlling statistically for the 2000-2008 Republican vote share. Low agreeableness predicts support for Trump but not Romney, a novel result relative to other geographically aggregated data but consistent with prior survey findings relating this trait to right-wing populism. Low empathic concern also predicts vote share for Trump but not Romney. Finally, the degree to which tweets tend to reference unfairness and defilement exclusively predicts shifts towards Trump. Our analysis suggests that people in geographic regions that shifted rightward beginning in 2016 were already expressing emotions consistent with Donald Trump's messaging in their social media postings before his political rise. Our analysis also provides novel evidence for the high value of aggregated social media data in elucidating voter psychology.

Significance Statement

Donald Trump's election signified a realignment of American political coalitions. We find that psychological characteristics, estimated from language used in social media posts made between 2009-2015 and aggregated at the level of U.S. counties, predicted shifts in voting patterns between the 2016-2024 presidential elections and earlier elections. Furthermore, many of these traits corresponded with themes of Trump's political messaging. We conclude that people who shifted rightward beginning in 2016 were likely seeking a candidate like Trump prior to his rise in Republican politics. We also show that geographically aggregated social media data appears to match better with predictions based on individual surveys than does geographically aggregated survey data, validating the societal importance of social media platforms making such data available.

Introduction

Donald Trump's unexpected victory over Hillary Clinton in the 2016 U.S. Presidential election surprised not only the public but also political scientists, journalists, and other professional observers. That election ultimately led Trump to become the dominant figure in the Republican party, profoundly reshaping his party and American political coalitions. There has been ongoing interest in the social characteristics of the voters who shifted towards Trump as scholars try to understand these shifts[1]. One important question is the degree to which his rise could have been anticipated by the deep affective, cultural, and ideological divisions that predated Trump's entry into politics. Some scholarly treatments have focused on perceived status loss and populist resentment among some segments of American society[2, 3]. We instead examine how aggregated psychological traits, expressed prior to Trump's political rise, predict support for him relative to prior Republican candidates.

One early explanation of the Trump voter, based on the regions where voters swung in Trump's favor and on his success with poorly educated voters, was that policies that led to outsourcing of blue-collar jobs created economic anxiety, which led to dissatisfaction with political elites and support for Trump. More careful analyses of survey data[4, 5], however, revealed that individuals either with personal financial hardship or in areas with high unemployment showed little to no increase in support for Trump in 2016 relative to Romney in 2012. Instead, these studies found that the primary predictors of shifts towards Trump were attitudes towards race and immigration, views on international trade and competitiveness, and shifts in social dominance orientation. The authors concluded that White voters who shifted towards Trump were particularly concerned about losing their majority status and economic privilege, following from a zero-sum view of racial and economic competition, rather than being motivated by actual economic hardship.

The present work addresses similar questions as those explored in earlier studies but adopts a different methodological approach. Rather than relying on surveys to assess voter opinion, we estimate psychological characteristics through linguistic analysis of geographically aggregated Twitter (now “X”) posts and relate these traits to aggregated county-level vote share. This approach complements the more traditional survey-based approach by capturing how individuals publicly express themselves in everyday discourse, without requiring self-reflection or direct questioning. We focus on three broad psychological domains: Big Five personality traits, empathy, and moral foundations. Personality has previously been linked to voter behavior, including support for Donald Trump, using both individual surveys and geographically aggregated data[6, 7]. Empathy and moral foundations are also compelling targets because they align with distinct features of Trump’s campaign rhetoric and have been shown to differ broadly between liberals and conservatives. If similar themes were already present in the language used by individuals in regions that later shifted toward Trump, this would suggest that such voters were predisposed to resonate with his messaging even before his political rise.

Personality traits have been the most frequently studied psychological measure predicting political behavior and have shown a relationship with vote choice in prior U.S. Presidential elections. Of the five factors that define personality, some studies have emphasized the role of Openness and Conscientiousness[8], others have suggested key roles for Extraversion and Agreeableness[9, 10], and others have shown relationships with as many as all 5 factors[11]. There is evidence across countries that low Agreeableness is a particularly strong predictor of populist voting patterns[6], especially right-wing populism[12]. An analysis based on data from the 2016 Republican primaries examined characteristics of Trump voters in particular, finding that the low Openness, low Agreeableness, high Extraversion, high Conscientiousness, and low Neuroticism predicted support for Trump relative to his primary rivals[13]. These authors also lay out a clear analysis as to why Trump's lack of a specific policy program led there to be a stronger alignment of personality traits between Trump and his voters than would be true for most other candidates.

Liberals have often been shown to demonstrate higher levels of empathy than conservatives. One notable study found that liberal voters across 3 different countries show higher empathic motivation and willingness to help in hypothetical scenarios[14]. Others have emphasized distinctions between conservatives empathizing with a tighter moral circle while liberals show a more universalist application of empathy[15]. Trump supporters in particular have been found to report lower levels of empathic concern, reflecting less care for others' feelings, but no difference in cognitive empathy, i.e., the ability to accurately perceive others' feelings[16]. This paper also associated a broader constellation of malevolent traits with support for Trump, including psychopathy and narcissism. These authors did not distinguish between support for Trump and conservatism more broadly, however. A survey of Europeans, though not peer reviewed, has shown that in addition to conservatives broadly reporting less empathy than liberals, supporters of right-wing populist parties generally display lower levels of empathy than supporters of more center-right parties[17]. Thus, there is reason to believe that the realignment of the Republican party towards right-wing populism in the Trump era could particularly appeal to those who are low in empathic concern. At the same time, there is evidence that empathic concern can deepen rather than reduce partisan polarization[18]. Given that polarization against Democrats is one factor driving Trump support[19], this suggests an alternative hypothesis that those with higher levels of empathic concern will be more rather than less likely to support Trump.

The analyses described above rely on surveys in which both psychological measures and political preferences are measured in the same individuals. Other work has associated aggregate measures of psychological traits with aggregate vote tallies. It is not a given that personality traits would vary systematically by geographic region, but a theoretical model has been proposed for how migration patterns, climate, and other factors lead to geographic sorting by personality[20]. This approach has shown a relationship between low Openness and support for the pre-Trump Republican party[21], as well as with support for Trump in particular[7, 22]. These effects are also not unique to the United States, as similar effects were shown with respect to the 2016 Brexit vote for the U.K. to leave the European Union[7]. These studies also found a relationship with higher Neuroticism predicting greater overall support for both Trump and Brexit as well as support for Trump relative to other Republicans. Similar results have also been shown in the domain of affect, based on self-report measures of subjective well-being. Specifically, geographic regions with low average levels of subjective well-being, measured from 2009-2016, tended to shift towards Trump in the 2016 election[23]. These findings suggest that negative emotionality plays a key role specifically in support for right-wing populism relative to other strains of conservatism.

The studies described in the preceding paragraph quantified psychological traits based on the geographic distribution of questionnaire responses. Here, we instead use digital trace data to quantify psychological traits. We are not the first to use digital trace data in this way, but we do so for a broader set of traits than prior work. One existing study was framed around a specific theory about how negative affect leads to support for right-wing populism[23]. Consistent with the earlier theory, anger, fear, and anxiety, estimated based on language use in the same Twitter dataset that we use here, predicted overall vote share for Trump, increases in support for Trump in 2016 over prior Republican vote share, and support for Trump in the 2016 primary[24]. A complementary analysis also showed similar relationships between negative emotions and support for Brexit in the UK. Another study with this Twitter dataset showed that counties in which language reflected low levels of social trust showed an increased preference for Trump relative to Mitt Romney and other past Republican presidential candidates[25]. Here, we hypothesize that the geographic distribution of a wide range of traits, quantified based on language use on social media, broadly relates to vote share for a candidate whose messaging is resonant with those traits.

Other prior work has examined how voting patterns predicted personality traits after controlling for demographic covariates in this same Twitter dataset[26]. They did not report the reverse analysis that we report here, however, of how personality traits predict voting patterns. They also did not examine how these relationships differed between Trump and prior Republican candidates. They found that Republican votes in 2012, 2016, and 2020 predicted low openness and high Extraversion, consistent with prior work. Other results were somewhat different from earlier findings: votes for Trump in 2016 and 2020 were associated with low Conscientiousness, and votes for Romney in 2012 were associated with high Agreeableness.

The final psychological construct that we examine is moral foundations. Moral Foundations Theory (MFT)[27, 28] categorizes human moral intuitions into core domains of care, fairness, loyalty, authority, and sanctity. Prior research shows that liberals and conservatives systematically differ in the foundations they prioritize: liberals emphasize care and fairness, while conservatives more often invoke loyalty, authority, and sanctity[29, 30]. In social media contexts, these moral foundations are often expressed through moral language. Linguistic expressions of right and wrong, pervasive in both political and everyday discourse on social media, often reflect users' underlying moral intuitions. Although some have questioned whether MFT truly reflects fundamental moral distinctions[31], it has been applied and validated in predicting a variety of real-world attitudes and behaviors[32, 33].

There is less work on whether the moral priorities of Trump voters differ from the broader pattern among conservatives. One relevant study examined Trump's own rhetoric in the 2016 and 2020 campaigns, compared to other Republican and Democratic candidates[34]. In general, this analysis found that Democrats used more language around moral foundations of care/harm and fairness, while Republicans were more likely to reference moral foundations of authority, sanctity, and loyalty, as would be predicted by MFT. However, Donald Trump's campaign was an outlier. Trump focused on fairness much more than his competitors in the 2016 Republican primary, but his messaging also diverged from Democratic rhetoric around fairness. Trump's rhetoric was unique in its emphasis on *violations* of moral norms around fairness, i.e., accusing others of being unfair and dishonest. Given these findings, measures of moral language could provide valuable insight into whether unique features of Trump's moral rhetoric aligned with moral priorities among regional communities that shifted in support towards Trump. Thus, we examine here whether county-level variation in the valence of moral language in tweets—specifically, how positively or negatively moral foundations are expressed—predicts support for Donald Trump in the 2016, 2020, and 2024 U.S. presidential elections.

We similarly examine whether empathy inferred from language use on Twitter predicts subsequent regional shifts in support towards or away from Donald Trump. Trump's rhetoric is often portrayed by journalists as reflecting a lack of empathy[35], and more recently, leading figures in Trump's movement have begun to explicitly frame empathy as harmful[36]. These indicators motivate an analysis of whether Trump's political ascent resonated with preexisting psychological dispositions related to diminished interpersonal concern. We use a lexicon that distinguishes between two facets of affective empathy: empathic concern, which motivates prosocial behavior aimed at alleviating others' distress, and empathic distress, which involves personally experiencing the distress of others[37]. While these two aspects of empathy are related, and both fall under the broader domain of affective empathy rather than cognitive empathy, empathic concern tends to motivate helping others while empathic distress can lead to feeling overwhelmed and disengaged[38, 39].

In the present study, the lexica provide numeric values for each word to quantify its association with a given trait, as described further in Methods. The underlying data are word frequencies aggregated at the level of U.S. counties, computed across a sample of 1.64 billion Tweets posted between July 2009 and February 2015 that included geotagging information[26, 40]. Lexica measuring personality traits[41], empathy[42, 43] and moral foundations[44] were applied to this dataset. These trait measures were then related with vote share data from the 2016, 2020, and 2024 general elections for U.S. President. Together, these measures are expected to elucidate the psychology of Trump voters in the years leading up to the consequential election of 2016.

Results

Each trait of interest was entered separately into a model with mean vote share for Trump across the 2016, 2020, and 2024 elections as the dependent measure. Control variables include mean G.W. Bush era (2000, 2004, and 2008) Republican vote share, the ratio of tokens in the Twitter data to population, to control for Twitter usage, and 13 additional variables identified in a prior study of geographic predictors of vote share[45]. See Methods for additional detail.

Personality

We first analyze the relationship between Big Five personality metrics and vote share. As shown in Figure 1 and Table 1, lower levels of Openness, Agreeableness, Conscientiousness, and Emotional Stability (i.e., higher Neuroticism) were significantly associated with higher vote share for Donald Trump across the 2016, 2020, and 2024 elections, while higher levels of Extraversion predicted increased support for Trump. These results indicate that for every 1 SD increase in one of these personality measures, Trump's vote share decreased by 2.01% for Openness, 0.91% for Agreeableness, 0.73% for Conscientiousness, and 0.61% for Emotional Stability (i.e., inverse Neuroticism), while it increased by 1.06% for Extraversion. Findings for all personality measures except Conscientiousness are robust in an alternative analysis that simultaneously models all Big Five personality traits; see SI Table 1 for details.

As a comparison condition, the same analysis was run with Mitt Romney's 2012 vote share as the dependent measure. The Seemingly Unrelated Regression (SUR) method[46] examines whether a given predictor variable has a significantly different coefficient when the dependent measure differs but two regression models are otherwise the same. A significant difference indicates that significantly more variance is explained when the coefficients for the relevant predictor variable are allowed to differ. Here, we used SUR regression to compare which psychological predictor variables predicted vote share for Trump differently than vote share for Romney. All coefficients were significantly different for Trump vs. Romney (see Table 1), as Romney's vote share was unrelated to Agreeableness, Conscientiousness, or Emotional Stability, in contrast to the robust effects described above for Trump. Openness and Extraversion were significant predictors in the same direction for both Romney and Trump, with Romney's vote share showing a 0.72% decrease for Openness and a 0.34% increase for Extraversion with a 1 SD increase in the personality measure. Still, there were also significant effects in the SUR regressions, indicating that for both of these variables, predictive power was reliably stronger for Trump vote share than for Romney vote share.

In addition to the SUR analysis, we employed a local spatial regression technique, Multiscale Geographically Weighted Regression (MGWR)[47], to assess whether the conditioned effects of the personality measures on vote share differed across different regions of the country. MGWR allows for spatial variation in regression coefficients, enabling us to examine how the relationships between personality traits and vote share vary at the county level. Since we have access to county-level aggregate data, we can model these spatially varying effects, identifying where certain personality traits exhibit stronger or weaker predictive power. This approach provides a finer-grained understanding of how psychological predictors of political support may operate differently depending on regional contexts.

The MGWR regressions for all 5 personality factors are presented in Figure 2. These analyses reveal distinct regional heterogeneity in how personality traits predict Trump vote share. The negative association between Openness and Trump support was robust and widespread, but strongest in the Northeast, South, and Midwest (Figure 2A). The positive relationship between Extraversion and Trump support was also localized to the Northeast and Southern United States, as well as in battleground Rust Belt regions such as Michigan, Ohio, and Pennsylvania (Figure 2B), suggesting that Trump's appeal to extraverted voters was particularly strong in these areas. The negative relationship between Agreeableness and Trump support was strongest in the West Coast and Northeast, while the Midwest and South showed weaker or non-significant effects (Figure 2C). Finally, Conscientiousness and Emotional Stability both showed negative associations with Trump support that were strongest in the Northeast and West (Figures 2D & 2E). This spatial variation highlights that while these personality traits are national predictors, their political salience appears to differ based on regional context.

Empathy

A similar approach was applied to data scored using the empathy lexicon. Here, when the two facets of empathy were analyzed separately, a 1 SD increase in empathic concern predicted a 1.14% decline in Trump’s vote share, while this variable did not relate to Romney’s vote share (Table 2; Figure 3A). The effect of empathic concern remained robust in an alternate regression with both variables modeled together (see SI Table 2). Empathic distress when modeled alone also showed a negative relationship with Trump vote share, as a 1 SD increase in empathic distress predicted a 0.64% decline in Trump's vote share (Table 2). However, this effect reversed when both empathy variables were modeled together (SI Table 2). These results suggest that when shared variance between empathic concern and empathic distress is removed, it is primarily lower levels of empathic concern rather than low empathic distress that predict higher vote share for Trump. Neither empathy measure was a reliable predictor of Romney's vote share, with the SUR models showing a significant difference between Trump and Romney for both empathy measures. The results from the MGWR analysis further demonstrate that the negative association between empathic concern and Trump vote share was apparent across most of the country, with the strongest effects apparent along the East Coast, in the Rust Belt, and in the West (Figure 3B).

Moral Foundations

Finally, language related to moral foundations was associated with vote share. The primary measure examined here is valence (Figure 4; Table 3), i.e., whether each moral foundation tended to be referenced in its positive form (referencing virtues) or in its negative form (referencing violations). Valence was negatively associated with support for Trump for moral foundations of fairness and sanctity. Specifically, for every 1 SD increase in the degree to which Tweets in a county that referenced fairness tended to be negative (i.e., cheating vs. fairness), Trump's vote share increased by 1.16%. Similarly, for every 1 SD increase in negativity in references to sanctity (i.e., degradation vs. sanctity), Trump's vote share increased by 1.24%. Romney's vote share was not significantly associated with valence for either fairness or sanctity, with SUR analyses showing a significant difference between the candidates on both measures. Higher vote share for Romney in 2012 was predicted, in contrast, by more positive valence for references to care, authority, and loyalty, with a 1 SD increase in positivity on each of these dimensions associated with increases in vote share of 0.39%, 0.34%, and 0.27%, respectively. The SUR regressions showed significant differences between the candidates for the effects on care and authority, and a marginal difference for loyalty.

Spatial analysis reveals striking regional patterns in how moral language predicted support for Trump (Figure 5). The link between negative fairness language (e.g., "cheating") and Trump support is strongest in the Northeast and West Coast. The association between negative sanctity language (e.g., "degradation," "filth") and Trump support is concentrated in the Northeast and West as well, but is also strong in the Upper Midwest, notably including the “blue wall” states of Wisconsin, Michigan, and Pennsylvania that shifted toward Trump in 2016 and 2024. This implies that moral concerns about purity and contamination were particularly salient drivers of the rightward shift in these specific communities. Spatial maps showing the distribution of effects of valence for other moral foundations, and effects of strength of moral foundations, are shown in SI Figures 1 and 2.

Similar analyses were run for the strength with which each moral foundation was evoked (regardless of valence). Here, we find that increased references to fairness, sanctity, and authority predicted higher vote share for Trump (see Table 4), with each 1 SD increase in strength on these factors associated with increased Trump vote share of 0.80%, 0.72%, and 0.51%, respectively. None of these effects were significant for Romney, with the possible exception of a marginal negative effect on sanctity, and SUR regressions showed significant differences between the candidates for all three measures. In contrast, vote share for Romney was greater with fewer references to care, as a 1 SD decrease in care strength yielded a 0.52%

increase in vote share, and was marginally greater in counties with fewer references to loyalty, with a 1 SD decline predicting a 0.16% increase in vote share, while these measures did not reliably predict Trump's vote share. SUR regressions showed that the effect of care differed significantly between the candidates, while the effect of loyalty showed a marginal difference.

Additional analyses relating the strength of positively-valenced terms and negatively-valenced terms with vote share are provided in SI Tables 3 and 4. For moral foundations of fairness and sanctity, these more fine-grained analyses align with results shown in Table 3, with higher Trump vote share corresponding to more negative and less positive language around these moral values. An additional result of interest is that Trump vote share is associated with more negative language around authority, while higher Romney vote share was associated with *less* negative language and more *positive* language around authority, with both of these effects differing between the two candidates.

Change over Time

Finally, while our primary analyses examine average Trump support across the 2016, 2020, and 2024 Presidential elections, we confirmed in supplemental analyses (SI Tables 5-8) that all reported effects were statistically reliable across each of these three electoral contests. Furthermore, every significant relationship was numerically stronger in 2020 than in 2016 and numerically stronger in 2024 than in 2020. SUR regressions also show that most of the reported relationships were significantly stronger in 2024 than in 2016 (Table 5). Specifically, all five personality dimensions (Extraversion, Emotional Stability, Agreeableness, Openness, and Conscientiousness) were more strongly related with Trump's vote share in 2024 than with his vote share in 2016, as were both empathic concern and empathic distress. For the moral foundation measures, the effect for valence of sanctity language was significantly stronger on 2024 vote share than on 2016 vote share, while the analogous effect for valence of fairness language was marginal, and no effects of moral strength reliably differed between time points.

Discussion

These analyses show that there are many psychological traits for which their geographic distribution, estimated by analyzing the language used by those posting on Twitter between 2009-2015, predicted swings in support towards Trump in subsequent presidential elections. Most notably, people in counties that swung towards Trump relative to prior elections were more likely to use language consistent with low agreeableness, low emotional stability, low conscientiousness, and low empathic concern, and to use language related to unfairness and impurity. These differed from results when the same analysis was applied to Mitt Romney's vote share in the 2012 presidential election. These analyses provide new insights regarding the relationship between psychological traits and voter behavior, expanding on prior studies in which geographic distribution of personality and affect has been related to geographically aggregated vote share. Social media data has (at least at times) been a rich and easily accessible data source, and as a methodological point, these analyses demonstrate the power of such datasets to produce novel insights.

The most striking conclusion, if we assume that the association between geographically aggregated traits and geographically aggregated votes reflects an association within individual voters, comes from considering the high level of alignment between Trump's public persona and the behavioral traits shown by Trump voters prior to his entry onto the political scene. For instance, estimates of Trump's own personality based on his public statements[48, 49] include low agreeableness, low emotional stability, high extraversion, and low conscientiousness, consistent with the personality traits of voters who swung towards Trump as shown in Table 1 and Figure 1. Concerns about being cheated also align with a unique feature of Trump's political rhetoric[34]. Additionally, as noted above, journalists have often identified Trump's rhetoric and his broader movement as reflecting a lack of empathy[35, 36]. Furthermore, another recent analysis, while not specifically about Trump, found greater use of language evoking sanctity violations when discussing hated outgroups in both German Nazi propaganda against Jews and in modern day hate speech on the far-right website Gab[33]. We found a similar linguistic signature to be more common in counties that swung towards Trump. Thus, Trump's rhetoric seems to have appealed to traits that those who would become his voters were already expressing. It is certainly possible, and even likely, that Trump strengthened those patterns of thinking among his voters, though we cannot address this point directly. The notable conclusion from our analysis is that he does not appear to have *introduced* these ways of thinking to his voters.

Another notable point is how these analyses relate to prior work associating personality traits with votes. We replicate prior findings relating low levels of geographically aggregated Openness to support for conservatism in general[21]. We also replicate studies associating low Openness and high Neuroticism in geographic regions, measured via self-report surveys, with support for both Trump and Brexit[7, 22]. We additionally replicate findings that previously had only been observed in studies that related individual-level personality traits with individual votes, namely in the domains of Extraversion and Agreeableness[9, 11]. Agreeableness has been negatively associated with support for populism, especially right-wing populism[12]. Thus, it would make sense for this variable to be associated with Trump support, but such an effect had not been shown in prior analyses based on geographically aggregated questionnaire data. High Extraversion has also been associated with conservatism in multiple studies, and in our data is a positive predictor of support both for Trump and Romney, but it also had not previously been shown to predict vote share on a geographically aggregated level.

The consistency of these findings supports the idea that social media data not only provides a valid tool for measuring the geographic distribution of psychological traits, but that it may capture aspects of regional psychological variation that large-scale questionnaire measures do not. Indeed, ref. 26 discusses the factors that could make geographically aggregated personality estimates from social media more accurate than those from questionnaire measures. For instance, reference group effects lead people to estimate their own personality relative to those around them, which is not a random sample of the population and thus could distort self-report measures. The estimates that we report, in contrast, score language use uniformly across the entire dataset. Our results also show the usefulness of publicly available datasets of aggregated social media data and of lexica that can estimate traits based on those data. The flexibility of this approach is particularly notable, as these resources can be recombined in nearly infinite ways to address novel questions that were not anticipated at the time when the data were collected. This flexibility is what allowed us to examine factors such as empathy and moral conviction without requiring a massive new data collection effort, and to examine how changes in these factors prior to the political realignment of 2016 predicted subsequent voting behavior for or against Donald Trump.

Most of the relationships between psychological traits and vote share were also stronger in 2024 than in 2016. This result accentuates the point raised in prior work[13] that even in 2016, support for Trump related particularly strongly with personality relative to other Republican primary candidates, which those authors suggest follows from his perceived lack of interest in policy. The strengthening of these relationships over time aligns with Trump's gradual move away from a traditional Republican policy agenda, and towards increased localization of power in Trump as an individual, over the course of his career in politics.

One limitation of this study is that we were unable to access a second social media dataset within which we could replicate these results on a different set of Tweets. We had aimed to geotag an alternate sampling of Twitter data, and potentially also to examine postings made more recently, but between changes to platform governance made by Elon Musk and other technical difficulties, this proved difficult. Thus, it remains to be confirmed whether all of the effects shown here would replicate in an independent dataset. Our analysis began as exploratory, and we did not preregister strong hypotheses at the outset. However, the results that we emphasize are all consistent with and build on prior literature, providing reason to believe that the results reported here are likely to be replicable.

Another possible concern in interpreting our results is that the social media posts underlying our psychological metrics were made many years prior to votes in the electoral data, particularly for the 2020 and 2024 elections. A substantial proportion of individuals would have moved, entered adulthood, or died in the over 15 years between the beginning of our Twitter dataset and the 2024 election. Still, the theory underlying the geographic analysis of aggregated personality data proposes that regions develop a distinct psychological profile that is roughly consistent despite specific individuals moving in or out of a place[20]. There is also empirical support for this hypothesis, as the rank ordering of personality across U.S. states, based on self-report scales, showed a similar level of consistency regardless of whether data were collected during the same time period or with a time interval of as long as 16 years in between[50]. Thus, we assume that our psychological metrics reflect dispositions that remain roughly stable across time.

This work contributes to broader understanding within political science research of the psychological underpinnings of the Trump phenomenon in American politics. Our findings suggest that even if Trump had never entered politics, the voters who would become his base of support may have been predisposed to seek a candidate with his personality characteristics and/or rhetorical style. Our work also suggests a creative way that the campaigns and media organizations may have been able to anticipate and model the realignment of American political coalitions that Trump represented in 2016. Specifically, it likely would be possible to model from geographically aggregated social media data, which would have been available prior to the election, where Trump's support was likely to increase or decrease relative to prior Republican vote share. These data could have been used by public pollsters to more accurately model public opinion, and by campaigns to direct resources more effectively based on which regions were more or less likely to vote for Trump than historical voting patterns would have suggested. The ability to better predict voter behavior, even when coalitions are shifting, will allow all stakeholders to make more effective decisions during electoral campaigns.

Materials and Methods

Data were originally obtained from Twitter, as a sampling of 10% of all Tweets from July 2009 to April 2014, and 1% of all Tweets from May 2014 to February 2015. The sampling originally included 37.6 billion Tweets, of which 1.78 billion could be geotagged, and of these, 1.64 billion were identified as English-language. Aggregated data have previously been released publicly with no usage restrictions as the County Tweet Lexical Bank[40].

The original authors of the personality and empathy lexica used here have made publicly available scores for a large sampling of words. Words were associated with personality traits in earlier work associating language use on Facebook users' profiles with their responses to personality questionnaires[41]. Prior work has associated this lexicon with the Twitter dataset used in the present study[26], though as noted in the Introduction, our analyses are distinct from those previously reported. The earlier work on empathy used two separate sources of data to quantify empathic concern and empathic distress. First, a group of online participants were asked to respond to news stories that were expected to evoke empathy[43]. Those responses were then presented to a second set of participants to rate on empathic concern and empathic distress. Finally, a computational model combined these two datasets to quantify the level of empathic concern and empathic distress typically associated with each specific word[42].

For both of these lexica, scores for each word were aligned with the word frequencies in the County Tweet Lexical Bank using a *merge* command from the *pandas* package in Python. All words not found in the relevant lexicon were dropped from the analysis. The score for a given word was multiplied by its usage frequency in all data localized to that county, yielding a total score. A weighted average score for the county was then obtained by summing the total scores for each word and dividing that sum by the summed number of instances of all scored words in data localized to that county.

Our approach to quantifying moral language in tweets builds on a vector-based dictionary (“vec-tionary”)[44]. This “vec-tionary” framework extends the traditional Moral Foundations Dictionary (eMFD)[51] by incorporating word embeddings, which represent terms as vectors in a high-dimensional semantic space. This allows for a more nuanced estimation of moral content in language. Using this method, we quantified moral language across three dimensions: (1) moral strength—the overall frequency with which a given moral foundation is referenced; (2) moral valence—the extent to which these references are positive (virtue-based) or negative (violation-based); and (3) raw valence scores—the frequency-weighted sums of *positive* and *negative* moral language, calculated separately for each foundation. This multidimensional approach provides a richer characterization of moral rhetoric than traditional count-based dictionaries. As with the other lexica, each county’s score was computed by weighting each word’s score by their frequency across all posts from that county and computing a weighted average.

The primary data source for our dependent measure, vote data aggregated by county, was obtained online from the MIT Election Data Science lab (DOI: 10.7910/DVN/VOQCHQ). This dataset includes vote totals for all major and minor party candidates in U.S. Presidential elections from 2000 to 2020, as well as the total number of votes across all candidates in each Presidential election. Data for the 2024 U.S. Presidential election, and data to fill in missing data from the 2020 results, were obtained from the following GitHub repository: https://github.com/tonmcg/US_County_Level_Election_Results_08-24 . For each election in each county, the proportion of votes for the Republican candidate, relative to the total number of votes for all candidates, was computed. The baseline proportion of Republican votes was estimated by averaging together the proportion of Republican votes in the 2000, 2004, and 2008 Presidential elections. Data from the 2012 Presidential election was used as a secondary dependent measure, as the final pre-Trump election. The primary measure of Trump vote share was computed by averaging Republican Presidential vote share across the 2016, 2020, and 2024 elections. For the state of Connecticut, data beginning with the 2024 election were only recorded using a new set of nine administrative regions rather than Connecticut's historical eight counties. Because all other data analyzed here used the old county boundaries, mean Trump vote share in Connecticut was computed based only on data from 2016 and 2020, and this state was excluded from analyses examining the 2016, 2020, and 2024 elections separately.

The design of each regression model was as follows:

$$\begin{aligned} TrumpVote_i = {} & \beta_0 + \beta_1 \cdot Predictor_i + \beta_2 \cdot GOPMean_i \ + \beta_3 \cdot SexRatio_i + \beta_4 \cdot \%Black + \ \beta_5 \\ & \cdot Hispanic_i + \beta_6 \cdot \%ForeignBorn_i + \beta_7 \cdot \%Insured_i + \ \beta_8 \cdot \%Age18to29_i \\ & + \beta_9 \cdot \%OverAge65_i + \beta_{10} \cdot Turnout_i + \beta_{11} \cdot \%ThirdPartyVotes_i + \beta_{12} \\ & \cdot \ In(PopDensity_i) + \beta_{13} \cdot Income_i + \beta_{14} \cdot Gini_i + \beta_{15} \cdot \%Manufacturing_i \\ & + \ \beta_{16} \cdot TokenPopulationRatio + \ \epsilon_i \end{aligned}$$

Here, TrumpVote denotes the average county-level vote share for Donald Trump across the 2016, 2020, and 2024 elections. For the primary analyses, each model includes one predictor of interest (e.g., a psychological trait) and various control variables. Control variables included Republican vote share averaged across the 2000, 2004, and 2008 elections, to specifically emphasize swings towards or away from Trump rather than conservatism more broadly. We also added the ratio of text tokens to the 2010 Census population in a county as a control variable, representing how broadly Twitter was being used in a given county. Other control variables were chosen based on past work[45]; for these variables, we averaged data from the 2015 and 2020 American Community Survey. These included demographic control variables (sex ratio, % Black, % Hispanic, % foreign born, % insured, % aged 18–29, % over 65), electoral variables (voter turnout, % third-party votes), and structural factors (log population density, mean income, Gini coefficient, % in manufacturing). The original set of demographic covariates also included the percentage of residents with a bachelors' degree, but this predictor had a variance inflation factor (VIF) over 7 in all models; with it removed, all remaining variables had a VIF under 5. Results from alternate models that retain this covariate are provided in SI Tables 9-12.

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Figures and Tables

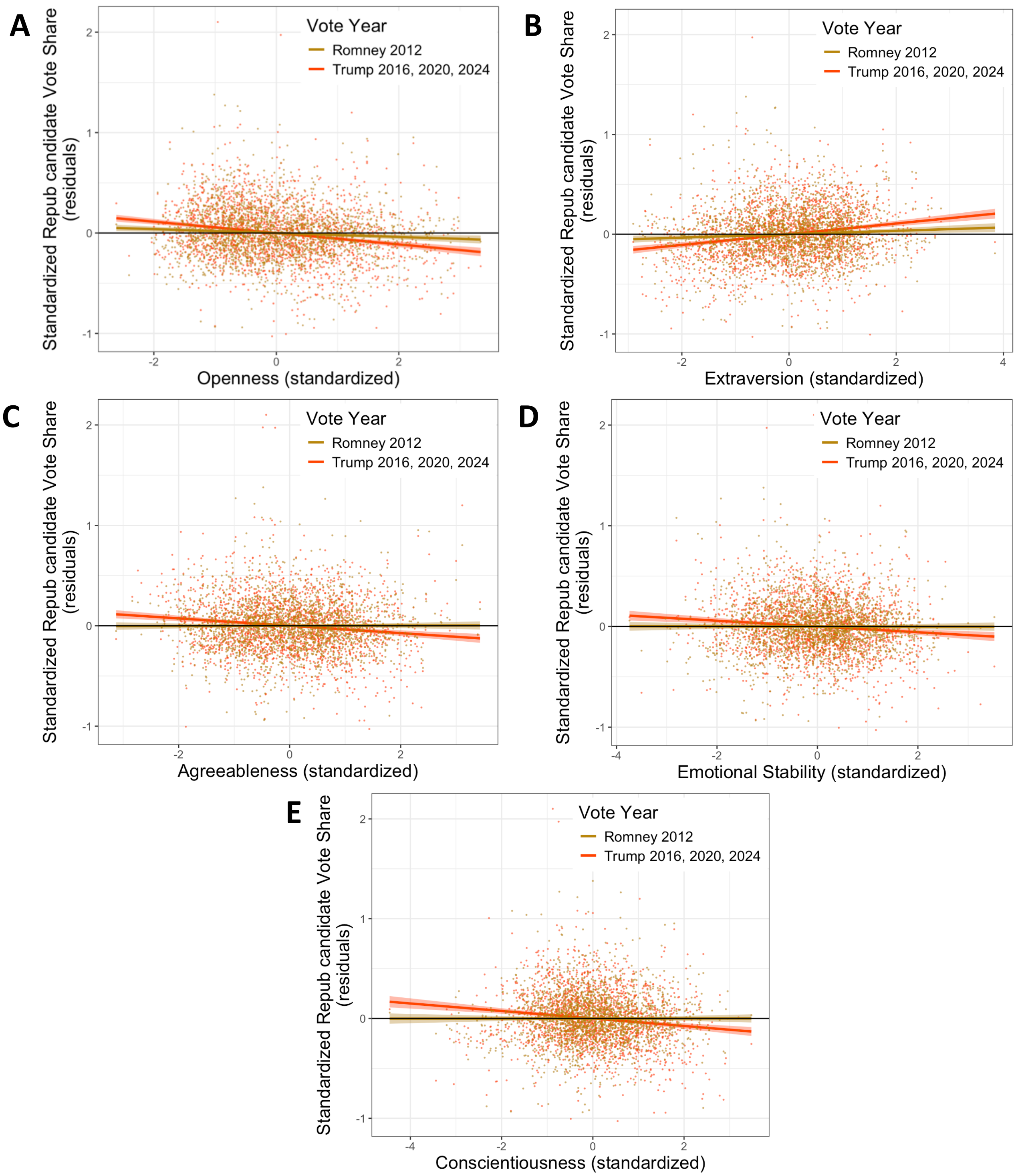


Figure 1. Personality variables that consistently predict vote share for Trump. (A) Lower Openness and (B) higher Extraversion predicts higher vote share for both Trump and Romney, but for both variables, effects are stronger for Trump. (C) Lower Agreeableness, (D) lower Emotional Stability (i.e., higher Neuroticism), and (E) lower Conscientiousness all predict higher vote share for Trump but have no relationship with Romney's 2012 vote share.

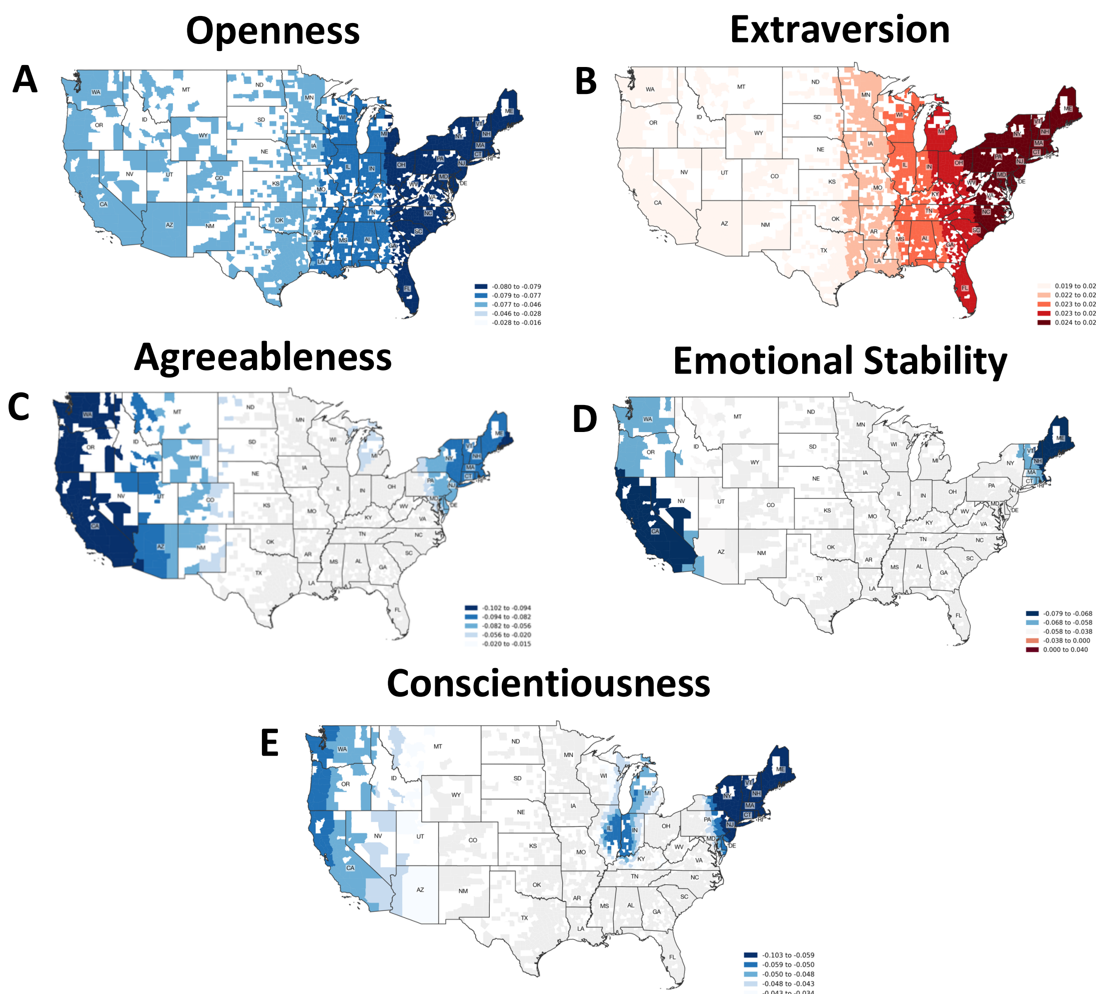


Figure 2. Spatial regression maps indicating the geographic distribution of the effects of (A) Openness, (B) Extraversion, and (C) Agreeableness, (D) Emotional Stability, and (E) Conscientiousness on vote share for Trump.

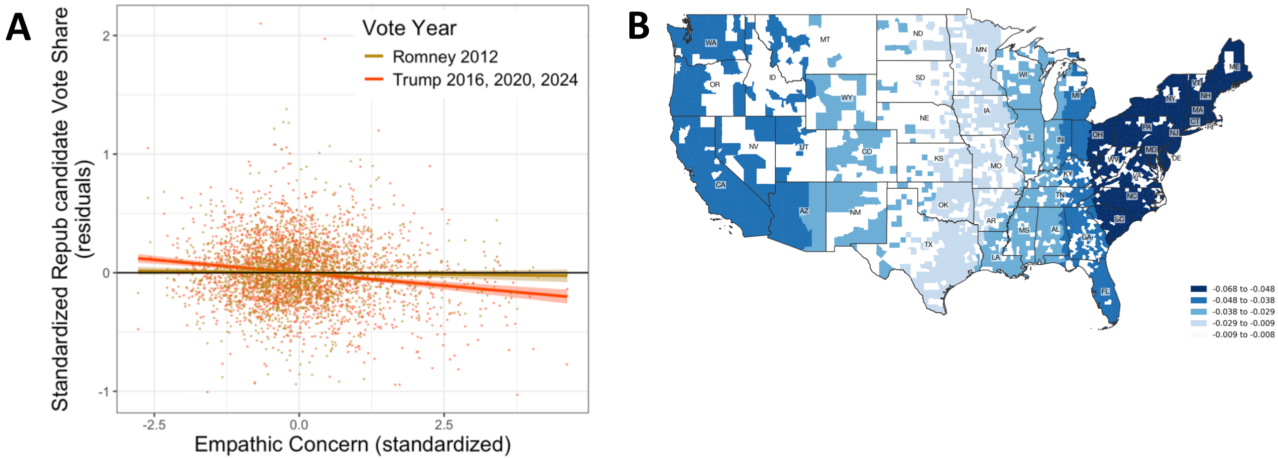


Figure 3. Higher levels of empathic concern are associated with lower vote share for Trump, as analyzed via (A) standard OLS regression and (B) MGWR spatial regression, but no such relationship is apparent for Romney.

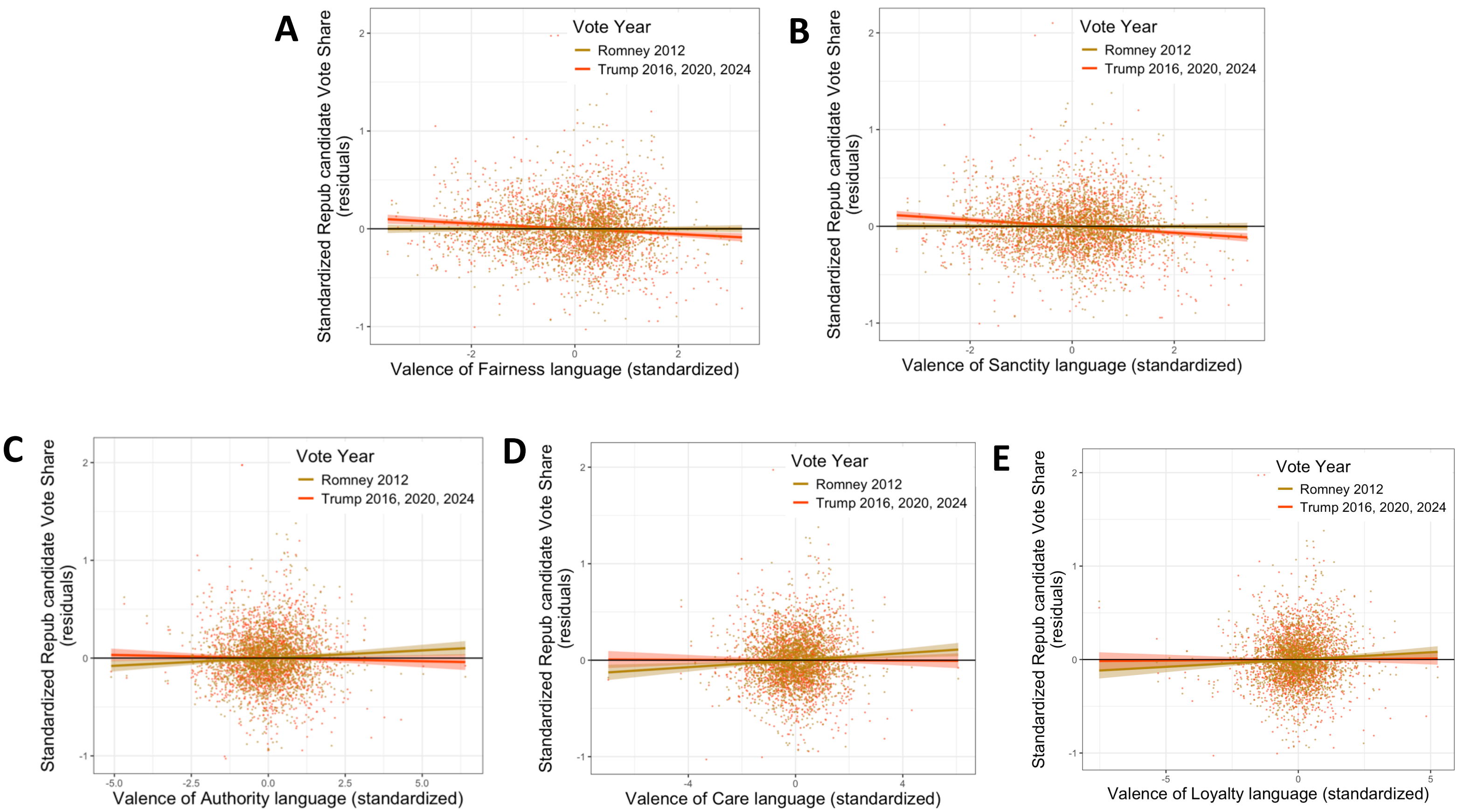


Figure 4. Relationships between the valence of references to moral foundations and vote share for Trump and Romney. More negatively-valenced language on (A) Fairness and (B) Sanctity is associated with greater vote share for Trump but not for Romney. More positively-valenced language on (C) Authority, (D) Care, and (E) Loyalty is associated with greater vote share for Romney but was not related to Trump's vote share.

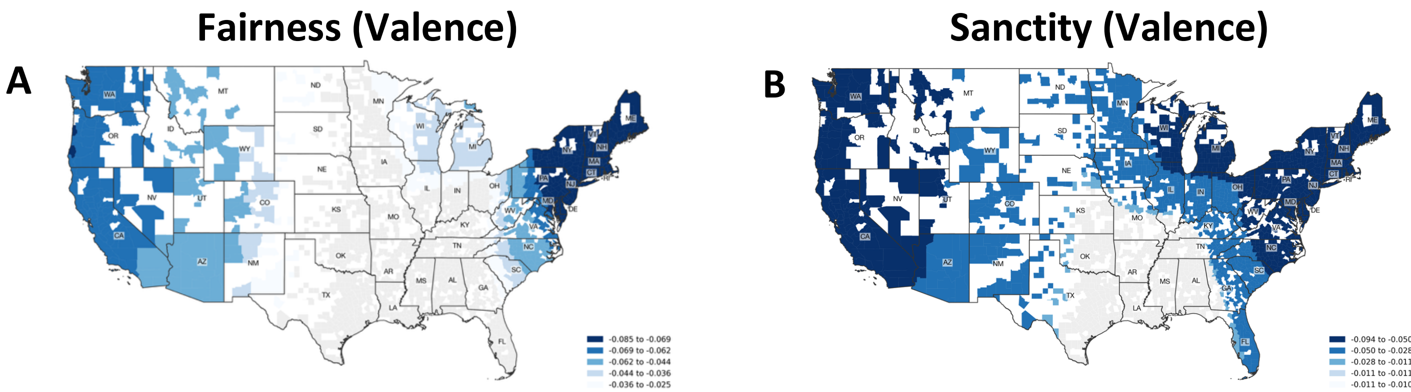


Figure 5. Spatial regression maps indicating the geographic distribution of the effect of moral valence in references to (A) Fairness and (B) Sanctity on Trump vote share.

Table 1. Relationships between each Big 5 personality factor and vote share for Trump and Romney, and SUR models showing differences between these effects.

	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Big 5:								
Extraversion	**0.075**	**10.16**	**< .001**	**0.024**	**3.49**	**< .001**	**26.01**	**< .001**
	p_{corr} < .001* **			**p_{corr} = .001**			**p_{corr} < .001*** **	
Emotional Stability (Neuroticism)	**-0.045**	**-5.67**	**< .001**	-0.001	-0.11	.91	**16.94**	**< .001**
	p_{corr} < .001* **						**p_{corr} < .001*** **	
Agreeableness	**-0.066**	**-7.79**	**< .001**	0.002	0.22	.83	**34.71**	**< .001**
	p_{corr} < .001* **						**p_{corr} < .001*** **	
Openness	**-0.147**	**-15.02**	**< .001**	**-0.051**	**-5.45**	**< .001**	**51.39**	**< .001**
	p_{corr} < .001* **			**p_{corr} < .001*** **			**p_{corr} < .001*** **	
Conscientiousness	-0.054	-7.13	**< .001**	0.000	0.05	.96	28.01	**< .001**
	p_{corr} < .001* **						**p_{corr} < .001*** **	

Table 2. Relationships between empathy and vote share for Trump and Romney, and SUR models showing differences between these effects.

	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Empathic Concern	**-0.074**	**-9.04**	**< .001**	-0.009	-1.22	0.22	**33.86**	**< .001**
	p_{corr} < .001* **						**p_{corr} < .001*** **	
Empathic Distress	**-0.042**	**-5.18**	**< .001**	-0.011	-1.55	0.12	**7.79**	**.005**
	p_{corr} < .001 **						**p_{corr} = .005** **	

Table 3. Relationships between valence of moral foundations and vote share for Trump and Romney, and SUR models showing differences between these effects.

	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Moral Foundations (Valence):								
Care/Harm	-0.001	-0.19	.85	**0.028**	**3.88**	**< .001**	**7.47**	**.006**
				$p_{corrected}$ < .001***			**$p_{corrected}$ = .008****	
Fairness/Cheating	**-0.075**	**-7.12**	**< .001**	0.001	0.06	.95	**28.03**	**< .001**
	$p_{corrected}$ < .001***						**$p_{corrected}$ < .001*****	
Authority/Subversion	-0.010	-1.23	.22	**0.024**	**3.37**	**< .001**	**10.07**	**.0015**
				$p_{corrected}$ = .002**			**$p_{corrected}$ = .0025****	
Loyalty/Betrayal	0.003	0.39	.70	**0.019**	**3.01**	**.003**	2.97	.085
				$p_{corrected}$ = .004**			$p_{corrected}$ = .085 ~	
Sanctity/Degradation	**-0.081**	**-8.23**	**< .001**	-0.003	-0.29	0.77	**34.45**	**< .001**
	$p_{corrected}$ < .001***						**$p_{corrected}$ < .001*****	

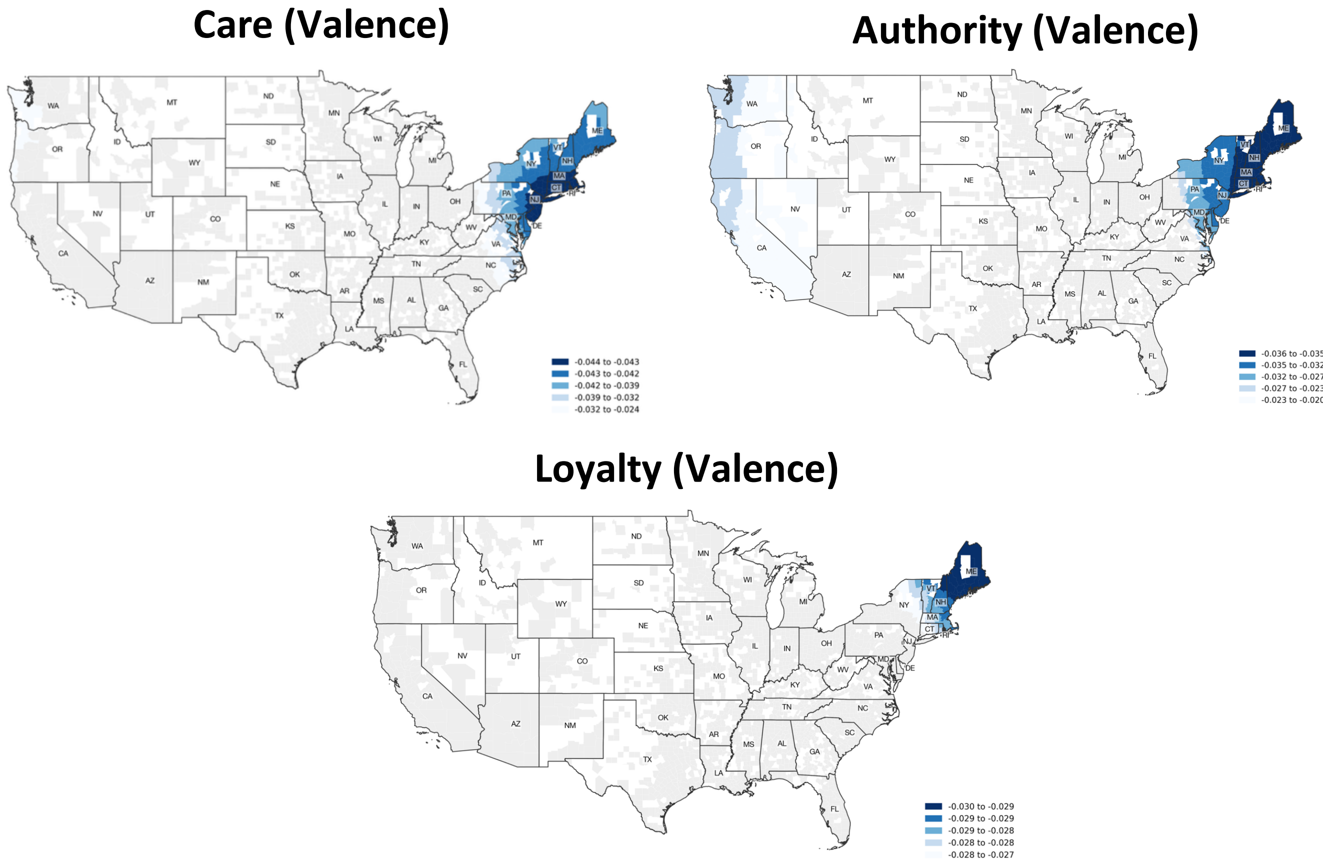
Table 4. Relationships between strength of moral foundations and vote share for Trump and Romney, and SUR models showing differences between these effects.

Moral Foundations (Strength):								
	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Care/Harm	0.007	0.93	.35	**-0.037**	**-5.41**	**< .001**	**18.48**	**< .001**
				$p_{corrected}$ < .001***			**$p_{corrected}$ < .001*****	
Fairness/Cheating	**0.052**	**5.26**	**< .001**	-0.005	-0.56	.58	**18.19**	**< .001**
	$p_{corrected}$ < .001***						**$p_{corrected}$ < .001*****	
Authority/Subversion	**0.033**	**4.54**	**< .001**	-0.005	-0.72	.47	**14.76**	**< .001**
	$p_{corrected}$ < .001***						**$p_{corrected}$ < .001*****	
Loyalty/Betrayal	0.006	0.84	.40	-0.012	-1.92	.055	3.65	.056
				$p_{corrected}$ = .091 ~			$p_{corrected}$ = .056 ~	
Sanctity/Degradation	**0.047**	**4.82**	**< .001**	-0.019	-2.18	.03	**25.33**	**< .001**
	$p_{corrected}$ < .001***			$p_{corrected}$ = .074 ~			**$p_{corrected}$ < .001*****	

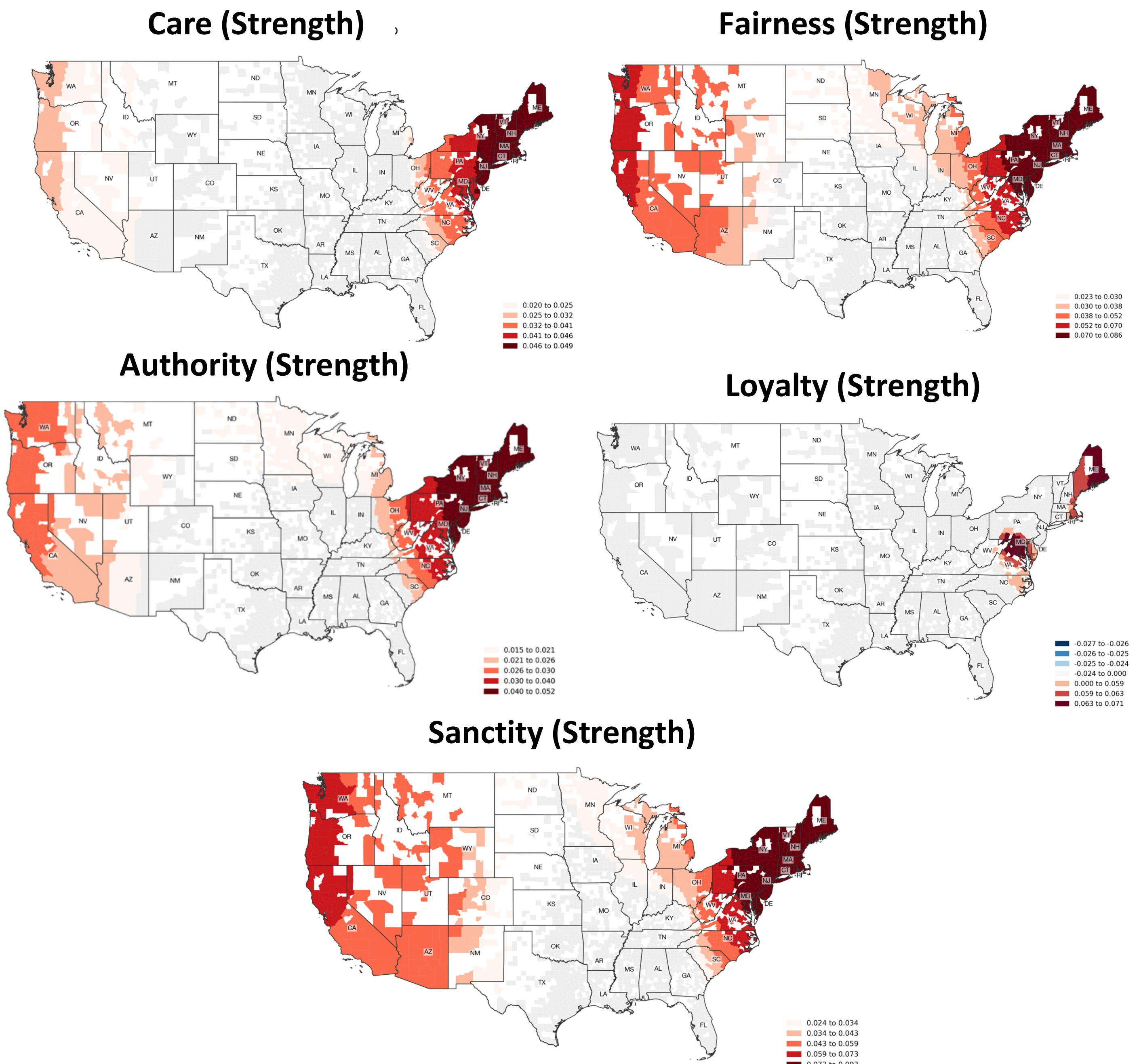
Table 5. Results of SUR analyses indicating the extent to which each psychological dimension predicted Trump's vote share more strongly for 2024 than for 2016.

Psychological Dimension	**χ^2**	**p_{uncorr}**	**p_{corr}**
Extraversion	**8.35**	**.004**	**.009****
Emotional Stability (Neuroticism)	**4.65**	**.031**	**.031***
Agreeableness	**5.36**	**.021**	**.026***
Openness	**29.38**	**< .001**	**< .001*****
Conscientiousness	**7.73**	**.005**	**.009****
Empathic Concern	**11.36**	**< .001**	**.0015****
Empathic Distress	**5.11**	**.024**	**.024***
Moral Valence: Care	0.08	.77	--
Moral Valence: Fairness	4.40	.036	.090 ~
Moral Valence: Authority	0.04	.83	--
Moral Valence: Loyalty	1.16	.28	--
Moral Valence: Sanctity	**7.11**	**.0077**	**.038***
Moral Strength: Care	0.39	.53	--
Moral Strength: Fairness	2.77	.096	--
Moral Strength: Authority	1.47	.23	--
Moral Strength: Loyalty	0.92	.34	--
Moral Strength: Sanctity	2.61	.11	--

Supporting Information (SI)



Supplemental Figure 1. Spatial regression maps showing effects on Trump vote share for additional valence of moral foundations of Care, Authority, and Loyalty (in addition to those shown in Figure 4 in the main text). These measures did not show significant effects at the national level in the GLM regression analyses but do show localized effects in the Northeast.



Supplemental Figure 2. Spatial regression maps showing effects on Trump vote share for strength of moral foundation language.

Supplemental Table 1. Alternate model predicting vote share for Trump and Romney, with all 5 personality variables entered simultaneously in the regression model, and SUR models showing differences in effects between Trump and Romney.

	Trump (2016-2024)			Romney (2012)			Difference		
	β	**t**	**p**	**β**	**t**	**p**	**χ^2**	**p_{uncorr}**	**p_{corr}**
Big 5:									
Extraversion	**0.046**	**5.27**	**< .001*****	0.011	1.24	.21	**8.64**	**.003**	**.005****
Emotional Stability (Neuroticism)	**-0.054**	**-4.58**	**< .001*****	-0.016	-1.40	.16	**5.45**	**.020**	**.025***
Agreeableness	**-0.050**	**-4.69**	**< .001*****	0.001	0.08	.93	**11.82**	**< .001**	**.0015****
Openness	**-0.114**	**-9.84**	**< .001*****	**-0.049**	**-4.37**	**< .001**	**16.51**	**< .001**	**< .001*****
Conscientiousness	**0.034**	**2.70**	**.007****	0.020	1.66	.097 ~	0.64	.43	--

Supplemental Table 2. Alternate model predicting vote share for Trump and Romney, with Empathic Concern and Empathic Distress modeled simultaneously in the regression model, and SUR models showing differences in effects between Trump and Romney.

	Trump (2016-2024)			Romney (2012)			Difference		
	β	**t**	**p**	**β**	**t**	**p**	**β**	**p_{uncorr}**	**p_{corr}**
Empathic Concern	**-0.113**	**-8.17**	**< .001*****	0.001	0.05	.96	**36.40**	**< .001**	**< .001*****
Empathic Distress	**0.047**	**3.50**	**< .001*****	-0.012	-0.95	.34	**10.36**	**.001**	**.001****

Supplemental Table 3. Relationships between strength of positive aspects of moral foundations and vote share for Trump and Romney, and SUR models showing differences between these effects.

Moral Foundations (Positive):								
	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Care/Harm	0.003	0.39	.69	0.008	1.23	.22	0.29	.59
Fairness/Cheating	**-0.044**	**-5.25**	**< .001**	-0.003	-0.35	.73	**13.32**	**< .001**
	$p_{corrected}$ < 0.001* **						**$p_{corrected}$ < .001*** **	
Authority/Subversion	0.008	1.16	.25	**0.018**	**2.82**	**.0049**	1.05	.30
				$p_{corrected}$ = .016*				
Loyalty/Betrayal	0.004	0.65	.52	0.009	1.43	.15	0.22	.64
Sanctity/Degradation	**-0.076**	**-8.98**	**< .001**	**-0.021**	**-2.72**	**.0065**	**22.74**	**< .001**
	$p_{corrected}$ < .001* **			**$p_{corrected}$ = .016***			**$p_{corrected}$ < .001*** **	

Supplemental Table 4. Relationships between strength of negative aspects of moral foundations and vote share for Trump and Romney, and SUR models showing differences between these effects.

Moral Foundations (Negative):								
	Trump (2016-2024)			Romney (2012)			Difference	
	b	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Care/Harm	0.004	0.49	.62	**-0.035**	**-4.86**	**< .001**	**13.02**	**< .001**
				$p_{corrected}$ < .001* **			**$p_{corrected}$ < .001*** **	
Fairness/Cheating	**0.077**	**7.06**	**< .001**	-0.003	-0.26	.79	**29.04**	**< .001**
	$p_{corrected}$ < .001* **						**$p_{corrected}$ < .001*** **	
Authority/Subversion	**0.025**	**3.05**	**.002**	**-0.023**	**-3.10**	**.002**	**18.83**	**< .001**
	$p_{corrected}$ = .004 **			**$p_{corrected}$ = .003** **			**$p_{corrected}$ < .001*** **	
Loyalty/Betrayal	0.001	0.095	.92	**-0.031**	**-4.46**	**< .001**	**9.32**	**.002**
				$p_{corrected}$ < .001* **			**$p_{corrected}$ = .002** **	
Sanctity/Degradation	**0.072**	**7.21**	**< .001**	-0.006	-0.67	.51	**33.32**	**< .001**
	$p_{corrected}$ < .001* **						**$p_{corrected}$ < .001*** **	

Supplemental Table 5. Relationships between personality factors and Trump vote share, separating out each of the three elections in which Trump was a candidate.

	Trump 2016			Trump 2020			Trump 2024		
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**
Extraversion	**0.057**	**8.85**	**< .001**	**0.079**	**10.27**	**< .001**	**0.088**	**10.26**	**< .001**
	p_{corr} < .001* **			**p_{corr} < .001*** **			**p_{corr} < .001*** **		
Emotional Stability (Neuroticism)	**-0.032**	**-4.52**	**< .001**	**-0.047**	**-5.61**	**< .001**	**-0.056**	**-6.08**	**< .001**
	p_{corr} < .001* **			**p_{corr} < .001*** **			**p_{corr} < .001*** **		
Agreeableness	**-0.052**	**-6.99**	**< .001**	**-0.065**	**-7.32**	**< .001**	**-0.080**	**-8.14**	**< .001**
	p_{corr} < .001* **			**p_{corr} < .001*** **			**p_{corr} < .001*** **		
Openness	**-0.104**	**-11.95**	**< .001**	**-0.156**	**-15.24**	**< .001**	**-0.181**	**-15.97**	**< .001**
	p_{corr} < .001* **			**p_{corr} < .001*** **			**p_{corr} < .001*** **		
Conscientiousness	**-0.037**	**-5.56**	**< .001**	**-0.057**	**-7.13**	**< .001**	**-0.068**	**-7.66**	**< .001**
	p_{corr} < .001* **			**p_{corr} < .001*** **			**p_{corr} < .001*** **		

Supplemental Table 6. Relationships between empathy and Trump vote share, separating out each of the three elections in which Trump was a candidate.

	Trump 2016			Trump 2020			Trump 2024		
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**
Empathic Concern	**-0.052**	**-7.21**	**< .001**	**-0.077**	**-9.00**	**< .001**	**-0.092**	**-9.65**	**< .001**
	p_{corr} < .001* **			**p_{corr} < .001*** **			**p_{corr} < .001*** **		
Empathic Distress	**-0.025**	**-3.62**	**< .001**	**-0.047**	**-5.61**	**< .001**	**-0.052**	**-5.53**	**< .001**
	p_{corr} < .001* **			**p_{corr} < .001*** **			**p_{corr} < .001*** **		

Supplemental Table 7. Relationships between moral valence measures and Trump vote share, separating out each of the three elections in which Trump was a candidate.

	Trump 2016			Trump 2020			Trump 2024		
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**
Care/Harm	-0.004	-0.65	.52	0.002	0.21	.83	-0.001	-0.13	.90
Fairness/Cheating	**-0.059**	**-6.38**	**< .001**	**-0.074**	**-6.75**	**< .001**	**-0.091**	**-7.40**	**< .001**
	$p_{corrected}$ < .001***			$p_{corrected}$ < 0.001***			$p_{corrected}$ < .001***		
Authority/Subversion	-0.011	-1.65	.10	-0.008	-1.02	.31	-0.009	-0.96	.34
Loyalty/Betrayal	-0.004	-0.59	.55	0.005	0.67	.51	0.007	0.90	.37
Sanctity/Degradation	**-0.060**	**-7.03**	**< .001**	**-0.082**	**-8.01**	**< .001**	**-0.098**	**-8.61**	**< .001**
	$p_{corrected}$ < .001***			$p_{corrected}$ < .001***			$p_{corrected}$ < .001***		

Supplemental Table 8. Relationships between moral strength measures and Trump vote share, separating out each of the three elections in which Trump was a candidate.

	Trump 2016			Trump 2020			Trump 2024		
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**
Care/Harm	0.005	0.74	.46	0.004	0.47	.64	0.012	1.32	.19
Fairness/Cheating	**0.041**	**4.79**	**< .001**	**0.049**	**4.69**	**< .001**	**0.065**	**5.64**	**< .001**
	$p_{corrected}$ < .001***			$p_{corrected}$ < .001***			$p_{corrected}$ < .001***		
Authority/Subversion	**0.027**	**4.24**	**< .001**	**0.032**	**4.18**	**< .001**	**0.040**	**4.67**	**< .001**
	$p_{corrected}$ < .001***			$p_{corrected}$ < .001***			$p_{corrected}$ < .001***		
Loyalty/Betrayal	0.002	0.36	.72	0.003	0.44	.66	0.011	1.46	.14
Sanctity/Degradation	**0.036**	**4.29**	**< .001**	**0.044**	**4.33**	**< .001**	**0.058**	**5.21**	**< .001**
	$p_{corrected}$ < .001***			$p_{corrected}$ < .001***			$p_{corrected}$ < .001***		

Supplemental Table 9. Alternate models including education level (% bachelor degree) as an additional confound variable, which was removed from the primary models due to high VIF. Relationships between personality and vote share for Trump and Romney, and SUR models showing differences between these effects, are shown.

	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Big 5:								
Extraversion	**0.063**	**9.71**	**< .001**	**0.021**	**3.03**	**.003**	**20.45**	**< .001**
	$p_{corr} < 0.001$***			**$p_{corr} = 0.006$****			**$p_{corr} < .001$*****	
Emotional Stability (Neuroticism)	**0.016**	**2.18**	**.03**	**0.017**	**2.24**	**.025**	0.09	.76
	$p_{corr} = 0.0495$*			**$p_{corr} = 0.032$***				
Agreeableness	-0.014	-1.86	.063	**0.017**	**2.15**	**.032**	**9.05**	**.003**
	$p_{corr} = 0.063$ ~			**$p_{corr} = 0.032$***			**$p_{corr} = .004$****	
Openness	**-0.103**	**-11.53**	**< .001**	**-0.039**	**-4.15**	**< .001**	**25.15**	**< .001**
	$p_{corr} < 0.001$***			**$p_{corr} < 0.001$*****			**$p_{corr} < .001$*****	
Conscientiousness	0.014	1.90	.058	**0.021**	**2.84**	**.005**	0.85	.36
	$p_{corr} = 0.063$ ~			**$p_{corr} = 0.008$****				

Supplemental Table 10. Alternate models including education level (% bachelor degree) as an additional confound variable. Relationships between empathy and vote share for Trump and Romney, and SUR models showing differences between these effects, are shown.

	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Empathic Concern	**-0.033**	**-4.51**	**< .001**	0.002	0.29	.77	**11.16**	**< .001**
	$p_{corr} < .001$***						**$p_{corr} = .0017$****	
Empathic Distress	**-0.020**	**-2.79**	**.005**	-0.005	-0.75	.46	1.98	.16
	$p_{corr} = .005$**							

Supplemental Table 11. Alternate models including education level (% bachelor degree) as an additional confound variable. Relationships between valence of moral language and vote share for Trump and Romney, and SUR models showing differences between these effects, are shown.

	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Moral Foundations (Valence):								
Care/Harm	**0.021**	**2.97**	**.003**	**0.034**	**4.79**	**< .001**	1.83	.18
	$p_{corrected}$ = .015*			**$p_{corrected}$ < .001*****				
Fairness/Cheating	-0.017	-1.82	.070	0.017	1.77	.077	**6.41**	**.011**
	$p_{corrected}$ = .11			$p_{corrected}$ = .077 ~			**$p_{corrected}$ = .034***	
Authority/Subversion	0.009	1.30	.19	**0.029**	**4.15**	**< .001**	4.25	.039
				$p_{corrected}$ < .001***			$p_{corrected}$ = .065 ~	
Loyalty/Betrayal	0.014	2.25	.025	**0.022**	**3.52**	**< .001**	0.90	.34
	$p_{corrected}$ = .062 ~			**$p_{corrected}$ < .001*****				
Sanctity/Degradation	-0.015	-1.69	.09	0.017	1.81	.07	**6.11**	**.013**
	$p_{corrected}$ = .11			$p_{corrected}$ = .077 ~			**$p_{corrected}$ = .034***	

Supplemental Table 12. Alternate models including education level (% bachelor degree) as an additional confound variable. Relationships between strength of moral language and vote share for Trump and Romney, and SUR models showing differences between these effects, are shown.

Moral Foundations (Strength):								
	Trump (2016-2024)			Romney (2012)			Difference	
	β	**t**	**p_{uncorr}**	**β**	**t**	**p_{uncorr}**	**χ^2**	**p_{uncorr}**
Care/Harm	**-0.025**	**-3.74**	**< .001**	**-0.047**	**-6.85**	**< .001**	5.20	.022
	$p_{corrected}$ < .001***			**$p_{corrected}$ < .001*****			$p_{corrected}$ = .06 ~	
Fairness/Cheating	0.010	1.08	.28	-0.017	-1.89	.059	4.44	.035
				$p_{corrected}$ = .06 ~			$p_{corrected}$ = .06 ~	
Authority/Subversion	0.006	0.89	.37	-0.012	-1.88	.06	3.88	.049
				$p_{corrected}$ = .06 ~			$p_{corrected}$ = .06 ~	
Loyalty/Betrayal	-0.009	-1.51	.13	**-0.016**	**-2.60**	**.009**	0.66	.42
				$p_{corrected}$ = .016*				
Sanctity/Degradation	-0.011	-1.27	.20	**-0.037**	**-4.12**	**< .001**	4.24	.039
				$p_{corrected}$ < .001***			$p_{corrected}$ = .06 ~	