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(Un)Happiness and Voting in U.S. Presidential Elections

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A rapidly growing literature has attempted to explain Donald Trump's success in the 2016 U.S. presidential election as a result of a wide variety of differences in individual characteristics, attitudes, and social processes. We propose that the economic and psychological processes previously established have in common that they generated or electorally capitalized on unhappiness in the electorate, which emerges as a powerful high-level predictor of the 2016 electoral outcome. Drawing on a large dataset covering over 2 million individual surveys, which we aggregated to the county level, we find that low levels of evaluative, experienced, and eudaemonic subjective well-being (SWB) are strongly predictive of Trump's victory, accounting for an extensive list of demographic, ideological, and socioeconomic covariates and robustness checks. County-level future life evaluation alone correlates with the Trump vote share over Republican baselines at $r = -.78$ in the raw data, a magnitude rarely seen in the social sciences. We show similar findings when examining the association between individual-level life satisfaction and Trump voting. Low levels of SWB also predict anti-incumbent voting at the 2012 election, both at the county and individual level. The findings suggest that SWB is a powerful high-level marker of (dis)content and that SWB should be routinely considered alongside economic explanations of electoral choice.

Keywords: subjective well-being, election, voting

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In the period since the 2016 U.S. presidential election, a growing number of studies have attempted to identify and characterize the people and places behind Donald Trump's victory. Historically, theories in economics and political science have stressed the role of "economic voting" in explaining electoral outcomes, a process whereby voters reward or punish incumbent parties for the state of the macroeconomy (Fair, 1978; Kramer, 1971). In this vein, many have pointed to factors such as stagnant wages among middle-class Americans and job losses—arising from growing mechanization, international trade exposure, and the general decline in domestic manufacturing—in driving support for Trump's candidacy (e.g., Autor, Dorn, Hanson, & Majlesi, 2017; Frey, Berger, & Chen, 2018). In contrast, studies in psychology and related fields have tended to challenge these purely economic explanations and have instead focused on factors such as group and status threat (e.g., Knowles & Tropp, 2018; Major, Blodorn, & Major Blascovich, 2018; Mutz, 2018), preferences for authoritarianism (MacWilliams, 2016), moral values (Enke, 2020), and personality traits like neuroticism (Obschonka et al., 2018).

What many of these economic and psychological explanations have in common is that they emphasize a strong sense of discontent among certain sections of the U.S. population. The reasons for this discontent are multiple, and the literature adding to them is growing quickly. However, the central point across the majority of these accounts is that there was a palpable sense of general unhappiness with the status quo in the United States. In this article, we develop a conceptual framework that links low levels of subjective well-being (SWB) with (a) anti-incumbent voting and (b) support for populist candidates. In doing so, we argue that SWB can be seen as a common psychological pathway to electoral

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choice. While more specific psychological, sociological, and economic accounts may help to explain why parts of the electorate are happy or unhappy, we suggest that these processes funnel into differences in SWB that in turn predict voting.

Various governments around the world are beginning to measure SWB on a large scale and use it as a measure of social progress (Durand, 2018; Krueger & Stone, 2014). Notwithstanding persistent gains in national income, the United States has fared relatively poorly on these alternative measures of national success over the past few decades, with SWB having fallen in the country, particularly among the less educated (Blanchflower & Oswald, 2019; Case & Deaton, 2020; Graham, 2017). Yet, despite this, the role of SWB in explaining electoral processes and outcomes has typically received little attention.[1]

In this article, we directly examine the role of SWB in explaining electoral outcomes. Using data on over 2 million Americans collected during the years preceding Trump's election by the Gallup Organization, we investigate how strongly predictive evaluative, experienced, and eudaemonic SWB measures were of the outcome of the 2016 presidential election at the county level. We reproduce these main county-level analysis using individual-level survey data by investigating the role of SWB in explaining incumbent approval ratings as well as the decision of whom to vote for in presidential elections.

Although we argue that low levels of SWB will increase the vote shares of candidates who are (a) nonincumbent and (b) populist, the 2016 presidential election does not allow us to distinguish between the two processes, because the challenger (Donald Trump) was both nonincumbent in terms of party affiliation and populist in terms of policy platform and rhetoric. By repeating our county- and individual-level analyses using data from the 2012 presidential election (Barack Obama vs. Mitt Romney), we are able to more cleanly test our predictions on SWB and incumbent voting in an election with a mainstream challenger. To more directly test our prediction on SWB and populist candidates, we also examine the role of county-level SWB in explaining the vote shares of Donald Trump and Bernie Sanders in the 2016 Republican and Democratic primary elections, respectively. An additional issue is the relationship between (un)happiness and incumbent voting when the challenger is not only nonincumbent but also a populist—that is, an open question is whether or not these two hypothesized relationships will be *additive* in nature. To shed light on this, we also pool the 2012 and 2016 data such that we can directly test for any difference in the magnitude of the relationship between (un)happiness and Republican voting in the two elections.

We carried out an extensive set of secondary analyses to establish the robustness of the relationship between county-level SWB and voting. Among other things, we investigated (a) the role of individual-level life satisfaction in predicting votes for Donald Trump in 2016 and Mitt Romney in 2012, conditional on a very rich set of demographic and socioeconomic covariates as well as a lagged dependent variable, (b) the association between individual-level SWB and presidential (dis)approval, (c) the "swing" toward Donald Trump in 2016 as well as simply the level of the Republican vote share in our county-level analysis, (d) including in the voting equation a comprehensive list of economic and demographic covariates, (e) relying on between-county variance within states and more restrictive spatial units of analysis like core-based statistical areas and commuting zones, (f) employing within-

county longitudinal models that consider *changes* in SWB and voting across President Obama's first and second terms and, thus, controlling for additional unobserved county variables, and (g) relying solely on SWB responses before Donald Trump entered politics, to ensure that any relationship is not driven by Trump's campaign influencing happiness.

Conceptual Framework

A long history of theoretical and empirical work in psychology suggests that people use their feelings as a source of information and as a guide to decision making (Schwarz, 1990). Whereas early work on *affect-as-information* focused solely on the way in which specific emotions provide information to people about their surroundings (Schwarz & Clore, 1983), the theory has been broadened to include a range of feelings and states (Schwarz, 2011). Here, we focus on the broad concept of SWB, which includes evaluations of how one's life is overall as well as the experience of positive and negative emotions. High levels of SWB are a signal that the situation is "benign" and need not be changed, whereas low levels of SWB are an indication of "threat" and suggest that things ought to be changed to repair the situation.

In line with this conceptual reasoning, it has been shown that negative emotional states decrease preferences for the status quo (Scheibehenne, Von Helversen, & Shevchenko, 2014). We extend this line of reasoning (a) to include a broader focus on SWB in general and (b) to behavior in the political sphere. The reliance on feelings for information is known to be particularly salient in situations in which information is complex and motivation is low, which is typically the case in the context of making political vote choices—where people's understanding of complex political and economic issues is limited (Campbell, Converse, Miller, & Stokes, 1960) and the probability of a single vote making a difference to the outcome is low (Downs, 1957).

We focus on two aspects of the political process: incumbent and populist voting. Incumbent voting refers to the propensity of voters to reelect sitting governments into office. We follow the ideational approach to defining populism, which suggests that it is a "thin-centered" ideology based on two core features: (a) a contention that there is a clear distinction between the body of virtuous "ordinary" people and the corrupt "elite" and (b) a belief that politics ought to be exclusively a reflection of the "will of the people." The ideology is thin-centered in the sense of limiting its claims about the political agenda to the above contentions and is able to mix and augment other elements of political ideology, such as nationalism (Mudde, 2017). We classify Donald Trump as populist because key themes in his campaign were focused on the

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[1] A small number of studies have begun to fill this gap and shown that people become happier when their chosen party is in power (Di Tella & MacCulloch, 2005) and observed that SWB is related to turnout intentions (Flavin & Keane, 2012). We build in particular on related analysis showing that increased "deaths of despair" are associated with the county-level Trump vote swing in 2016 (Goldman et al., 2019) and that well-being is related to voting intentions and election outcomes in Europe and the United States (Herrin et al., 2018; Liberini, Redoano, & Proto, 2017; Ward, 2020).

corruption of U.S. elites and included an emphasis on the will of the people.[2]

Drawing on this conceptual framework, we expect people who evaluate the state of their lives positively overall, as well as those who experience more positive and fewer negative emotions, to use these feelings as an indication that the incumbent political party is competent. Given this, they will see comparatively little reason to change the party in office and vote to reelect them for a further term, rather than take a chance on a challenger. Conversely, people with low levels of SWB will see this as evidence that the governing party is of low quality and ought to be replaced to repair the situation.

Hypothesis 1: Low levels of subjective well-being will increase the vote share of nonincumbent candidates.

Whereas anti-incumbent voting focuses on the choice between political parties, populism has more to do with a rejection of the mainstream political system more generally. Nevertheless, the dynamics are similar: People with high levels of SWB will see the current political situation as a benign context that does not need to be changed, whereas those with low levels of SWB will perceive the system in a more negative manner. The populist promise of radical change speaks closely to people experiencing unhappiness, because this unhappiness is a cue to them that change is needed.[3] Thus, low levels of SWB will predict a greater rejection of the system and a higher propensity toward populist candidates.

In addition, populism not only is a set of beliefs but also tends to entail a more emotional—and negative—style of communication (Nai, 2018), which is likely to speak most strongly to those who most perceive their lives to be less satisfying (and experience more negative and fewer positive emotions in their day-to-day lives). In this sense, populism may "activate" unhappiness politically by rhetorically proposing an electoral choice that promises the cessation of the state of unhappiness. As such, descriptively, populists may moderate the relationship between unhappiness and voting, such that a stronger relationship between unhappiness and vote shares is observed for populist candidates.

Hypothesis 2: Low levels of subjective well-being will increase the vote share of populist candidates.

In addition to these two main hypothesized relationships, an open question remains as to the nature of the relationship between (un)happiness and incumbent voting when the challenger is not only nonincumbent but is also a populist. That is, a further research question we explore in the data are whether the two hypotheses are additive or not.

Finally, it is worth noting that the two hypotheses do not necessarily stand in contention with the existing literature linking different variables to political choice. Rather, in this framework, SWB can be seen as a common psychological pathway to electoral choice. While various accounts may explain why some voters are happier than others, it is these differences in SWB that, in turn, predict voting decisions.

Study 1a: County-Level Evidence of SWB and Voting in 2016

Data and Method

We constructed county-level measures of SWB using the Gallup Daily Poll, which, since 2008, has surveyed a large random sample of U.S. adults about various political, economic, and well-being topics on a daily basis. Between 2008 and 2012, we were able to observe the SWB of around 1,000 adults per day. At the beginning of 2013, this changed to around 500 adults per day. Around 60% of interviews were conducted via cell phone and 40% via landline.

SWB is typically defined along four main dimensions: life evaluation, positive affect, negative affect, and purpose (Diener, Suh, Lucas, & Smith, 1999). In the Gallup Daily Poll, *life evaluation* is measured via the Cantril Ladder, which asks respondents to rate their life as a whole, both today and how they expect it to be 5 years from now. Affective measures are combinations of reports of whether the respondent experienced yesterday each of: happiness, enjoyment, and laughter (*positive affect*), as well as stress, worry, and sadness (*negative affect*). Finally, *purpose* (or eudaemonic well-being) combines reports of respondents liking what they do every day and how often they learn new things.[4]

We aggregated the SWB responses to the county level and linked these measures to election results. To maximize the accuracy and geographic coverage of our county-level SWB estimates, in our main analysis we pooled the daily surveys from the day after Barack Obama's first inauguration in January 2009 to the day before the 2016 presidential election (yielding a total of just over 2 million individual survey responses) and used these measures to predict the 2016 election result. In further analyses (discussed in more detail in subsequent studies below), we split the responses into Obama's first and second terms in office, to create a two-period longitudinal panel of counties (at the expense of precision in these county-level SWB measures).

We use two main outcome measures: (a) the level of the Trump vote share in 2016 and (b) our preferred measure, the Trump swing in 2016. The latter is the Republican two-party vote share in 2016 compared with the average Republican vote share at the previous four presidential elections. We focus principally on the swing because our main interest is in which counties Donald Trump was electorally successful in 2016 over and above what would normally be expected of a Republican candidate in any given county—and not in which areas of the country generally or historically are more Republican or Democratic.[5]

In our main analysis, we estimated linear regression models via weighted least squares, with each county's observation weighted by the number of survey respondents. This allowed us to account for heterogeneity in the sample size of the Gallup poll across counties and the differential measurement error in the county-level SWB estimates that this inevitably introduced into the analysis. In a series of robustness checks, we instead estimated unweighted

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[2] Donald Trump's candidacy arguably also included significant strains of the related concepts of nativism and authoritarianism, a point we return to more fully in the Discussion.

[3] Whether this desired change is forward or backward looking is an issue that we return to in more detail in the Discussion. It may be that a desire for a populist change is actually a desire to go back to the status quo ante (or at least to stop further progressive social change from happening). In any case, it is a desire to change from the current political status quo.

[4] Full details on question wordings are included in the online supplemental materials.

[5] A long-standing literature examines this relationship between SWB and political ideology/affiliation (Napier & Jost, 2008; Wojcik, Hovasapian, Graham, Motyl, & Ditto, 2015). We return in more detail to this point in the Discussion.
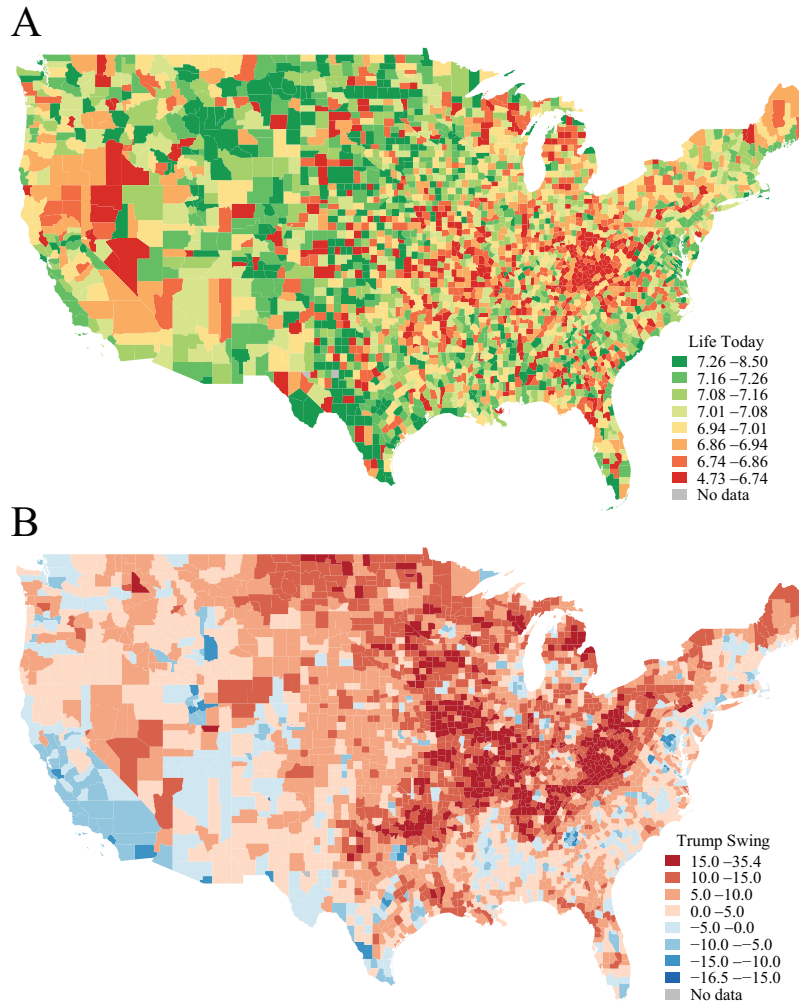
A

B

Figure 1. Life evaluation and the Republican vote swing in 2016 across U.S. counties. (A) Shows the county means of the life evaluation question (on a scale of 0 to 10) in the Gallup Daily Poll between January 2009 and October 2016. (B) Shows the Trump vote swing (Δ [Trump % - GOP Avg. % 2000–2012]). See the online article for the color version of this figure.

ordinary least-squares regressions using counties with sample sizes only over a minimum threshold (see online Supplemental Materials Figure S4).

Results

Raw predictive power of SWB. Figure 1 shows a county map of the Trump vote swing, together with a county map of life evaluation.[6] We find the two to correlate at $r = -.53$, with the largest swings toward Donald Trump occurring in the areas with lowest SWB. The bivariate correlation between the Trump swing and future life evaluation, which we show graphically in Figure 2, is even stronger, at $r = -.78$ (see online Supplemental Materials Table S3 for a full correlation matrix of all of the main variables). Much of Trump's support, over and above Republican baselines, came from areas with the bleakest outlook for the future state of people's lives.[7]

Figure 3 assesses the comparative raw predictive power of SWB and a number of variables typically used in academic and policy discourse to explain electoral outcomes, such as trade exposure, unemployment, wages, education, moral values, and racism. Entered together in a regression equation predicting the Trump swing, economic variables are able to explain around 33% of the variance in the election result. In a separate regression, demographics and geography account for around 63%. However, the highest percentage of variance—over 66%—is explained by the SWB variables. Entering each explanatory variable into a separate bivariate regression, we find the single strongest predictor of the county-level

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[6] See online Supplemental Materials Figure S2 for analogous maps of the other SWB measures.

[7] Figure 2 suggests, at least visually, that the relationship is broadly linear. We test more formally for nonlinearities and confirm this in the online supplemental materials (see Table S16).
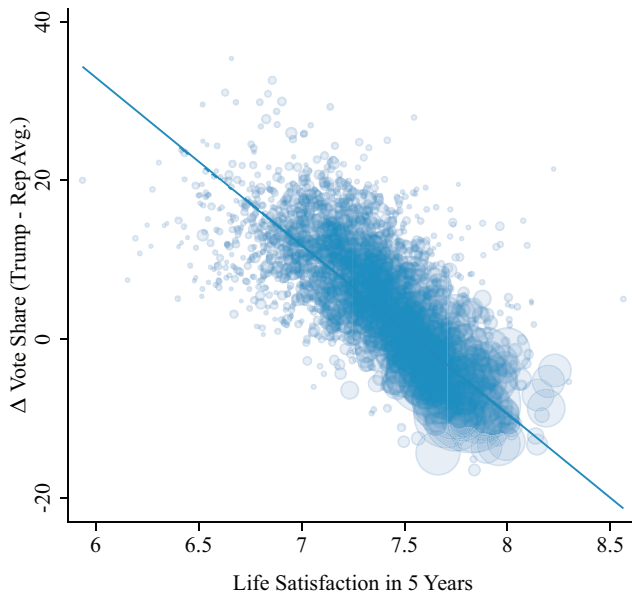
Figure 2. Future life evaluation and Trump voting across U.S. counties. Each county is weighted by the number of survey respondents in the Gallup poll. Linear line of fit shown. See the online article for the color version of this figure.

Trump vote swing to be future life evaluation, which by itself accounts for over 60% of the variance in his electoral success.

Main regression analyses. Table 1 reports multivariate regression models. Here, we included controls for a number of observable county characteristics and a series of state fixed effects, such that we were effectively comparing counties in the same state with one another.[8] Both evaluative measures of SWB are strongly and negatively associated with large differences in the Trump vote share. We *z*-scored all of the explanatory variables so that they have a mean of zero and a standard deviation of one. Thus, in column 1 of Table 1, a coefficient of 7.31 suggests that a decrease of one standard deviation in county-level life satisfaction is associated with an increase of 7.31 percentage points in the Republican vote share in 2016. Higher levels of positive affect and purpose are also associated with smaller Republican vote shares, while negative affect is not strongly associated with the level of the 2016 vote.

In columns 6 to 10 of Table 1, we move on to our preferred outcome measure, namely the Trump vote swing. For each of our five dimensions of SWB, happier counties are less likely to have swung toward Donald Trump. A decrease of one standard deviation in county-level future life satisfaction is associated with an increase of 4.41 percentage points in the Republican vote share in 2016, over and above what would historically be expected given the previous four presidential elections.

While negative affect was not predictive of the Trump swing in the bivariate analysis (see Figure 3), higher levels of emotions such as stress, worry, and sadness are positively associated with Trump voting in the multivariate analysis. This is largely because of the inclusion of population density in the equation: Although cities voted more strongly against Trump, the data suggest that people living in urban areas also generally experience more worry and

stress in their day-to-day lives. Once we compare city to city and rural to rural by holding population density (and other demographics) constant, a clear and significant positive relationship emerges between negative emotions and support for Trump. Conversely, positive emotional experiences are more equally distributed across counties of differing demographics, and in each case, the SWB coefficient remains relatively stable with and without these covariates in the equation.

Secondary analyses. We carried out an extensive set of secondary analyses to establish the robustness of the relationship between SWB and voting in the 2016 election.

Omitted variables. Our main models examined the association between SWB and Trump voting by making comparisons between counties within any given state, accounting for a range of observable characteristics of these counties. One concern with this approach, however, was that despite controlling for a rich set of covariates, any observed findings may be because of unobserved heterogeneity across counties. We conducted three supplementary analyses to test the sensitivity of our findings.

First, in online Supplemental Materials Table S4, we find that our results are robust when including a more exhaustive set of county-level observable demographic, geographic, and economic covariates. Second, an alternative method in which to control for such characteristics is shown in online Supplemental Materials Table S9. Here, we ran individual-level regression models predicting each of our SWB measures, controlling for a rich set of explanatory variables such as age, gender, race, income, and education. We then aggregated the residuals from these regressions to the county level and find our main results to be unchanged. Third, whereas in our main analysis, we exploited within-state variation in SWB and voting, we also estimated models relying on much more restrictive variation within commuting zones, core-based statistical areas, and even within counties over time (see Study 1c below). In online Supplemental Materials Table S5, even when comparing counties within very small neighboring clusters, our main findings remain evident.

Alternative outcomes. In our main analysis, we considered both the level of the 2016 Republican vote share and the swing compared with the previous four elections. We also assessed the relative ability of our SWB measures to explain alternative "Trump swings," such as his vote share compared with John McCain's and Mitt Romney's, and in online Supplemental Materials Tables S11 and S12, we find very similar results.

Interactions. To test whether the SWB–voting relationship held up in areas of different socioeconomic and demographic makeups, we also interacted covariates—such as race, income, population density, and level of education—with our measures of SWB in the vote share equation. In addition, we tested whether the SWB–voting relationship holds up equally well in swing counties and safely Republican or Democratic counties. In interaction mod-

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[8] These multivariate regression models are best thought of as sensitivity checks. Given that many county characteristics may themselves be generating the variation in SWB we are interested in, "controlling" for an exhaustive set of covariates inevitably increases the likelihood of misspecification. We included here in our main analysis a relatively parsimonious set of "controls," focusing in particular on the most policy-relevant factors, and in further sensitivity tests, we included a more exhaustive set of observable characteristics (see below).
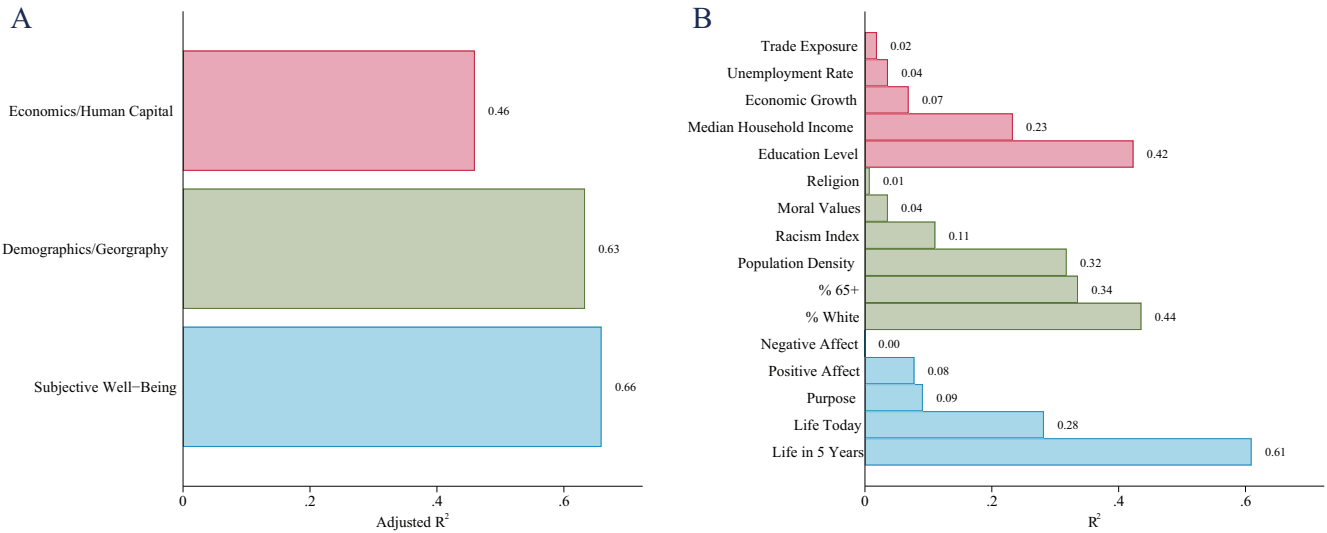
Figure 3. Benchmarking predictors of Trump voting: Each bar represents the R^2 from a separate weighted least squares regression, in which the dependent variable is the Trump vote swing. Subjective well-being measures are the county-mean response to survey items in the Gallup Daily Poll between January 2009 and October 2016. (A) Grouped Regressors (B) Bivariate Regressions. See the online article for the color version of this figure.

els, we find that the significant negative relationship between psychological well-being and Trump voting is evident, regardless of whether the county is rich or poor, highly or less educated, or predominantly white or racially more diverse (see online Supplemental Materials Table S15). Consistent patterns are found in swing and safely Democratic or Republican areas of the country, with the gradient of the relationship tending to be stronger in swing counties as well as counties that previously voted strongly for the Democratic Party (see online Supplemental Materials Table S7).

Subjective economic sentiment. It may be argued that even when controlling for the objective state of the economy, any significant association between SWB and the election result may be reflective of people's *economic mood* rather than their broader, nonmaterial SWB. Thus, we also included two measures of subjective economic evaluation in the regression analysis, both of which were drawn from the same Gallup poll as the SWB measures. These asked respondents to rate the "economic conditions in this country today" as well as whether they are getting better or worse. In online Supplemental Materials Table S6, we find that our results are robust, even when controlling for subjective and objective economic factors at the county level.

Reverse causation. Did low SWB help to elect Donald Trump, or did Donald Trump's campaigning lower the SWB of his likely voters? Given that his campaigning stressed the negative state of the country and pointed to an exploitation by the elites, the hypothesis that Trump's campaigning caused low SWB is plausible. We investigated whether the data are consistent with this hypothesis by considering county well-being data collected only before the start of 2015, well before Trump announced his candidacy (or even entered politics). In that way, the well-being estimates are unlikely to be the result of the messaging of the Trump campaign. As can be seen in online Supplemental Materials Table S8, we observe a similar pattern of findings, with low pre-2015

SWB predicting a higher Trump vote swing, across the domains of SWB and while controlling for demographic and economic covariates. Thus, we find no support for the hypothesis that our main results are attributable to the Trump campaign causing unhappiness in the electorate.[9]

There is a second sense in which politics may have caused low SWB, rather than low SWB causing electoral choice. Republican voters may have been unhappy during the Obama years precisely because their chosen party was not in power, which may have yielded the negative correlation between SWB and the Trump vote.[10] The way we set up our main analyses largely addressed this concern: We focused on the swing toward Trump from what would be expected from prior Republican vote shares. In other words, the main outcome measure already takes into account the expected political leaning of the counties. However, to investigate this alternative explanation more directly, we turned to the individual level: We leveraged a question in the Gallup Daily Poll on respondents' general party affiliation. We regressed individual SWB on individual political party affiliation, and aggregated only the remaining (residualized) variance in SWB not accounted for by individual political affiliation to the county level. We find that even after giving individual party affiliation the opportunity to account for individual SWB, our main findings are reproduced,

[9] Similarly, we also find consistent results when using pre-2015 county-level SWB as an instrumental variable for 2015–2016 county-level SWB in a two-stage least-squares analysis.

[10] A related concern is that Republicans may have given exaggeratedly negative answers during the Obama presidency to paint a bleak picture of the state of the country's happiness. This is similar in nature to a concern that is often raised in the economic voting literature, whereby partisan bias leads supporters of nonincumbent parties to give evaluations of the economy that are exaggerated downward (Evans & Andersen, 2006).

Table 1
Subjective Well-Being and Trump Voting in 2016

Dependent variable	Trump vote share in 2016						Δ (Trump − Rep avg. 2000–12)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Life evaluation: Today	−7.31*** (0.57)					−3.59*** (0.22)				
Life evaluation: Future		−11.73*** (0.59)					−4.41*** (0.22)			
Positive affect			−1.54** (0.59)					−2.65*** (0.24)		
Negative affect				0.26 (0.72)					1.50*** (0.26)	
Purpose					−4.06*** (0.61)					−2.61*** (0.24)
Median income (ln)	3.99*** (0.50)	3.84*** (0.46)	2.26*** (0.54)	2.01*** (0.52)	2.44*** (0.51)	−0.36 (0.22)	−0.64*** (0.24)	−0.86*** (0.25)	−1.18*** (0.25)	−1.05*** (0.24)
Unemployment rate	−1.35** (0.65)	−0.50 (0.62)	−0.98 (0.70)	−0.81 (0.70)	−1.01 (0.68)	0.14 (0.35)	0.53 (0.41)	0.08 (0.40)	0.30 (0.42)	0.28 (0.39)
Economic growth	−0.36 (0.42)	−0.14 (0.39)	−0.54 (0.45)	−0.58 (0.45)	−0.55 (0.45)	−0.50* (0.20)	−0.45* (0.19)	−0.54*** (0.20)	−0.58*** (0.20)	−0.59*** (0.20)
Racism	1.93*** (0.57)	1.34*** (0.46)	2.27*** (0.58)	2.32*** (0.59)	2.08*** (0.58)	0.97*** (0.19)	0.79*** (0.19)	1.06*** (0.21)	1.09*** (0.22)	1.01*** (0.22)
% Religious	2.13*** (0.55)	0.88* (0.50)	1.89*** (0.59)	1.86*** (0.59)	2.01*** (0.57)	0.84*** (0.21)	0.33 (0.21)	0.75*** (0.21)	0.68*** (0.22)	0.80*** (0.21)
Population density (ln)	−13.46*** (0.41)	−8.06*** (0.49)	−13.84*** (0.45)	−13.72*** (0.48)	−14.03*** (0.43)	−4.03*** (0.16)	−2.02*** (0.20)	−4.41*** (0.16)	−4.38*** (0.17)	−4.36*** (0.17)
Counties	3000	3000	3000	3000	2994	3000	3000	3000	3000	2994
R²	0.633	0.706	0.586	0.585	0.595	0.636	0.672	0.595	0.574	0.591

Note. Robust standard errors in parentheses. State fixed effects are included in all models. Within-state R^2s are reported. Each county is weighted in the regression analyses by the number of respondents in the Gallup survey. All explanatory variables are z-scored such that they have a center of zero and a standard deviation of one.
* $p < .10$.   ** $p < .05$.   *** $p < .01$.

with low values in all four domains of residualized SWB significantly predicting the Trump vote (see online Supplemental Materials Table S9).

Populism in the primaries.   To more directly test Hypothesis 2, we assessed whether our SWB measures are predictive of Donald Trump's performance in the 2016 Republican presidential primaries. We find in online Supplemental Materials Table S13 that even among Republican candidates, Donald Trump's populist candidacy was supported most strongly in the unhappiest counties of the country. We also examined voting in the Democratic primaries and investigated the extent to which our county-level SWB measures are able to predict votes for Bernie Sanders, whose campaign was more populist than that of his opponent, Hillary Clinton—in the case of Sanders, he advocated for restoring the country to the will of the people from the exploitation of "the 1%" elites. In online Supplemental Materials Table S14, we show that lower levels of evaluative SWB and higher levels of negative affect are associated with stronger vote shares for Sanders. We find support for Hypothesis 2 within both political parties.

Study 1b: County-Level Evidence of SWB and Voting in 2012

Evidence that low levels of SWB are predictive of Trump voting in 2016 is supportive of both Hypotheses 1 and 2. However, because a populist candidate ran against an incumbent, it is difficult to distinguish between the two predictions that unhappiness will increase anti-incumbent and populist voting. To more clearly test Hypothesis 1, we turned to the 2012 election, where the sitting president ran against a mainstream (i.e., nonpopulist) challenger, Mitt Romney.

Data and Method

We again used the Gallup Daily Poll, but this time looked solely at responses recorded in the survey during Obama's first term. We used the same definitions of SWB, and our empirical analyses mirror those of the 2016 models.[11] We entered our county-level measures of SWB into a voting equation predicting (a) the Romney vote share in 2012 and (b) the Romney vote share compared with the Republican vote share at the previous four presidential elections.

Results

In Table 2, we find that higher levels of evaluative SWB are associated with higher vote shares for the incumbent president. When predicting the level of the 2012 vote share, neither of our affective SWB measures is significantly related to the electoral outcome. When considering the results of the 2012 election compared with historical baselines, we find that all four of our SWB measures are significantly related to voting. For each of our SWB dimensions, unhappier counties were more likely to vote for the nonincumbent Republican Party.

We conducted a number of further checks to establish the robustness of these results. When comparing counties within more restric-

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[11] The purpose questions were added to the Gallup Poll after 2012 and are not included here.

Table 2

Subjective Well-Being and the 2012 Presidential Election

Dependent variable	Romney vote share in 2012				Δ (Romney − Rep avg. 1996–2008)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Life evaluation: Today	−5.93*** (0.59)				−2.35*** (0.22)			
Life evaluation: Future		−10.25*** (0.67)				−3.53*** (0.20)		
Positive affect			0.23 (0.63)				−2.19*** (0.25)	
Negative affect				0.64 (0.71)				2.09*** (0.29)
Median income (ln)	5.26*** (0.46)	5.25*** (0.43)	4.42*** (0.49)	4.48*** (0.48)	0.60*** (0.17)	0.56*** (0.17)	0.51*** (0.17)	0.38** (0.17)
Unemployment rate	−1.15 (0.75)	−0.62 (0.68)	−0.23 (0.76)	−0.33 (0.76)	−0.03 (0.21)	0.20 (0.20)	0.06 (0.23)	0.08 (0.23)
Economic growth	−0.59 (0.57)	−0.20 (0.55)	−0.59 (0.59)	−0.58 (0.59)	−0.37* (0.21)	−0.23 (0.20)	−0.36* (0.21)	−0.36* (0.21)
Racism	1.40** (0.56)	1.01** (0.49)	1.65*** (0.57)	1.63*** (0.57)	0.88*** (0.18)	0.75*** (0.17)	0.92*** (0.19)	0.91*** (0.18)
% Religious	2.08*** (0.52)	1.07** (0.48)	1.93*** (0.54)	1.92*** (0.54)	1.31*** (0.15)	0.95*** (0.15)	1.29*** (0.16)	1.22*** (0.16)
Population density (ln)	−10.36*** (0.38)	−6.82*** (0.46)	−10.57*** (0.40)	−10.64*** (0.42)	−2.36*** (0.15)	−1.15*** (0.16)	−2.60*** (0.15)	−2.65*** (0.15)
Counties	2976	2976	2976	2976	2976	2976	2976	2976
R^2	0.530	0.596	0.499	0.500	0.373	0.438	0.357	0.361

Note. Robust standard errors in parentheses. State fixed effects are included in all models. Within-state R^2s are reported. Each county is weighted in the regression analyses by the number of respondents in the Gallup poll. All explanatory variables are *z*-scored such that they have a center of zero and a standard deviation of one.
* $p < .10$.   ** $p < .05$.   *** $p < .01$.

tive geographical clusters, we continued to find (online Supplemental Materials Table S21) that unhappier locations more strongly voted against the incumbent president. In online Supplemental Materials Table S19, we show that the main correlations were robust when including a more exhaustive set of observable county characteristics, including subjective economic sentiment (online Supplemental Materials Table S20).

Study 1c: Longitudinal County-Level Evidence

In addition to looking separately at the role of SWB in explaining the outcomes of the 2012 and 2016 presidential elections, we pooled the data to look at both simultaneously. This served two principal purposes. First, to allay any remaining fears related to omitted variables in the 2016 analysis, we were able to estimate longitudinal models, in which we examined changes in SWB and voting from 2012 and 2016—and, thus, looked solely at variation within counties over time. Second, it enabled us to examine more closely whether the effects of populist and anti-incumbency voting are additive or not, by comparing the strength of the association between SWB and Republican voting in 2012 and 2016.

Data and Method

We first pooled the 2012 and 2016 SWB and voting measures to create a dataset with around 6,000 county—year observations. We estimated weighted least-squares regression equations predicting a county's Republican vote share. We controlled for the same set of covariates and fixed effects as above and included an indicator variable for the year of the election. Our SWB measures were then interacted with the year indicator.[12]

To estimate within-county longitudinal models, we considered the change in SWB from the first term of Obama's presidency to the second term. This had the significant benefit of allowing us to account for any other county characteristics that are constant over time and not included in our main models (e.g., elements of culture, geography, and climate). The majority of the variance in SWB is between counties rather than within counties over time (see online Supplemental Materials Figure S5 for estimates of the high within-county autocorrelation of SWB); however, counties do vary over time, and we used this variation to estimate a regression of the change in Republican vote share from 2012 to 2016 on the change in SWB over the same period.[13] We *z*-scored the explanatory change variables such that each Δ has a mean of zero and a standard deviation of one.

Results

In Table 3, we can see that for each of our four main SWB measures, changes over time are predictive of changes in Republican voting. For each of the measures, counties that became unhappier over time swung more strongly toward Donald Trump in 2016. In columns 5 to 8, this remains the case even when controlling for changes in the state of the county-level economy over the same period, measured by the changes from 2012 to 2016 in state personal income per capita and state unemployment rate.

In Figure 4, the slope of the SWB–voting relationship is steeper in 2016 than in 2012. In online Supplemental Materials Table S22, we show these models, which include the full set of covariates and fixed effects as in the previous analyses, more fully. Here, we find that the interaction term between the two SWB measures and the 2016 year indicator is negatively signed and significantly different

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[12] Because affective measures of SWB were not predictive of the 2012 vote share, we limited our analysis here to our evaluative SWB measures.

[13] When splitting the data into two periods in this way, the problem of smaller counties having very low response rates in the Gallup Daily Poll becomes more acute. Furthermore, longitudinal models are typically more susceptible to attenuation bias resulting from measurement error. Measurement error typically changes from period to period, making it more likely that any observed *changes* are a result of noise. Accordingly, we restricted the sample in these analyses to include only the 1,328 counties that have at least 150 respondents during the first period. For robustness, in online Supplemental Materials Figure S6, we tested differing sample size thresholds and find results that are consistent with our main findings. In line with measurement error biasing estimates toward zero, we find that relying on counties with high sample sizes increases the magnitude of the relationship between SWB and voting.

Table 3
Longitudinal Evidence: Within-County Analysis

	Δ Republican vote share (2016−2012)							
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Life today	−1.94***(0.52)				−1.72***(0.50)			
Δ Life in 5 years		−2.39***(0.62)				−2.45***(0.62)		
Δ Positive affect			−2.01***(0.51)				−1.92***(0.50)	
Δ Negative affect				−0.87*(0.52)				−0.63 (0.54)
Δ log income					−1.90** (0.61)	−1.99** (0.61)	−1.95** (0.61)	−1.98**(0.61)
Δ Unemployment					−0.97** (0.49)	−0.97* (0.50)	−0.94* (0.49)	−0.87* (0.50)
Observations	1328	1328	1328	1328	1328	1328	1328	1328
R^2	0.011	0.014	0.011	0.002	0.047	0.052	0.048	0.039

Note. Robust standard errors in parentheses. Each county is weighted by the average number of respondents in the Gallup survey across the two periods. The sample is restricted to counties that have at least 150 respondents during the first period. See Figure S6 in online supplemental material for sensitivity to using differing sample size thresholds.
* $p < .10$. ** $p < .05$. *** $p < .01$.

from zero. This suggests that a populist candidacy has added pull on unhappy voters over and above a mainstream nonincumbent candidacy.

Study 2: Individual-Level Evidence of SWB and Incumbent Approval

The preceding analysis at the county level shows a clear and strong relationship between SWB and voting outcomes. However, this ecological evidence remains open to the critique that any observed relationships may simply reflect an ecological fallacy.[14] Thus, we supplemented our county-level analysis with individual-level evidence. We first looked at presidential approval (Study 2) and then moved on to individual-level evidence of voting (Study 3).

Data and Method

While the Gallup Daily Poll did not include a question on voting intention, the Gallup World Poll included a question on presidential approval between 2010 and 2016. Around 1,000 respondents were asked on an annual basis about various aspects of their SWB and whether or not they approve of the current president.

We estimated logistic regression models predicting whether or not the respondent disapproved of Barack Obama.[15] In all models, we included a rich vector of demographic and socioeconomic covariates, including age, gender, education, and income, as well as a full set of state and year fixed effects. We *z*-scored each of our five dimensions of SWB such that they have a mean of zero and a standard deviation of one in the sample. For ease of interpretation, we report exponentiated logistic coefficients, or odds ratios.

Results

Table 4 shows that low levels of life satisfaction predict disapproval of the job being done in office by Barack Obama. An odds ratio of 0.91 suggests that an increase of 1 *SD* in life satisfaction (equivalent to a shift of around 1.9 points in the 0–10 life ladder) decreases the likelihood of disapproving of Obama by around 9%, holding constant a range of demographics such as income, education, and age (see online Supplemental Materials Table S25 for full reporting of all coefficients).

In Model 2, we replaced life satisfaction with future life satisfaction in the equation and, much like in the county-level analysis, find a generally stronger relationship. People with a higher future life satisfaction are more likely to have supported President Obama. In Models 3 to 5, when looking at both positive and negative affect as well as purpose, we find similarly that higher levels of SWB increase the likelihood of approval of his leadership.

Study 3a: Individual-Level Evidence of Life Satisfaction and Voting in 2016

Evidence of a robust relationship between SWB and presidential approval is suggestive; however, it may still be the case that people do not in fact vote this way. We supplemented this evidence by turning to a survey conducted around the time of the election, in which actual voting behavior was recorded.

Data and Method

We used the American National Election Studies (ANES), which in 2012 and 2016 included a life satisfaction question. Each survey included two waves, one pre- and one postelection. In the preelection survey, respondents were asked about their demographics, previous voting behavior, and the question: "All things considered, how satisfied are you with your life as a whole these days?" Answers were elicited on a 5-point ordinal scale from *not at all* to *extremely*. We assigned numerical values to these responses and *z*-scored the variable such that it has a mean of zero and a standard deviation of one. In secondary analyses, we instead introduced each ordinal response category separately into the voting equation (rather than assuming a cardinal measure of life satisfaction).

In the postelection survey, respondents were asked whether they voted, and if so, whom they voted for. We looked at voters who

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[14] That is, even if unhappier counties were much more likely to vote to elect Donald Trump, it may still be that unhappier individuals were no more likely to have voted for the Republican candidate.
[15] We drop answers of "Don't know" from the analysis. This analytical choice does not affect the results of the article.
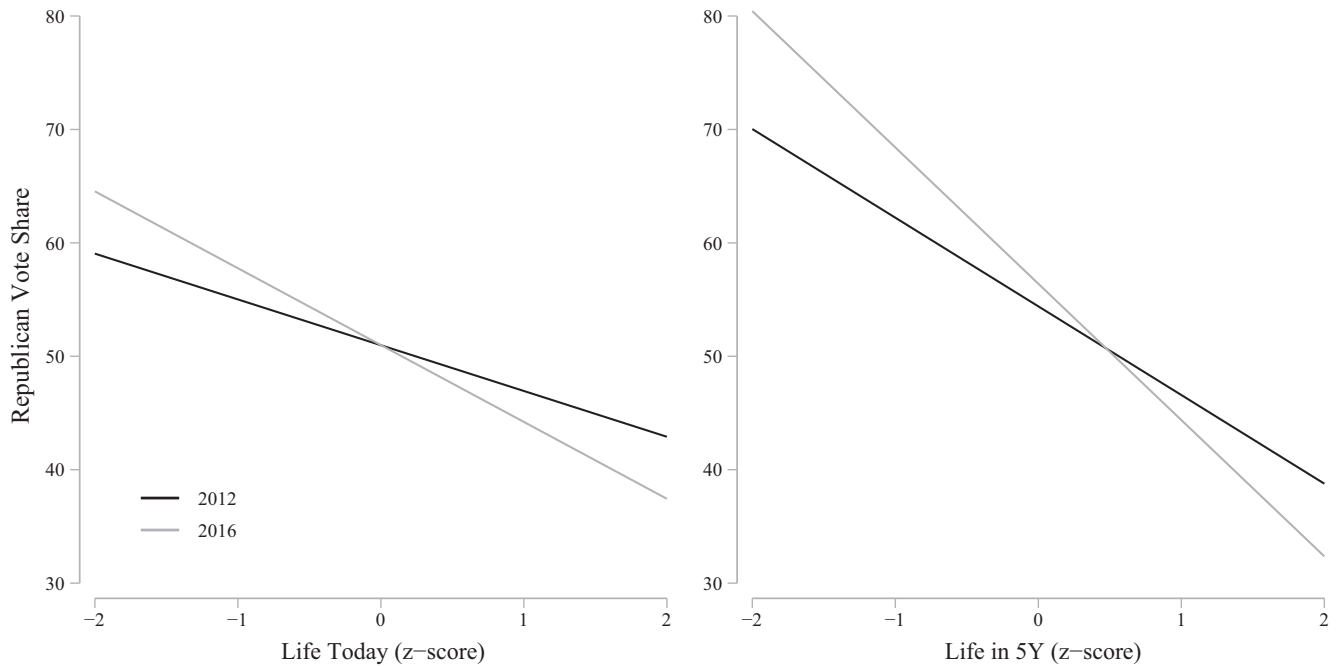
Figure 4. County-Level Life evaluation and voting in 2012 and 2016. Each panel shows the slope of the relationship between subjective well-being and the Republican Party vote share in 2012 and 2016, from a pooled analysis in which SWB is interacted with the year. These models include state fixed effects and a full set of observable covariates. For full reporting of these models, see online Supplemental Materials Table S22.

voted either Republican or Democrat, and created an indicator variable equal to 1 if the respondent voted for Donald Trump. We estimated logistic regression models predicting vote choice. In our most basic model, we controlled for the demographics of respondents, including gender, age group, race, and detailed religious denomination fixed effects. We then added into the equation more restrictive controls. We began by including educational attainment, income-band fixed effects, and a series of employment status fixed effects. We then added in measures of interpersonal trust and a 1–7 ideology scale, running from extremely liberal to extremely conservative. Finally, indicator variables were included referring to whom the respondent voted for at the previous election (Obama, Romney, other, or no vote), and a set of state fixed effects such that

we compared between individuals in similar geographical locations.

Results

Table 5 shows that low levels of life satisfaction predict voting for Donald Trump at the individual level. An odds ratio of 0.82, reported in column 1, suggests that an increase of 1 *SD* in life satisfaction (equivalent to an increase of 0.93 on the 1–5 scale) decreases the odds of voting for Trump by around 18%. This finding remains stable when adding in a series of more restrictive control variables in columns 2 to 5. In online Supplemental Materials Table S26, rather than use the life satisfaction question as a

Table 4

Individual-Level Subjective Well-Being and Presidential Approval

	Disapprove of Obama = 1				
Dependent variable	(1)	(2)	(3)	(4)	(5)
Life today	0.909*** (0.027)				
Life in 5 years		0.844*** (0.026)			
Positive affect			0.859*** (0.028)		
Negative affect				1.149*** (0.038)	
Purpose					0.897*** (0.029)
Observations	5,356	5,356	4,379	4,379	4,379
Log-likelihood	−3468.6	−3458.4	−2834.8	−2836.8	−2840.3

Note. Odds ratios reported from logistic regression models. Robust standard errors in parentheses. *Source:* Gallup World Poll July 2010 to July 2016. All models include state and year fixed effects, and further controls for gender, age, age^2, education, (log) household income, urban/rural status. SWB variables are z-scored such that they have a center of zero and a standard deviation of one.
* $p < .10$.   ** $p < .05$.   *** $p < .01$.

Table 5
Individual-Level Subjective Well-Being and Voting in 2016

Dependent variable	Voted Trump = 1				
	(1)	(2)	(3)	(4)	(5)
Life satisfaction (z-score)	0.823*** (0.040)	0.830*** (0.043)	0.813*** (0.057)	0.826** (0.063)	0.820** (0.064)
Gender and age	Yes	Yes	Yes	Yes	Yes
Race and religion FEs	Yes	Yes	Yes	Yes	Yes
Education FEs	No	Yes	Yes	Yes	Yes
Income and employment FEs	No	Yes	Yes	Yes	Yes
Trust and ideology	No	No	Yes	Yes	Yes
2012 vote choice FEs	No	No	No	Yes	Yes
State FEs	No	No	No	No	Yes
Observations	2,471	2,471	2,471	2,471	2,471
Log-likelihood	−1363.3	−1305.2	−820.1	−651.8	−629.1

Note. FE = fixed effect. Odds ratios reported from logistic regression models. Robust standard errors in parentheses. *Source:* Studies 2016 ANES data. The sample is all those who reported voting in the 2016 presidential election. Life satisfaction is z-scored such that it has a center of zero and a standard deviation of one.
* $p < .10$. ** $p < .05$. *** $p < .01$.

continuous measure, we entered each of the responses as a separate indicator variable (leaving out "extremely" as the omitted category). Here, we find an exponentiated logistic coefficient on being "not at all" satisfied with life overall (compared with extremely) of around 2.4. This suggests that being extremely unhappy more than doubles the odds of voting for Donald Trump.

We again investigated whether our findings are attributable to Republicans being unhappy precisely because their chosen party was not in power before the election (i.e., reverse causality). We did so by including a lagged dependent variable—that mirrors the logic of focusing on the Trump vote over and above Republican baselines. We find that the results are robust to this powerful control.

We also interacted respondents' previous votes with life satisfaction in the equation. In online Supplemental Materials Table S28, we see that the impact of low life satisfaction on Trump voting was most pronounced among previous Obama voters. That is, much of the effect appears to have been driven by unhappy (previous) Democrats. This is consistent with finding at the ecological level that low levels of SWB are predictive of a strong swing toward Donald Trump compared with prior Republican baselines.

Study 3b: Individual-Level Evidence of Life Satisfaction and Voting in 2012

We repeated the analysis in an analogous fashion for the 2012 election. As in the county-level analysis above, this allowed us to more directly test Hypothesis 1, without the complication of there being a populist candidate involved. Moreover, we pooled the 2012 and 2016 individual-level data to directly test whether any effect of SWB on voting was stronger in 2016 than in 2012.

Data and Method

We used the 2012 ANES, which as in 2016, included a 5-point life satisfaction question in the preelection survey and a voting question in the postelection follow-up survey. The empirical analyses otherwise mirror those of Study 3a above. In addition, we pooled the 2012 and 2016 data and estimated a logistic regression

model predicting Republican voting. In this model, we included an indicator variable indicating the year 2016 and interacted this year indicator with our measure of life satisfaction.

Results

In online Supplemental Materials Table S29, we find that an increase in life satisfaction is associated with a decrease in the likelihood of voting for Mitt Romney. This remains the case even when controlling for a lagged dependent variable (i.e., whom the respondent voted for in 2008) as well as rich set of demographic, socioeconomic, and ideological characteristics. Comparing with the coefficients in Study 3a, we can see that the slope of the relationship is generally smaller than that observed in the 2016 analysis. Pooling the two election studies, we are able to show this more formally (online Supplemental Materials Table S30). We find a significant interaction between life satisfaction and the indicator variable for 2016. We show this difference in slope graphically in Figure 5.

Discussion

Drawing on over 2 million responses to the Gallup Daily Poll, we find that levels of SWB strongly predict the result of the 2016 presidential election at the county level. Decreases in current and future life satisfaction of one standard deviation are associated with a bump to the Trump vote share of around four percentage points, over and above what would ordinarily be expected of a Republican in a given county. That is, if evaluative SWB had been higher by a (county) standard deviation in Florida, Pennsylvania, or Michigan, these states—and, thus, the United States—would have elected Hillary Clinton in 2016.

While evaluative, hedonic, and eudaemonic measures of SWB are all predictive of the electoral outcome in 2016, evaluative measures are the most strongly related to both the level of voting for and the electoral swing toward Donald Trump. This pattern appears robust under a variety of analytic choices. This provides suggestive evidence that electoral choice is based more strongly on overall cognitive assessments of welfare than on emotional states, at least when aggregated over years as in our analyses. In the same
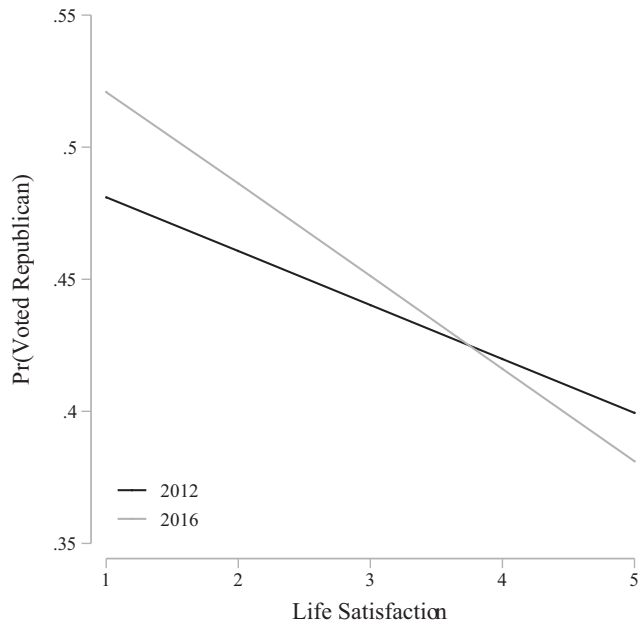
Figure 5. Individual-level subjective well-being and voting in 2012 and 2016. Predictive margins are plotted from a logistic regression in which the outcome variable is voting Republican (vs. Democrat). Source: 2012 and 2016 ANES data, pooled. The regression model also includes demographic control variables and a full set of state fixed effects. $N = 6,569$.

vein, it may also suggest that evaluative dimensions of SWB, in particular, act as common pathways that integrate psychological processes such as group and status threat. However, caution is warranted with this preliminary interpretation: Emotions are typically conceptualized as transient states that fluctuate from moment to moment, and as also affecting behavior on those timescales.[16] Our analytic strategy is not well suited to establish the relative importance of emotions (as typically conceptualized) compared against evaluative measures of SWB, and there is a need for future research on the issue. Our results ought not be interpreted as speaking to the short-term impact of mood states on electoral choice in the days preceding the election (cf. Healy, Malhotra, & Mo, 2010).

We distinguished in our theoretical framework between antiincumbent (Hypothesis 1) and populist voting (Hypothesis 2). Our analysis of the 2012 election provides a clear test of the prediction that happier voters will be more likely to vote to reelect incumbent politicians. The 2016 Trump versus Clinton election suggests a similar finding; however, the issue is more complex, given that the eventual winner was both nonincumbent and populist. Nevertheless, our finding that unhappiness was associated with voting for Donald Trump and Bernie Sanders in their respective primary contests provides direct support for Hypothesis 2. Even among the challenger party, the least happy counties voted more strongly for the more populist candidate (Trump), and even among the incumbent party, unhappier areas voted more strongly for the more populist candidate (Sanders).[17]

The current findings do not contradict the literature that has established psychological processes such as group and status threat as predictors of Trump voting or the literature that has tied eco-

nomic realities to political choice. On the contrary, this study integrates them descriptively: We propose that SWB can be understood as a *common psychological pathway* to electoral choice. While more specific social psychological and economic accounts may help to explain *why* parts of the electorate were unhappy and experienced discontent, our findings strongly suggest that these processes funnel into differences in SWB—that, in turn, are highly predictive of voting for (or against) the status quo.

We find, at both the county and individual levels, that the slope of the relationship between happiness and Republican voting was steeper in 2016 than in 2012. One interpretation of this is that the two effects predicted in hypotheses 1 and 2 are *additive*. This provides support for the idea that unhappiness activates those who would like to replace the incumbent as well as those who would like to change the elements of the system identified by the populist narrative as causing unhappiness.

The data we used are observational, and the findings are descriptive rather than causal. Nevertheless, the results appear to be strongly robust to a wide variety of alternative analytic choices and robustness checks. They do not appear to be driven by either (a) reverse causality or (b) unobserved heterogeneity. Relying solely on well-being reports before Donald Trump entering the political sphere does not meaningfully change the observed patterns, and the results replicate within counties in longitudinal analyses. Moreover, all of our county-level results are evident at the individual level and, importantly, hold up when conditioning on a lagged dependent variable (as well as a rich set of other observable characteristics like income, age, gender, religion, and race). However, future research should look for natural experiments or adopt longitudinal designs in which the SWB of a cohort of voters is measured across time and across multiple elections, to establish that the relationships observed in this study show the same causal patterns. The literature linking SWB to voting is new, and replications are needed in other contexts to demonstrate that the findings are not specific to the (recent) U.S. electoral context.

While the literature on SWB and vote choice is relatively new, a more long-standing literature has examined the relationship between SWB and political ideology and has generally found that more conservative people report higher life satisfaction.[18] Our study overlaps with this work in its replication of the finding that

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[16] Emotional states aggregated over long time scales may also capture trait-level differences in the experience of affect, such as the negative emotionality associated with neuroticism (see, e.g., Obschonka et al., 2018).

[17] In our theoretical framework, we focused on the extent to which low levels of SWB contributed to votes against the status quo, both in terms of the incumbent government as well as "politics-as-normal" in a more general sense (populism). Whether low SWB voters are voting for change in a forward or a backward direction is an open question, however, and should form the basis of interesting further research. It may be, for example, that a vote against the political status quo in 2016 was in a sense a vote against even more change happening (e.g., a woman becoming president or continuing the legacy of the first black president), as the refrain "make America great *again*!" may suggest. Previous work has proposed that Trump voters may have seen the status quo in 2016 as a continuation of the progressive social change under Barack Obama (Azevedo, Jost, & Rothmund, 2017).

[18] Possible explanations range from differences in demographics and cultural values (including religiosity) to the supposition that conservative system justification protects from the SWB-reducing effects of social and economic inequalities (Napier & Jost, 2008). Others have pointed to the possibility that measured differences in SWB are because conservatives merely self-enhance more in self-report (Wojcik et al., 2015).

differences in self-reported SWB between Republicans and Democrats are not fully accounted for by demographic and economic covariates, religiosity, or income inequality (online Supplemental Materials Tables S9 and S4). We did not explicitly investigate the role of candidate ideological causes of well-being differences. Rather, we principally focused on the relationship between SWB and electoral choice, which holds within predominantly Republican and Democratic counties alike. Most pointedly, in our individual-level analyses, we find that low life satisfaction predicts Trump voting even when holding constant self-reported ideology and previous voting behavior; thus, reproducing our results even when comparing Republican-to-Republican and Democrat-to-Democrat voters. Our findings are unlikely to be reducible to differences in SWB between conservatives and liberals, and instead point to a larger pattern between SWB and electoral choice.

Although we have focused our discussion on the thin-centered ideology of populism and its principal components of antielitism and people-centrism, it is clear that Donald Trump's campaign was also defined by the related concepts of nativism and authoritarianism. Further research may seek to disentangle the effect of SWB on each of these types of candidate. Research in social psychology has shown, for example, that negative emotions such as fear and anger contribute to support for right-wing, authoritarian candidates (e.g., Jost, 2019; Vasilopoulos, Marcus, Valentino, & Foucault, 2019). In general, we find the effects of low SWB to have been stronger in the primaries for Trump than for Sanders (whose populism did not incorporate an anti-immigrant strand), which provides some initial suggestive evidence for an ideological asymmetry whereby nativist right-wing populism draws in more unhappy people than left-wing, nonnativist strands of populism. One potential reason for this is that unhappier people may welcome simple explanations for their state of unhappiness, particularly ones that place blame on (external) others (cf. Hameleers, Bos, & de Vreese, 2017) such as immigrants and other minorities.[19]

Governments around the world are beginning to set their sights "beyond GDP" and are increasingly seeing SWB as a complementary measure of progress and a fundamental goal of public policy (Graham, Laffan, & Pinto, 2018; Krueger & Stone, 2014). Organizations like the OECD, European Union, and U.S. National Research Council have produced reports and guidelines on the measurement of SWB, and a number of national statistics offices worldwide have begun to systematically collect "happiness" data on a large scale (European Commission, 2009; National Research Council, 2014; OECD, 2013). Increasingly, governments are using these data (a) as an official measure of national performance, (b) to guide and inform public policymaking decisions, and (c) as a key outcome measure in the evaluation of government programs (Durand, 2018). The analyses presented in this article suggest that this type of SWB data are of clear political relevance and that using it to guide and evaluate public policy may pay an electoral dividend. Our analyses also suggest that measuring SWB may be critical for our understanding of recent changes to the political landscape, as populist politicians in particular appear to capitalize on low levels of subjective well-being.

stance, Donald Trump was also new to politics as a politician. This potentially made him even more strongly antiestablishment in the eyes of voters than a "regular" nonincumbent populist would have been. All of these issues are open to further research because, in our data and setting, it is difficult to disentangle these effects, given that we have a limited number of elections and candidates to study.

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[19] A potential further reason for the particularly strong relationship between low SWB and Republican voting in 2016 is that in addition to being anti-incumbent in terms of party affiliation and populist in policy

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