Despair and Voter Turnout in the United States

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Abstract

Context: Deaths of despair, a term used to capture rising mortality rates among Americans who appear to be suffering from growing mental and physical distress, have received added attention from those seeking to understand this disturbing trend. Yet it is unclear how, if at all, despair influences the political behavior of the people and communities where it is most prominent. The authors contribute to the health and politics literature by examining whether personal and community-level despair shapes political participation.

Methods: The authors examine the relationship between despair and voter turnout using novel data at both the aggregate and individual levels. First, a custom survey is used to test whether despair is associated with individual-level voter participation in several recent elections. Second, a new measure of community despair is developed at the county level that spans nearly 20 years to assess whether there is a relationship between despair and voter turnout in U.S counties.

Findings: The results suggest that higher levels of despair lead to lower turnout rates at both the individual and community levels.

Conclusions: This study suggests that the effects of experiencing despair are far reaching and shape political behavior among individuals and within communities.

Deaths of despair, a term used to capture rising mortality rates among Americans who appear to be suffering from growing mental and physical distress, have received a great deal of attention from scholars seeking to understand the underlying causes of this disturbing trend (e.g., Case 2015; Case and Deaton 2020). Yet it is still unclear how, if at all, despair has influenced the political behavior of the people and communities where it is most prominent. This study looks to better understand the political consequence of despair by examining how increasing hopelessness among the public influences political participation.

The existing literature suggests despair in the U.S. is growing as result of several recent economic and societal changes. The loss of well-paying, stable jobs and the unions often associated with them, along with the broader stagnation of wages and mobility since the 1980s, has led many to lose a sense of purpose and belonging. These issues are then exacerbated by the lack of adequate health care, food insecurity, and minimal safety net policies in the U.S. relative to other advanced societies (Case and Deaton 2020; 2022).

While most of this literature focuses on despair-related deaths, we argue that the broader patterns of despair that cause these tragic deaths likely have wide-ranging political effects. Living with despair can produce feelings of being left behind by society, instability, the belief that government has failed, and the perception that the political system is unresponsive to your needs. All of these factors may also be associated with a general breakdown in a person's social ties. Furthermore, these effects are likely to reach beyond the individuals who directly experience despair. The afflictions associated with despair, like poor mental health, drug and alcohol abuse, and suicide, are likely to have negative effects on one's family members, friends, and community more broadly. As a result, we expect despair to have a community-wide influence on political behavior.

This study connects theories on the underlying causes of despair and political participation to develop expectations regarding the relationship between despair and voter turnout. More specifically, we focus on how the individual and contextual factors associated with despair have a negative effect on electoral participation. At the individual level, we argue that the broad negative health effects associated with despair lead to feelings of ineffectiveness, isolation, and alienation that reduce one's propensity to vote. These same negative health outcomes, and the economic and societal factors that promote despair, also diminish levels of social cohesion in communities where despair is prevalent. This breakdown in social ties is also expected to have a negative effect on electoral participation at the community level.

To test these relationships, we examine novel data at both the individual and aggregate levels. First, we use a custom survey to test whether despair is associated with individual-level voter participation in recent elections. Second, we develop a new measure of community despair at the county level that spans nearly 20 years to assess whether there is a relationship between despair and voter turnout in U.S counties. Our results demonstrate the political consequences of a troubling rise in hopelessness among the American public.

Despair in the United States

As a result of medical advancements, prevention, and behavioral changes, the United States experienced a dramatic decline in mortality throughout the 20th century (Woolf and Schoomaker 2019). By some estimates, during this time period mortality decreased by more than 70%, with similar trends found in other wealthy countries (Case and Deaton 2015; 2020). While most rich nations continued to see similar downward trends at the turn of the century, mortality rates in the U.S. began to reverse course. Although this reversal was not immediately noticed by public health officials, the flooding of prescription opioids in American towns and the addiction that followed was an initial sign of a growing problem. As prescription opioid-related deaths spiked by 400% in the early 2000s (Okie 2010; Volkow et al. 2014; Beauchamp et al. 2014), stricter regulations on the drugs led many users to turn to more accessible and less expensive drugs like heroin (Cicero et al. 2014) and fentanyl (Spencer et al. 2019).

As observers focused on the U.S. opioid crisis and began to better understand it, many have argued that opioid abuse is a signal of larger societal and economic issues in the country (Macy 2018; Quinones 2015). In their seminal work on what Case and Deaton (2015) later refer to as "deaths of despair" (Case 2015), the authors document the rise in all-cause mortality among Americans beginning in the 2000s and show that this increase is largely a result of deaths due to drug overdoses, alcohol poisoning, and suicide among middle-aged adults. Importantly, Case and Deaton (2020) suggest that the rise in these deaths of despair stem from an economic system that no longer works for many people and a related, but distinct, breakdown in social cohesion. These factors have in turn led to a dismantling of the U.S. working class along with many losing a sense of purpose and belonging.

From an economic perspective, part of the rising deaths of despair story is related to the structural changes to jobs and incomes over the last several decades. For Case and Deaton (2020), the now well documented growth in American economic inequality (Hacker and Pierson 2010; Piketty and Saez 2003; Piketty and Zucman 2020) and decline in economic mobility (Chetty et al. 2017) are broader indicators of how the life for working class people has changed. The well-paying union jobs in towns with strong manufacturing sectors have largely gone away. While some of these places have recovered to some extent in terms of job replacement, these jobs tend to offer lower wages, fewer opportunities for professional growth, and higher levels of instability. Existing studies show that factors like economic instability and the loss of manufacturing jobs as associated with higher levels of despair (Blanchflower and Oswald 2020; Knapp et al. 2019). Those most susceptible to these economic changes, particularly when it comes to the link between the economy and despair, appear to be middle-aged adults without a college degree. When examining how education is related to deaths of despair, there is a clear distinction between those with and without a four-year degree, where a large portion of these deaths have occurred among those without a college education (Case and Deaton 2022).[1]

There is also evidence that recent economic changes have been accompanied by a loss of social cohesion. Scholars have argued that growing levels of inequality have led to stronger distinctions between the haves and have-nots, not only in economic terms but also from social and cultural perspectives. Those who do not benefit in an unequal society also feel higher levels of status threat, which can lead to more conflict among groups (Delhey and Dragolov 2014). Status threat and group conflict among the white working class has more recently been emphasized in light of increases in right-wing authoritarianism (Cramer 2016; Hochschild 2018; Nolan and Weisstanner 2022). Case and Deaton (2020) also point to trends in low levels of trust, declining marriage rates, lower church attendance, and lower participation rates in social groups as signs of deteriorating social ties (also see Putnam 2000). This breakdown in social cohesion is thought to precipitate despair, which is consistent with other research on how social relationships have an important influence on health outcomes (House et al. 1988; Kawachi 1997).

[1] However, see Novosad et al. (2022) for evidence that many estimates of mortality by education are often overestimated due to selection bias. That is, the general increase in educational attainment over time in the U.S. and the broad categories typically used to measure education have led to biased mortality estimates. After making statistical adjustments to account for this bias, the authors demonstrate that there has been an increase in mortality concentrated in the bottom 10% of educational attainment among non-Hispanic whites (Novosad et al. 2022).

In addition to the economic and societal issues that likely formed the basis for growing despair in the U.S., political choices have also played a role. As discussed above, the magnitude of despair-related deaths among Americans is unmatched by any other rich nation. The U.S. lags behind nearly every other wealthy country in almost every domain of publicly supported social policy. When compared with places that have not seen similar increases in deaths of despair, the U.S. is generally worse off when it comes to access to general health care, access to prenatal and maternal care, unemployment benefits, housing costs, the cost of childcare, quality of public education, and access to higher education (Case and Deaton 2020; Sterling and Platt 2022). The connection between social policy and despair is also supported by several studies examining differences in policy choices and health outcomes at the state level (Montez 2020; Montez et al. 2020; Montez and Farina 2021).

To this point we have mainly focused on describing the rise in deaths of despair and the most likely explanations for why despair has taken hold of so many Americans. At the same time, it is important to note two general caveats related to the deaths of despair narrative. First, there is a great deal of nuance and uncertainty regarding (a) what explains the rise in drug overdoses, alcohol poisoning, and suicide deaths and (b) the extent to which these deaths of despair contribute to rising mortality rates. On the former point, while a number of studies find that economic factors can influence health outcomes in numerous ways (Adda and Fawaz 2020; Autor et al. 2019; Pierce and Schott 2020), the opioid epidemic had an outsized effect on drug deaths in the U.S. Currie and Schwandt (2021) demonstrate that the accessibility and marketing of the most recent class of opioids, rather than economic factors, is largely responsible for the rise in drug overdoses (also see Ruhm 2022). On the latter point, the causes of rising U.S. mortality rates are complicated and clearly go beyond deaths of despair (Harris et al. 2021). For instance, Mehta et al. (2020) suggest that the long-term mortality decline is due to cardiovascular disease while drug-related deaths are likely responsible for short-term declines.[2]

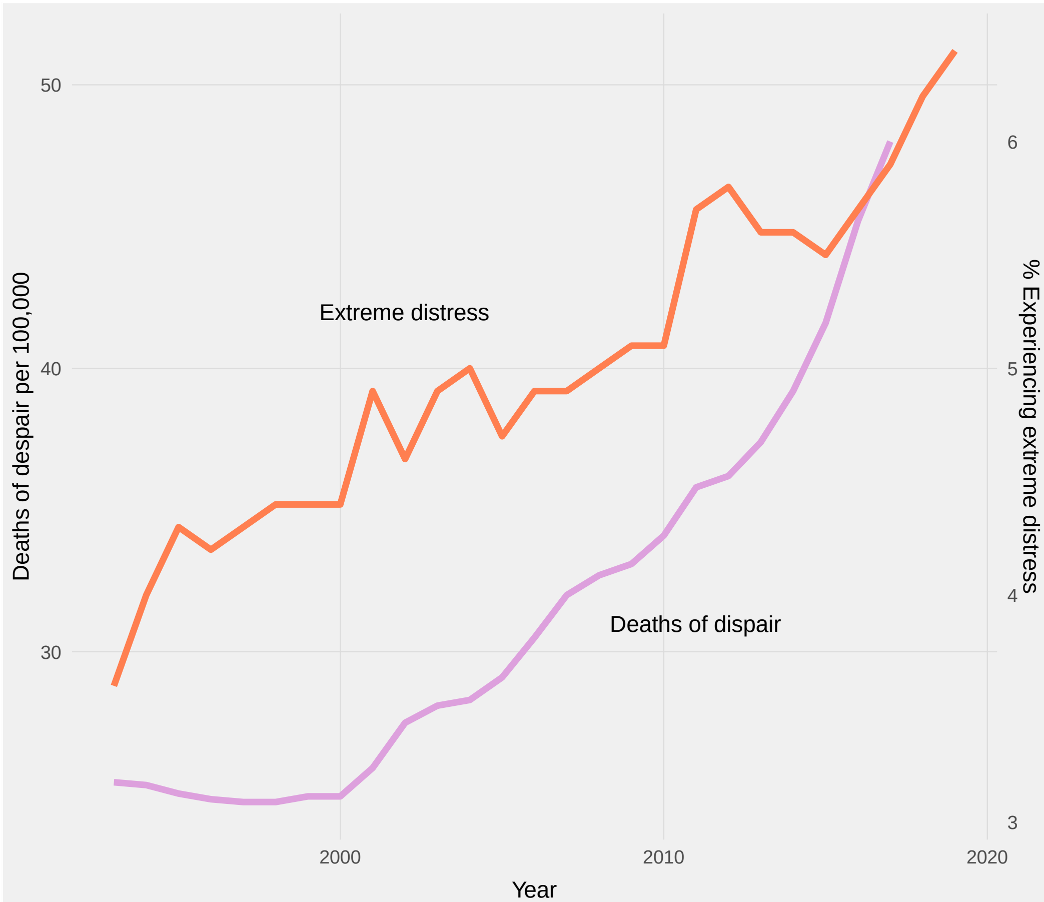
While we believe is it important to point out the open questions regarding the deaths of despair hypothesis, our study is not dependent on Case and Deaton's argument given that we focus on the relationship between despair and electoral participation. This brings us to the second caveat related to the deaths of despair literature: existing research does very little to systematically define or measure the concept of despair (Shanahan et al. 2019). Most studies assume that the deaths resulting from drug overdoses, alcohol poisoning, and suicide imply the presence of despair. While we do not dispute that these tragic deaths likely arise from some form of despair, we believe that relying solely on mortality to understand despair will omit a potentially large portion of the public who experience despair. In other words, we are interested in despair as the underlying cause of the deaths that are typically examined in the current literature.

Unfortunately, while despair is a commonly used term to describe a state of hopelessness, it is "not a well-defined diagnostic category, let alone one with a clinically validated measure (Case and Deaton 2022, 4)." Scholars have, however, made progress on understanding and measuring despair. For instance, Rehder et al. (2021) adopt several existing cognitive models (for instance, major depressive disorder or PTSD) to better understand despair. Shanahan et al. (2019) note that despair is likely present "not only in cognitions but also in emotions, behaviors, and biology (855)," and go onto to describe four domains of despair (Shanahan et al. 2019).

[2] Mehta et al. also point out that "It is also plausible that some of the explanations for rising drug-related deaths and stagnating CVD [cardiovascular disease] mortality are common. For example, social and economic despair may contribute to both (2020, 7000)."

While this emerging literature moves us closer to a systematic definition of despair, the field has not yet produced agreed upon measures of despair. Blanchflower and Oswald (2020) develop a particularly useful measure of what they call "extreme distress," a concept closely related to despair. Their proxy for despair is created using a survey question from the Behavioral Risk Factor Surveillance System (BRFSS) asking: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" The authors focus on those respondents who answer that all 30 days have been bad mental health days, suggesting "a sense of exceptional bleakness of life (Blanchflower and Oswald 2020, 1538)." They produce estimates of despair in the U.S. from 1993 to 2019, which we reproduce in Figure 1 below, and show that the measure closely tracks the rise in deaths of despair.

Figure 1. U.S. Trends in Despair



Source: Behavioral Risk Factor Surveillance System and Case and Deaton (2015).

We build on Blanchflower and Oswald's work in our study for several reasons. First, considering the multiple domain perspective from Shanahan et al. (2019) discussed above, conceptually their measure is broad enough to tap into elements of despair if it includes multiple cognitive and emotional elements . Second, the measure is parsimonious, allowing us to use a single survey question to capture these multiple dimensions of despair. Third, the question used for this measure has been asked frequently enough on existing surveys to give us the ability to measure despair over time. Fourth, Blanchflower and Oswald (2020) find that one of the strongest predictors of this measure is poor employment conditions, which is consistent with existing explanations for why despair might be on the rise. Finally, as we discuss in more detail below, the measure is associated with deaths of despair as hypothesized in the deaths of despair literature. That is, higher levels of despair are related to more deaths of despair. Therefore, we use this question to assess despair among respondents in our original survey and by developing an aggregate measure of despair at the county level, which we detail in the county analysis section of the paper. We recognize that this measure of despair has limitations. As this literature evolves, it will be important for future research to develop an agreed upon standard for measuring despair. We now turn to a discussion of how despair is expected to influence political participation.

Despair and Voter Turnout at the Individual Level

In this section we develop several connections between what we know about despair and the factors that shape voter turnout. Since we are interested in how both individual-level and community-level despair influences political participation, we consider existing voting behavior theories that help explain participation based on individual characteristics and contextual factors. We first discuss a number of common attributes among the people and places that experience despair and characteristics among those who are more likely to participation in elections. Then, we offer several direct mechanisms that link despair to turnout.

The extensive literature on political participation offers a strong theoretical basis for why some people participate in elections while other do not. A central emphasis of the seminal work on participation is how and why individual characteristics play a role in political activity. The effect of socioeconomic status (SES), typically composed of a person's income, education, and occupation, has been consistently shown to shape voter turnout, where higher SES leads to a greater propensity to vote (Verba and Nie 1972; Wolfinger and Rosenstone 1980). This relationship is often explained in terms of the resources and skills required to participate in elections. Higher incomes and more prestigious jobs are associated with the ability and time needed to cast a ballot. Those with higher levels of education are often better equipped to understand the election process and to seek out information about candidates and voting. Other scholars have emphasized the importance of civic norms and the mobilization component of political participation (Verba et al. 1995). From this view, education is a good indicator of one's sense of civic duty, where viewing voting as a civic responsibility makes it more likely for a person to cast a ballot. Those with more financial resources are often more likely to be asked to participate in elections, which is another factor associated with higher turnout.

While the demographic factors thought to drive political participation are similarly related to levels of despair, we argue that despair has a direct link to participation beyond these individual-level factors. Importantly, a growing literature on public health and political outcomes has demonstrated that poor physical health, low levels of general well-being, and depression all lead to declines in participation (Cahill and Ojeda 2021; Landwehr and Ojeda 2021; Ojeda 2015; Ojeda and Pacheco 2019; Ojeda and Slaughter 2019; Pacheco and Fletcher 2015). The mechanisms connecting health to participation can be broadly categorized into two areas: the physical limitations and mental difficulties that often coincide with poor health. Those in poor health regularly report having physical restrictions, a lack of energy, and pain. Because participation in elections requires some level of physical exertion, these physical limitations can lead to lower levels of turnout (Pacheco and Fletcher 2015). Similarly, apathy and low levels of enthusiasm reduces an individual's motivation to participate in elections (Ojeda 2015).

We expect despair to influence voter turnout for similar reasons. Pain appears to be an attribute of despair and often viewed as a precursor to the opioid epidemic (Case and Deaton 2020; 2022). Hopelessness is a fundamental characteristic of despair and likely leads to disengagement from politics in similar ways that depression decreases turnout (Ojeda 2015).

There is significant conceptual overlap between depression and despair. Both concepts involve some level of physical pain as well as feelings of hopelessness. That said there are two reasons to suspect that they are distinct enough to lead to independent associations with voter turnout. First, conceptually, some people who experience a state of hopelessness (e.g., despair) may not exhibit the other symptoms of depression (e.g., loneliness, psychosomatic problems, etc.). This differentiation suggests that depression alone cannot distinguish between individuals who feel despair and those who do not. Second, despair is an intense or extreme state of being whereas depression exists along a continuum. Individuals can experience *occasional* bouts of depressive symptoms whereas despair is more of a constant, extreme state of hopelessness. To this extent, only the individuals who score extreme high on depression may also be feeling despair. Similarly, some people who score high on depression may not feel despair. We test these arguments empirically below.

George et al. (2023) discuss several characteristics of despair that can give us further insight into the additional mechanisms linking despair to political participation. First is the lack of a social role and feelings of purposelessness that have been associated with despair. These feelings are likely to reduce the civic connectedness thought to be an important element of participating in elections (e.g., Verba et al. 1995). The second is the feeling of alienation and social isolation more generally. Scholars studying how alienation can limit people's participation in politics have argued that those who feel they are unable to influence their government and that they do not have meaningful choices among candidates and issues are less likely to vote (e.g., Southwell 1985). Given that a lack of political response or an altogether indifferent government are common themes in accounts of rising despair in the U.S., it is likely that this form of alienation among those who experience despair will have a limiting effect on turnout.

Despair and Voter Turnout at the Community Level

Altogether, the above discussion suggests that individuals who experience despair will be less likely to participate in elections. What about the community effects of despair on voter turnout? An important question is whether individual-level despair can have social effects on the broader community. Although we are unaware of any studies that examine this question, social networks are known to have a substantial influence on health outcomes. Social connections have been found to foster social support (e.g., emotional engagement with family and friends), provide access to vital resources (e.g., childcare), and create various types of social pressures (e.g., developing social norms; for a review see Zhang and Centola 2019). Along similar lines, scholars have suggested that exposure to the stressful life events related to despair (e.g., widespread job loss and neighborhood decline) can lead to communitywide loss of culture and values, along with increases in substance abuse and poor health outcomes (Evans-Campbell 2008; Rehder et al. 2021). From this perspective, the breakdown in social cohesion associated with despair is likely to amplify the negative attributes of despair within communities, leading to lower overall levels of voter participation in those places.

Even for those who do not directly experience despair, it is still likely that despair will have community-level effects. While the voter participation literature often emphasizes individual factors (as mentioned above), there is extensive work demonstrating that social factors play an important role in shaping voting behavior. Social interaction is an important driver of politics (Huckfeldt and Sprague 1987) and political participation is no exception (Plutzer 2017). Scholars have demonstrated that social networks and social context are central in influencing whether someone votes (Campbell 2013; Cho et al. 2006; Gerber et al. 2008; Gimpel et al. 2004; Leighley 1990). Networks and context affect participation in numerous ways, including the development of civic norms (Campbell 2006; Pacheco 2008; Putnam 2000), enforcement of those norms (Gerber et al. 2008), and facilitating political information sharing and political discussion (Mcclurg 2003). In other words, where people live, the composition of their environment, and the people they interact with can all shape the extent to which they participate in politics.

Given our earlier discussion regarding the negative, communitywide effect despair has on social cohesion, we argue that places where despair is prevalent are also likely to have lower levels of political participation. The breakdown in social ties driven by despair – including higher levels of status threat, more perceived group conflict, and less general participation in social activities – can create an environment where civic norms and the communication of political information are diluted. Therefore, we believe contexts where despair is common can have a cascading effect on political participation where voter turnout is less common. In the next section, we discuss our approach to examining whether individual-level and community-level despair influences electoral participation.

Analysis Overview

Our analysis has two parts. First, we examine the results of a custom survey representative of the adult U.S. population to assess whether those who exhibit characteristics of despair are less likely to have participated in the 2018, 2020, and 2022 elections. This study allows us to test whether despair among individuals leads to the expected outcome of less engagement in politics. Second, we use a newly developed measure of aggregate despair at the county level to examine whether higher levels of county despair are associated with lower levels of aggregate voter turnout within counties. This analysis gives us the opportunity to test the relationship between despair and turnout over time and provide evidence or our claim that despair can affect politics by collectively influencing communities where despair is prevalent.

In both studies we measure despair by following Blanchflower and Oswald's (2020) approach to measuring despair using their concept of extreme distress (see the discussion above). Recall that there is no agreed upon measure of despair and most studies of despair rely on observing deaths of despair. While deaths of despair are certainly important, instances of despair that tragically end in death are also the most extreme cases. We opt for using Blanchflower and Oswald proxy measure of despair to assess experienced despair among individuals and to more broadly capture levels of despair at the community level. We provide more information about our data, measures, and analyses in the sections below.

Study 1: Individual-Level Analysis using the CMS

We use the 2022 Collaborative Midterm Survey (CMS) to explore the relationship between despair and voter turnout at the individual level. The CMS is an NSF funded multimethod, multimode survey that boasts a sample size of 19,000 Americans and organized through Cornell's Roper Center for Public Opinion Research (Enns, Barry, and Schuldt 2022). Three organizations – Gradient Metrics, the Iowa Social Science Research Center, and SSRS – were selected to collaborate on the survey, which included a core set of identical questions as well as team specific modules. The Iowa module polled nearly 7,000 respondents through non-probability samples using two web vendors (N=3,756 from Ipsos, N=2500 from YouGov) as well as a probability sample of cell and landline telephone calls (N=274). For more information, see the methodological documentation provided by the Roper Center for Public Opinion Research.[3] With the proper use of weights, estimates are generalizable to the US non-institutionalized adult population at the national level as well as in CA, FL, and WI, which were oversampled.

The Ipsos survey and the phone survey asked respondents to provide their first and last name, street, city, and zip code; we used these unique identifiers to match respondents to the National Voter File (NVF) provided by Catalist. We were able to successfully match 76% of the respondents from the phone survey (N=132) and 57% of the Ipsos survey (N=2,127) to the NVF. People who misreport voting often look like those who vote, which suggests that vote models are likely biased when reporting the demographic and attitudinal correlates of voting behavior (Ansolabehere and Hersh 2012; see also Highton and Wolfinger 2001; Citrin et al. 2003). As we describe below, we use vote validation measures where possible to measure turnout with the assumption that if the respondent did not match the NVF then they did not vote, regardless of how they self-reported on the survey.[4]

Measuring Voter Turnout

We use a combination of self-reported turnout and vote validation to measure turnout. All respondents are asked to self-report their voting behavior in the 2018, 2020, and 2022

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[3] Data on PII is securely stored at the University of Iowa's Social Science Research Center. PII information is not available publicly and is blinded from team researchers.

[4] Twenty-three percent of respondents report voting in the 2020 election, but do not appear in the NVF. Misreports are much more likely for the 2022 election with 46% of respondents reporting voting in the 2022 election, but do not appear in the NVF.

elections.[5] In addition, we have vote validation measures for the 2020 and 2022 elections for respondents in the Ipsos and phone survey who matched with the NVF. Because voting tends to persist over time (e.g., Green and Shachar 2000; Plutzer 2002), we create a scale of turnout, which ranges from 0 to 1 by combining the self-reports in 2018 (for all respondents), the self-reports in 2020 and 2022 (for the YouGov sample), and the vote validation measures for the 2020 and 2022 elections (for the Ipsos and phone samples) (Cronbach's alpha = .72). We only use self-reported voting in cases where vote validation is unavailable (e.g., for the 2018 election and for respondents in the YouGov sample). The mean level of electoral participation is .50 with a standard deviation of .39.

Measuring Despair

To measure despair, we asked respondents the following "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good." The mean number of days is 7 and 36% of respondents answer zero days. We follow the lead of others (Blanchflower and Oswald 2020) and code individuals who gave the highest answer feasible (30 days out of 30) as having despair. This measurement strategy captures the intensity of the concept of despair as noted by previous research. Six percent of our sample indicated that "every day of my life is a bad day," which is in line with national numbers; in 2019, 6% of the US population indicated having extreme distress (Blanchflower and Oswald 2020 Table 1). Demographic patterns are generally consistent with previous research. We find, for instance, that individuals with a high school degree or less report higher levels of despair (8%) compared to those with a college

[5] The question wording for the 2022 turnout measure differs depending on if the survey was conducted before or after November 8 (Election Day). If before, respondents were asked "How likely are you to vote in the November 8 election for Congress;" 29% reported that they had already voted. If after Election Day, respondents were asked "Which of the following statements best describes you" to which 65% report that they voted.

degree or higher (4%) and that women report slightly higher levels of despair (6%) compared to men (5%).

As we discussed earlier, there is conceptual overlap between despair and depression. It is also likely that individuals who are experiencing despair or depression are also likely to self-report poorer health or that those who are experience despair also exhibit depressive symptoms. To measure depression, respondents were asked how often over the past two weeks they were bothered by little interest or pleasure in doing things as well as feeling down, depressed, or hopeless to which answers include not all, several days, more than half the days, or nearly every day. Thirty-eight percent of respondents who answered "nearly every day for the past two weeks" to both depression questions indicated that every day of their life in the past month was bad (e.g., had a score of 1 on the despair measure). In fact, we would expect some overlap since both questions ask about frequency over a specific time period (two weeks for depression and a month for despair). Since depression exists along a continuum, we combine answers to the two depression questions to create a depression scale (Cronbach's alpha = .86) with a mean of .62 and a standard deviation of .83. The correlation between our binary measure of despair and the depression scale is .27 (indeed an additional reason to dichotomize our despair measure is to reduce the possibility of multicollinearity; the correlation between the continuous measure of despair and the depression scale is .52). Self-rated health status (SRHS) was measured by a five-point Likert scale ranging from poor to excellent. The correlation between our measure of despair and SRHS is -.16.

We create an additional variable called *occasional depression* to better differentiate between individuals who sometimes have depressive symptoms, but who are not severely depressed (and potentially in despair). We do this by creating a binary variable where individuals who indicated that they experienced either little interest or pleasure in doing things or feeling down, depressed, or hopeless “several days” or “more than half the days” were coded as a 1 and otherwise, 0.

We find little evidence that despair is related to vote misreporting. In multivariate analyses (available upon request), we find a statistically significant association between depression and misreporting in 2020 (*B*=.18***), a statistically significant association between SRHS and misreporting in 2020 (*B*=.14***) and 2022 (*B*=.20***), and no association between despair and misreporting in either election.

Control Variables

We control for demographic variables typically associated with turnout (see, for instance, Brady et al. 1995) including voter registration, education (measured as three binary variables: high school degree or less, some college or associate, college degree or higher with high school degree or less as the omitted category), age (measured as four binary variables: 18-29, 30-49, 50-64, and 65+ with 18-29 year old category omitted), race (measured as four binary variables: non-Hispanic white, non-Hispanic black, non-Hispanic other, and Hispanic with non-Hispanic white as the omitted category), gender (1=female), marital status (1=married, 0=else), and income (measured as three binary variables: less than $40,000, $40,000 to $99,999, and $100,000 or over with less than $40,000 omitted). We include a measure of partisan strength; the expectation is that individuals who strongly identify with their party affiliation are more likely to turn out. Finally, because individuals are more likely to vote out if they live in a state with competitive elections (Gimpel et al. 2007), we include fixed effects for state of residence.

Methods and Results

We estimate standard OLS regression models and weight all models using the survey specific weights. Given that both the despair and depression variables are predicated on frequency, we present sequential models where Model 1 isolates the association between despair and turnout without controlling for depression. Model 2 includes both the despair and depression variables. Finally, Model 3 includes the despair variable and the binary variable measuring occasional depression. Results are reported in Table 1. As shown in Model 1 in Table 1, despair is negatively associated with voter turnout while controlling for SRHS. Individuals who indicate that every day of their life in the past month was bad have scores on the vote scale that are .04 lower than those who did not report extreme despair. The despair coefficient is statistically significant while controlling for other variables that matter including voter registration, education, income, and partisan strength. Curiously, the model suggests that SRHS is negatively associated with voting; according to the model, individuals who report being in excellent health have a voter turnout score that is .05 lower than those who report being in poor health. This association holds even if we omit despair from the model and additional analyses suggest that this result is not due to multicollinearity.

This result goes against previous literature that finds a positive association between SRHS and self-reported voting (e.g., Pacheco and Fletcher 2016). We suspect our results have to do with the fact that we use vote validation as well as differences in how individuals interpret the SRHS question and response categories. As noted earlier, SRHS is associated with vote misreporting in both the 2020 and 2022 elections. Additionally, the SRHS is known to suffer from interpersonal incomparability, which may lead to biased inferences and invalid analyses if not corrected. Indeed, in one study that corrects for interpersonal incomparability, SRHS is not associated with voter turnout (Pacheco 2019). Understanding how measurement error influences our inferences regarding the association between SRHS and voter turnout is a fruitful endeavor for future research.

Table 1. The Association of Despair on Voter Turnout in 2018, 2020, and 2022 using the Collaborative Midterm Survey and Individual Level Analyses (N=5,839) State Fixed Effects included but not shown

	Model 1		**Model 2**		**Model 3**	
	b/(rob. se)		b/(rob. se)		b/(rob. se)	
Despair	-.04	**	-.01		-.05	**
	(.02)		(.02)		(.01)	
Depression			-.03	***		
			(.005)			
Occasional Depression					-.05	***
					(.02)	
SRHS	.-.01	**	-.01	**	-.01	**
	(.004)		(.004)		(.004)	
Registered to vote	.36	***	.36	***	.36	***
	(.01)		(.01)		(.01)	
Some college or Associate Degree	.03	***	.03	***	.03	**
	(.01)		(.01)		(.01)	
BA Degree or Higher	.08	***	.08	***	.08	***
	(.01)		(.01)		(.01)	
30-49 Years Old	.08	***	.08	***	.08	***
	(.01)		(.01)		(.01)	
50-64 Years Old	.24	***	.22	***	.23	***
	(.01)		(.01)		(.01)	
65+ Years Old	.39	***	.36	***	.37	***
	(.01)		(.01)		(.01)	
Female	-.02	***	-.02	***	-.02	**
	(.008)		(.008)		(.01)	
Black, non-Hispanic	.01		.01		.01	
	(.01)		(.01)		(.02)	
Other, non-Hispanic	-.01		-01		-.01	
	(.02)		(.02)		(.02)	
Hispanic	.003		.004		.005	
	(.01)		(.01)		(.01)	
Married	.003		.002		.002	
	(.009)		(.009)		(.009)	

$40k-$99,999	.06	***	.05	***	.06	***
	(.01)		(.01)		(.01)	
$100k or higher	.08	***	.08	***	.08	***
	(.01)		(.01)		(.01)	
Strength of Partisan Identity	.08	***	.09	***	.08	***
	(.008)		(.008)		(.01)	
Constant	-.18	***	-.15	***	-.14	***
	(.04)		(.04)		(.04)	

* p<0.05, ** p<0.01, *** p<0.001

As shown in Model 2 in Table 1, the coefficient on the despair variable fails to reach statistical significance when controlling for the depression scale. The model predicts that for every one unit increase on the depression scale, voting decreases by .03. This is a substantively large effect. An individual who is not depressed (e.g., has a score of 0) has a voter turnout score that is .09 points higher than an individual who is most depressed (e.g., has a score of 3). One interpretation of our findings in Model 2 is that the reason despair is not statistically associated with voting is because of its overlap with depression. In this case, depression might mediate the association between despair and voting, which would suggest that depression has a direct effect on political participation, not despair. Another interpretation, however, is that because both measures are frequency based, extreme values are capturing the same concept. Individuals who score high on the depression scale are those with the severest depressive symptoms and are also likely to be in despair.

We find suggestive evidence for this latter explanation in Model 3, which replaces the depression scale variable with the variable the measures occasional depression. As shown in Model 3, we find that *both* occasional depression and despair are negatively associated with voting and statistically significant; these results align with Landwehr and Ojeda (2020) who find that those with the severest depressive symptoms are the least likely to participate in politics. We suspect that Landwehr and Ojeda (2020) were picking up on despair.[6]

Study 2: County-Level Analysis using Aggregate Data

In the previous section we provide evidence demonstrating that individuals with high levels of despair are less likely to participate in elections than those who do not report experiencing despair. We now turn to our analysis of aggregate despair and voter turnout in U.S. counties. In this analysis, we develop a measure of despair at the county level and analyze whether counties that experience higher levels of despair also have lower levels of voter turnout. One important advantage of this aggregate level analysis is that we can examine the effects of aggregate despair over time within local areas rather than limiting our analyses to individual-level, cross-sectional comparisons. Using the panel study design described below, we are able to isolate the effects of despair within counties, meaning cross-county effects are held constant (Angrist and Pischke 2009). Additionally, as we discuss above, we argue that despair not only has political consequences for the people who directly experience it, but it can also influence the family, friends, and communities in contexts where despair is most prevalent. Although the aggregate analysis does not allow us to directly test whether society-level despair is influencing voter turnout, it is one potential implication of our results. In the end, we view the results of this analysis combined with our individual-level survey analysis as collectively contributing to evidence that supports our central hypothesis.

[6] We present additional models looking at elections separately in the Appendix. Table A5 reports the association between despair, occasional depression, and SRHS with self-reported turnout in 2018, 2020, and 2022. Table A6 reports similar models for administrative turnout in 2020 and 2022. We are hesitant to infer much from these models since voting is habitual, the determinants of self-report turnout are different from administrative measures of turnout, and elections in isolation are idiosyncratic. As shown, our inferences vary depending on the election and measure used for turnout.

Measuring County-Level Turnout

We use the percentage of adult residents in each county who cast a ballot in presidential elections from 1996 to 2012 as our measure of voter turnout. County voting data for the 1996 election are from the census's USA Counties database.[7] Voter counts for the 2000-2012 elections were retrieved from the MIT Election Lab.[8] We use these two data sources along with estimates of the adult population in each county to create our percentage turnout variable.[9]

Measuring County-Level Despair

To estimate aggregate levels of community despair, we use survey data from the Behavioral Risk Factor Surveillance System (BRFSS).[10] The BRFSS, established by the Centers for Disease Control and Prevention (CDC), is a monthly survey designed to collect health behavior data at the state and local levels. It is widely used for public health research and by state and local officials to assist in health-related policy decisions. Following the work of Blanchflower and Oswald (2020), we use the following BRFSS question as a proxy of despair: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" In addition to the responses to this question, the BRFSS also includes each respondent's county of residence for its surveys fielded between 1993 and 2012.

We focus on the county level in our analysis because it allows us to approximate the concept of a community while also being the smallest geographic area we can identify among respondents in the BRFSS. Additionally, the county is a meaningful geographic designation for

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[7] The data can be accessed at: https://www.census.gov/library/publications/2011/compendia/usa-counties-2011.html.
[8] These data are available at: https://electionlab.mit.edu/data.
[9] County population data are from the NIH: https://seer.cancer.gov/popdata/download.html. Unfortunately, Census estimates of citizen voting age population begins in 2000. For consistency throughout the elections held in the 1996-2012 period we rely on estimates of the county-level adult population in our calculations of voter turnout.
[10] Data and documentation for the survey can be found at: https://www.cdc.gov/brfss/index.html.

the specific purposes of our analysis. Counties are often responsible for managing elections and regularly provide economic, social, and health services to their residents.

Although the BRFSS is a relatively large survey – in some years it includes more than 400,000 respondents – many of the over 3,000 counties in the U.S. end up with fairly small sample sizes. This means we cannot use simple averages (even with survey weights) to estimate levels of aggregate despair within counties for a given year. Instead, our approach is to use a version of multilevel regression and post-stratification (MRP) to develop a measure of county despair over time. MRP is a measurement strategy that allows for the estimation of opinion at local levels of geography using typical national opinion polls. Research shows that MRP provides accurate estimates of state and local opinion even when using a single national survey (Lax and Phillips 2009a; Lax and Phillips 2009b; Lax, and Phillips 2012; Pacheco 2014; Park et al. 2006). As we describe next, we extend the traditional MRP approach by modeling BRFSS data to allow for our estimates to vary across states and over time, referred to as dynamic MRP (Gelman et al. 2018; Smith et al. 2020).

Estimating opinion using dynamic MRP (DMRP) involves two steps. The first is to model individual responses to the survey question of interest using multilevel logistic regression. In this case we are interested in those respondents in the BRFSS who experience extreme distress. As mentioned above, we accomplish this by using the bad mental health days question. Those respondents who report experiencing 25 or more bad mental health days are coded 1 and all others are coded 0.[11] This measure is modeled as the dependent variable as a function of basic demographic and geographic characteristics of the survey respondents. Similar to pervious work, the multilevel logistic regression models include the following characteristics: race (black, white,

[11] We use the 25+ bad mental health days, rather than the 30 or more days threshold we use in the individual level analysis, to help with model convergence.

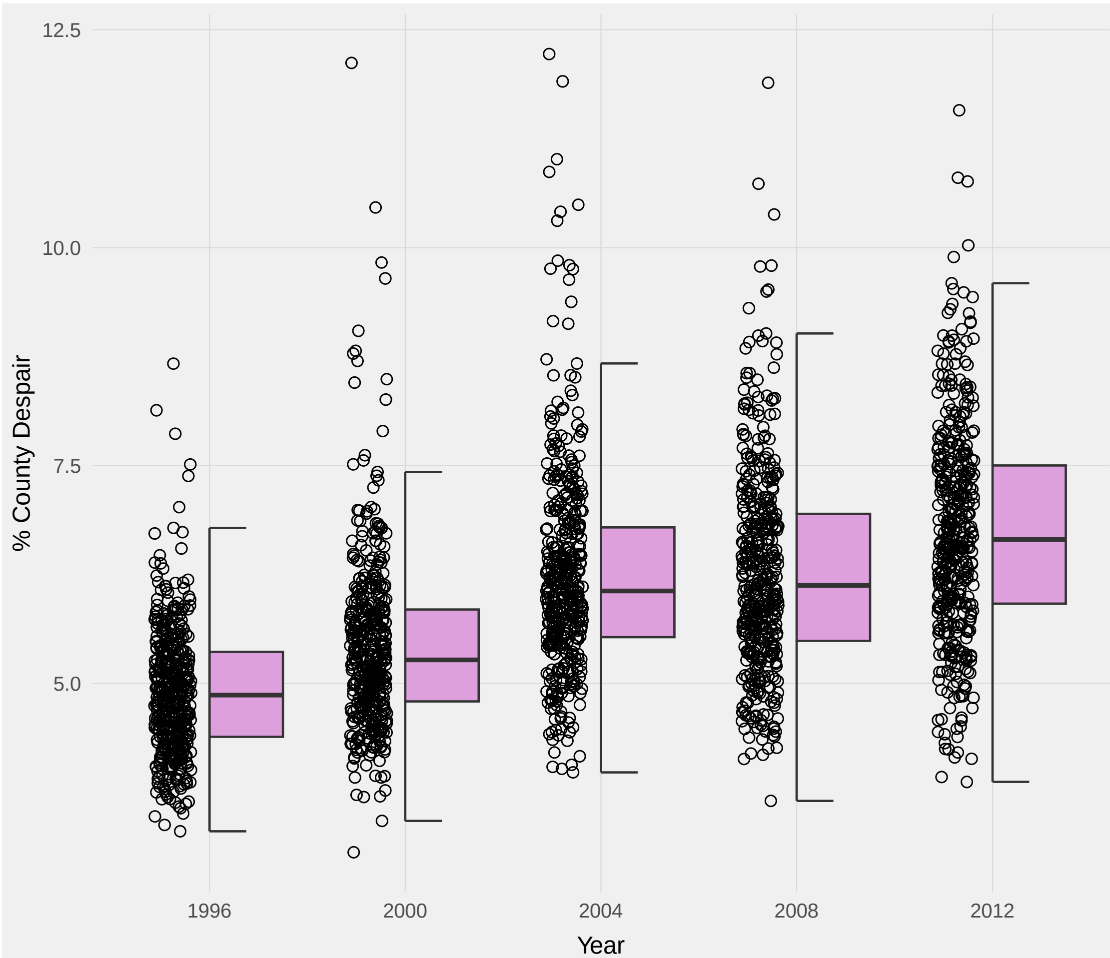
or other), gender (female or male), age (18-29, 30-44, 45-64, or 65+), education (less than high school graduate, high school graduate, some college, or college graduate), county of residence, the percentage of those 25 and older with a bachelor's degree in each county, county-level unemployment rate, a time trend, and each presidential election period between 1993-2012 (more on this below).

The results of the multilevel regression model are then used to predict the probability of experiencing despair for every possible individual type (e.g., a white female who is 30-44 years of age with some college education living in Cuyahoga County, Ohio). These probabilities are then used in the second step of the estimation, which is post-stratification. Post-stratification is the process of weighting each individual type probability estimate by the actual proportion of each type in the population using data from the U.S. Census. This part of the procedure adjusts for any differences between the individuals surveyed in each county and the true county population. Although we can obtain join distributions for age, gender, and race at the county level from the census, joint distributions are not available for all four demographic characteristics we use in our model – that is, age, gender, race, and education. To address this issue, we construct what Leemann and Wasserfallen (2017) call *adjusted synthetic joint distributions*. For this procedure we begin with the joint distributions for age, gender, and race from the census. Then, we use correlations from the BRFSS data among age, gender, race, and education to extend the census joint distributions to account for education. This approach is shown to increase the prediction precision of MRP estimates relative to models that use only the available joint distributions data (Leemann and Wasserfallen 2017).

Additionally, the initial multilevel regression model mentioned above is estimated using completely pooled data. In other words, all available survey respondents for all available years are included in a single logistic regression model of individual opinion. Because we are interested in how despair influences voter turnout, we group the annual BRFSS surveys into presidential election periods between 1993-2012. Specifically, we group survey responses into the following four-year periods: 1993-1996, 1997-2000, 2001-2004, 2005-2008, and 2009-2012. This allows us to interact each election period with county of residence so that a random effect is allowed for every county-election period combination. This is the dynamic part of the DMRP estimation procedure, which allows for unique estimates of opinion for each county over time by using all available information in one model. The result is a series of county-level estimates for each presidential election period between 1996-2012 indicating the percentage of residents within each county who have experienced despair. Additional details about the measure and estimation procedure can be found in the Appendix.

An important limitation of the BRFSS data is that it does not provide county of residence indicators for respondents residing in counties with small populations. The result is that we end up with estimates of despair for fewer counties in earlier election years. As populations grow over the period covered by the survey data, we have a greater number of counties with despair estimates. Specifically, the counties with estimates of despair for the 1996 election period cover 68% of the total U.S. adult population, 74% in the 2000 period, 81% in 2004, 97% in the 2008 period, and 97% in the 2012 period. This limitation means that we likely underrepresent rural counties in our estimates, a data issue that has been discussed by other researchers (Bennett 2013). While deaths of despair have been found to be more prevalent in rural areas (Lee et al. 2023), we do not have a theoretical reason to believe that the effect of despair on political participation is stronger or weaker in rural places. In any case, we interpret any findings based on our county-level measure of despair with this limitation in mind.

Figure 2. County-Level Despair Over Time



Note: County-level estimates of despair created by the authors based on measure developed by Blanchflower and Oswald (2020). The plotted data only include counties that have estimates of despair in all five time periods.

In Figure 2 we plot our estimates of county-level despair. As expected, given previous research on despair in the U.S. (Blanchflower and Oswald 2020), the plot demonstrates that the average level of despair across counties has increased from 1996 to 2012. It is also clear from the figure that the number of counties with more than 10% of residents experiencing despair has grown over this time period.[12] In the Appendix we present additional evidence that supports the validity of the measure by demonstrating that our county-level measure of despair is closely associated with county-level deaths of despair mortality rates. Using straightforward two-way difference-in-difference models we show that our measure of county despair significantly predicts county deaths of despair (see Appendix Table A1).

Control Variables

Our models assessing the relationship between despair and voter turnout also statistically control for a number of additional county-level factors. We include the percentage of the population who are 18-29 years of age (reference), 30-44 years old, 45-64 years old, and 65 years and older. Gender is accounted for using a variable measuring the percentage of the population who are female. We also include percent White (reference), percent Black, and all other races, along with a measure of the percentage of the population identifying as Hispanic. County education rates are accounted for by including a variable measuring the percentage of those over 25 years of age who have a bachelor's degree. Measures of county-level per capita income (in thousands of dollars), unemployment rates and poverty rates are also controlled for in our models. Finally, in models that can accommodate the measure (more on this below), we include rural-urban continuum codes.[13] The summary statistics for all of the variables can be found in Appendix Table A2.

[12] Figure 2 only includes counties that have estimates of despair in all time periods. This is done because the BRFSS includes additional county indicators over time as county populations increased, and it is possible that this could lead to bias in the extent to which we observe an over time increase in despair. We present a similar plot in the Appendix that includes the full sample of counties we have despair estimates for along with the limited sample of counties with complete data for all time periods. Our main observation that despair has increased over the time period in our analysis does not change based on the sample being used.

[13] Age, gender and race estimates were calculated using the NIH's population data (https://seer.cancer.gov/popdata/download.html). Education estimates and the rural-urban continuum codes are from the USDA's Economic Research Service (https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data). Unemployment rates are from the Bureau of Labor Statistics (https://www.bls.gov/lau/tables.htm#mcounty) and poverty rates from the Census

Methods and Results

Given that we are interested in analyzing county panel data, we use two general approaches to modeling the relationship between despair and turnout. First, we estimate two-way fixed effects models where county voter turnout is regressed on our measure of despair, control variables, and fixed effects for each county and election year, and a lagged dependent variable to account for over time dynamics. This setup allows us to focus on how within county changes in despair effect voter turnout (Angrist and Pischke 2009).

The second approach we use, sometimes referred to as the within-between model, uses random effect estimates rather than fixed effects. For these models we create separate mean-centered variables over time within counties and variables representing the overall county averages in order to clearly estimate within county and between county effects. Using the within county mean-centered variables still allows us to isolate the within state effects while avoiding some limitations of the two-way fixed effects models with panel data (Bartels 2015; Hamaker Muthen 2020). When using the within-between model we also include a rural-urban continuum measure. Because this variable does not vary over the time period under analysis it cannot be included in the fixed effects models. Finally, we account for any trending in the dependent variable, not already captured by the lagged dependent variable, by included time trend variables in the within-between models.

Below we present the results of four regression models, two models for each modeling approach. The only difference between the two models for each approach is that the first examines the effects of despair on voter turnout at time *t*, while the second examines the effects of despair at time *t-1*. This allows us to assess the dynamics of how despair influences political

(https://www.census.gov/library/visualizations/time-series/demo/census-poverty-tool.html). Per capita income data are from the Bureau of Economic Analysis (https://apps.bea.gov/regional/downloadzip.cfm).

participation. That is, we estimate the instantaneous and lagged effects of despair on turnout. All the reported results include robust standard errors to account for the panel data. Two-way fixed effects models include fixed effects for counties and election years. Within-between random effects models include mean-centered variables over time within counties and variables representing the overall county averages (identified with superscript *B*). The within-between models also include time trend variables which are not reported in the table to preserve space

The results of the four models are reported in Table 2. Our main interest is in the estimated coefficients for the measure of county despair. For models 1 and 3, the coefficients on despair at time t (i.e., $Despair_t$) are both negative, as expected, but neither is statistically different from zero. In models 2 and 4, however, both coefficients on lagged despair (i.e., $Despair_{t-1}$) are negative and statistically significant. These results suggest that increases in despair in past election periods lead to decreases in county-level voter turnout. Substantively, if despair increases in a given county by 3 percentage points (this is the approximate change from the 10th to 90th percentile of despair), turnout would be expected to decrease by about 1 percentage point during the subsequent presidential election. As we show in Figure 3, changing county despair from the approximate minimum of 3% to the maximum of 14% is predicted to reduce voter turnout by nearly 3 percentage points.

Examining the between county effects shown in models 3 and 4, we can also compare turnout among counties with more or less despair on average. In both models the estimated coefficients on average levels of despair (i.e., $Despair^B$) are negative and statistically different from zero. This suggests that those counties with higher average levels of despair are more likely to experience lower levels of political participation.

Table 2. The Effect of Despair on Voter Turnout in U.S. Counties

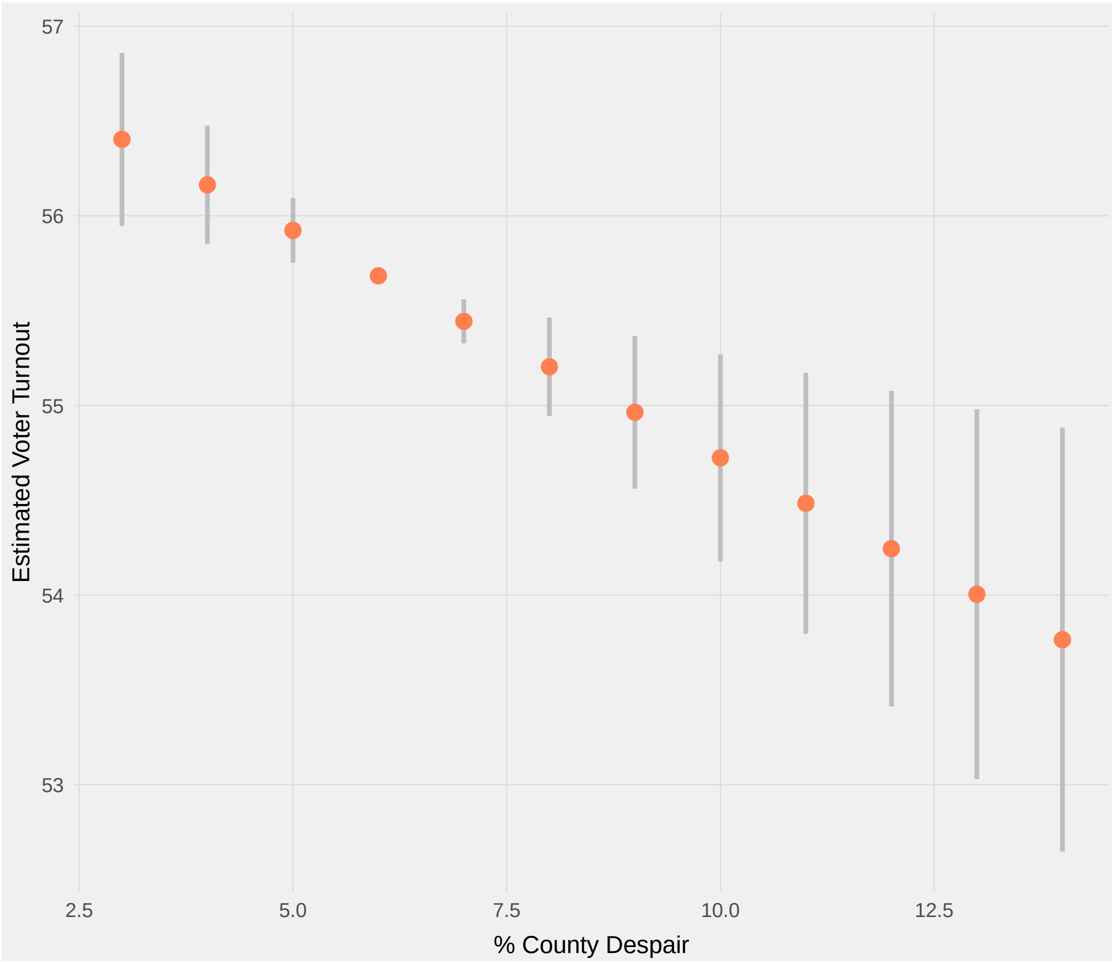
	Two-way fixed effects models		Within-between random effects models	
	(1)	(2)	(3)	(4)
	b/(rob. se)	b/(rob. se)	b/(rob. se)	b/(rob. se)
$Turnout_{t-1}$	.28***	.33***	.89***	.92***
	(.02)	(.02)	(.008)	(.008)
$Despair_{t}$	.008		-.06	
	(.06)		(.07)	
$Despair_{t-1}$		-.24**		-.30***
		(.07)		(.08)
% Age 30-44$_{t}$	.12	.04	.31***	.46***
	(.08)	(.10)	(.05)	(.06)
% Age 45-64$_{t}$	.39***	.13	.44***	.52***
	(.08)	(.11)	(.05)	(.06)
% Age 65 over$_{t}$	.24**	.08	.20***	.36***
	(.09)	(.13)	(.06)	(.06)
% Female$_{t}$	.75***	1.02***	.28**	.21
	(.18)	(.29)	(.10)	(.11)
% Black$_{t}$	.05	.21*	-.07*	-.07*
	(.08)	(.09)	(.03)	(.03)
% Other races$_{t}$	-.40***	-.29**	-.41***	-.27***
	(.09)	(.10)	(.07)	(.08)
% Hispanic$_{t}$	-.14**	-.13*	-.10***	-.09**
	(.05)	(.06)	(.03)	(.03)
% Bachelor's degree$_{t}$	.06	.13	.06	.05
	(.07)	(.10)	(.04)	(.04)
Per capita inc$_{t}$	.04	.07*	.05**	.04
	(.02)	(.03)	(.02)	(.02)
Unemployment rate$_{t}$	.37***	.45***	.21***	.22***
	(.04)	(.06)	(.04)	(.04)
Poverty rate$_{t}$	.10	.13	-.04	-.05*
	(.07)	(.08)	(.03)	(.03)
Rural/urban			.07***	.13***
			(.02)	(.02)
$Despair^{B}$			-.27***	-.45***
			(.06)	(.06)
% Age 30-44^{B}			.04	.08*
			(.03)	(.03)
% Age 45-64^{B}			.24***	.14***
			(.02)	(.03)
% Age 65 over^{B}			.03	.07**
			(.02)	(.02)
% Female^{B}			.11***	.02
			(.03)	(.03)

% Black^{B}			.08***	.07***
			(.004)	(.004)
% Other races^{B}			-.02	-.03*
			(.01)	(.01)
% Hispanic^{B}			-.01**	-.006
			(.005)	(.005)
% Bachelor's degree^{B}			.10***	.05***
			(.01)	(.01)
Per capita inc^{B}			-.07***	-.05***
			(.01)	(.01)
Unemployment rate^{B}			.06*	.02
			(.03)	(.03)
Poverty rate^{B}			-.10***	-.05**
			(0.02)	(.02)
Constant	-24.7**	-29.985*	-4.57***	-59.41***
	(9.3)	(13.342)	(3.10)	(3.72)
N	6167	4468	6167	4468

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note: Entries are estimated coefficients with robust standard errors in parentheses. Two-way fixed effects models include fixed effects for counties and election years. Within-between random effects models include mean-centered variables over time within counties and variables representing the overall county averages (identified with superscript *B*). The within-between models also include time trend variables which are not reported in the table to preserve space.

Figure 3. Estimated Effect of County Despair on Voter Turnout



Note: Estimated effects are based on results from Table 2, model 2. Vertical lines represent 95% confidence intervals.

As a robustness check, we also include the results of models that do not include control variables. These analyses reproduce the models presented in Table 2 but only include our measure of despair. The results, which are consistent with those in Table 2, can be found in the Appendix (see Table A3). Additionally, as we noted earlier, while we are unable to explicitly test whether our county-level results indicate a social effect of despair on voter turnout that reaches beyond individual-level despair we believe it is one potential implication of our results. To further explore this question, we also examine whether the effect of despair on turnout grows in magnitude in places where aggregate levels of despair are higher. We examine this question by modeling the non-linear effects of despair using polynomials. The results, which we include in the appendix, suggest that the effect of despair grow stronger as county-level despair increases. Put differently, the negative effect of despair on turnout increases in magnitude at higher levels of despair. As we show in Appendix Figure A2, changing county despair from 3% to 14% (the approximate minimum and maximum observed values) leads to an estimated decline in turnout of about 6 percentage points when using the results from the non-linear models.

Conclusion

The more than two-decade rise in deaths of despair in the U.S. – that is, the increase in mortality as a result of deaths due to drug overdose, alcohol poisoning, and suicide – has alarmed many observers (Case 2015; Case and Deaton 2015; Macy 2018). This dramatic increase in despair is particularly troubling given that most other wealthy countries have not experienced similar trends (Sterling and Platt 2022). Research has only begun to identify the causes of this growing despair among Americans, but evidence points to an economy that increasingly fails to support many working-class families, inadequate public policy that is unable to address low wages and weak job prospects, and a breakdown in social cohesion that is related to these economic problems.

While many scholars have focused on better understanding what is causing deaths of despair, and for good reason, we believe it is also important shed light on how growing levels of despair more broadly are altering the political world. This study contributes to the existing literatures on health politics and political behavior by expanding our understanding of how current American societal structures facilitate despair and lead people to withdraw from the political system. We connect theories on the underlying causes of despair and political participation to develop expectations regarding the relationship between despair and voter turnout.

Specifically, we suggest that the physical limitations, feelings of apathy, purposelessness, alienation, and isolation associated with despair leads many who experience despair to withdraw from participating in elections. In addition to the individual-level effects of despair on turnout, we argue that community-level despair also reduces participation in the aggregate. This latter claim is based on our understanding of how the breakdown in social ties related to growing despair is likely to affect electoral participation. Research on social context and networks has demonstrated that where people live, the composition of their environment, and the people they interact with can all shape the extent to which they participate in politics. Therefore, places where despair is prevalent are also likely to have lower levels of political participation. The breakdown in social ties driven by despair – including higher levels of status threat, more perceived group conflict, and less general participation in social activities – can create an environment where civic norms and the communication of political information are diluted. This suggests the possibility that contexts of despair can dampen community electoral participation.

We test these expectations using original data in studies at both the individual and community levels. At the individual level, we ask custom survey questions on the Collaborative Midterm Survey that allow us to proxy despair and assess whether those who experience despair are less likely to vote. Our results suggest that despair is negatively associated with casting a ballot and that despair is unique from bouts of occasional depression.

Our analysis of how community-level despair shapes voter participation examines a newly developed measure of despair over time within U.S counties. Using survey data from the Behavioral Risk Factor Surveillance System, we use dynamic multilevel regression and post-stratification to estimate levels of despair within counties in presidential election years between 1996-2012. Time series panel data estimates of the effects of county-level despair on aggregate measures of county turnout provide evidence supporting our claim that places where despair is more prevalent also have lower levels of voter participation.

Two important limitations of this study include existing questions regarding the conceptualization and measurement of despair, as well as the extent to which our analysis has established a causal relationship between despair and voter participation. As we note earlier, we believe the Blanchflower and Oswald (2020) measure of despair works well for the purposes of this study. At the same time, the measure is an imperfect one and we are confident that scholars will continue to advance our understanding of despair and how best to measure the concept. While the analyses we present do not definitively establish a causal relationship between despair and turnout, we believe the evidence from our two studies collectively make a strong case that despair has important political consequences. Future studies should focus on identifying research designs (e.g., long-term panel studies) that will be better able to demonstrate a causal link between despair political participation.

The results we present are the first to our knowledge to demonstrate the political consequences of growing despair in the U.S. The evidence suggests that the effects of experiencing despair are far reaching and extend beyond the tragic deaths of despair. Our study is a first step to better understanding this ongoing American crisis, as we expect despair shapes the political world in multifaceted ways outside of the context of electoral participation.

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Appendix

We develop estimates of county-level despair using data from the Behavioral Risk Factor Surveillance System (BRFSS). Even with the overall large sample sizes collected by the BRFSS, the number of respondents from many counties can be small. Because of this, using simple averages at the local county level (even with survey weights) to measure despair would lead to inaccurate estimates. To improve the accuracy of our county-level measure of despair, we use an estimation approach known as dynamic multilevel regression and post-stratification (DMRP). We provide details of the process in the main text, including how the BRFSS bad health days questions is modeled in the first stage and the estimates are weighted in the second stage (i.e., post-stratification).

We selected the following model for the first-stage multilevel logistic regression model after considering several alternative specifications:

$$\Pr(\text{despair}_i = 1) = \text{logit}(\beta_0 + \alpha_{j[i]}^{race,gend} + \alpha_{k[i]}^{age} + \alpha_{l[i]}^{educ} + \alpha_{p[i]}^{county} + \alpha_{q[i]}^{year} + \alpha_{r[i]}^{county,year} + \beta_1 * unemp_p + \beta_2 * pctcol_p + \beta_3 * trend)$$

The *race,gend* variable is a six-category measure that combines race (black, white, or other) and gender (female or male), *age* is a four-category measure of respondent age (18-29, 30-44, 45-64, or 65+), *educ* is a four-category measure of educational attainment (less than high school graduate, high school graduate, some college, or college graduate), *county* is county of residence, *year* is an indicator for election year, *county,year* is the interaction of county and election year (this allows for our dynamic estimates), *unemp* is the county-level unemployment rate, *pctcol* is the percentage of those 25 and older with a bachelor's degree in each county, and *trend* is a time trend.

We use the above model as the basis for our estimates of despair because it produced the best model-fit statistics among a series of model specifications. These alternative models include the same individual-level measures (i.e., race, gender, age, and education) while changing the following: including county-level unemployment without a time trend, a model with only county-level education without a time trend, a model without a time trend but all other covariates listed above, and a model with all covariates in the above model but with the addition of a time-squared term. The above model had the best overall fit after assessing the AIC and BIC across all model results.

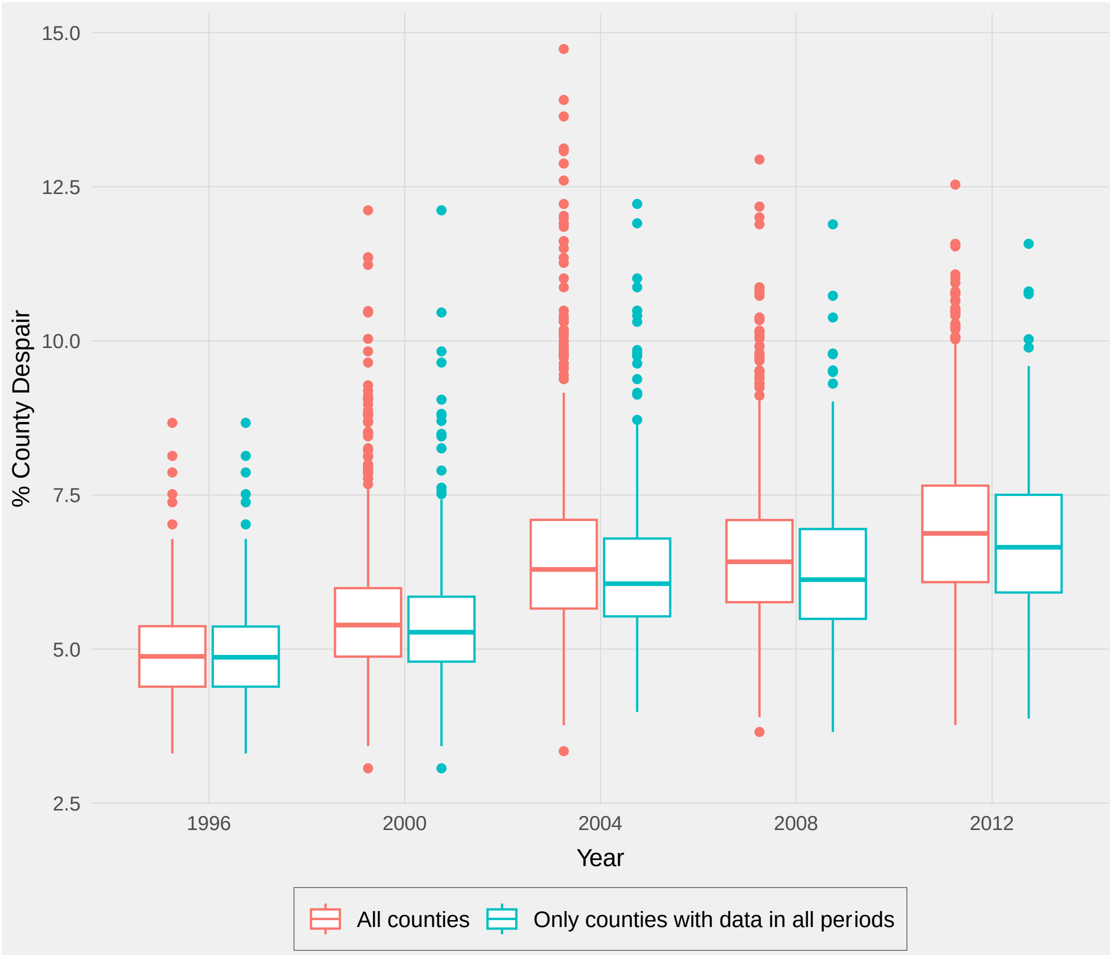
In the main text we discuss the results of our county-level despair measure and note that the overall average level of despair based on our estimates increases over time as expected, giving us evidence that the measure reflects what is known about deaths of despair in recent years. To add to our confidence in the validity of our measure, we also examine whether our county estimates of despair predict county-level deaths of despair as defined by Case and Deaton and others. Although we do not expect to observe a one-to-one relationship between despair and deaths of despair – clearly, all of those who experience despair will not die as a result – we can anticipate a positive association. That is, in counties where despair is higher we expect to observe higher levels of mortality resulting from drugs, alcohol, and suicide.

We identify deaths of despair by following the coding scheme used by the Social Capital Project's (2019) report on despair mortality trends, which extends Case and Deaton's (2015) seminal research.[14] Mortality data were collected using the CDC Compressed Mortality File.[15] Five-year windows are used to correspond with the election years covered by our county despair estimates. Using multiple years to estimate deaths of despair reduces the amount of suppressed data due to low county death counts.[16] The CDC data provide mortality rates per 100,000 people in crude (i.e., unadjusted) and age adjusted rates.

The two versions of county-level despair mortality rates are used as the dependent variables in straightforward difference-in-difference regression models using our estimates of county despair as the independent variable. The results are presented in Appendix Table A1. The first pair of estimates include a lag of the dependent variable in the models while models 3 and 4 do not. The estimated coefficients on county despair are all positive and statistically different from zero. These results show that our measure of despair is related to despair mortality rates, providing us with additional evidence that our measure accurately represents our central concept of interest in this study.

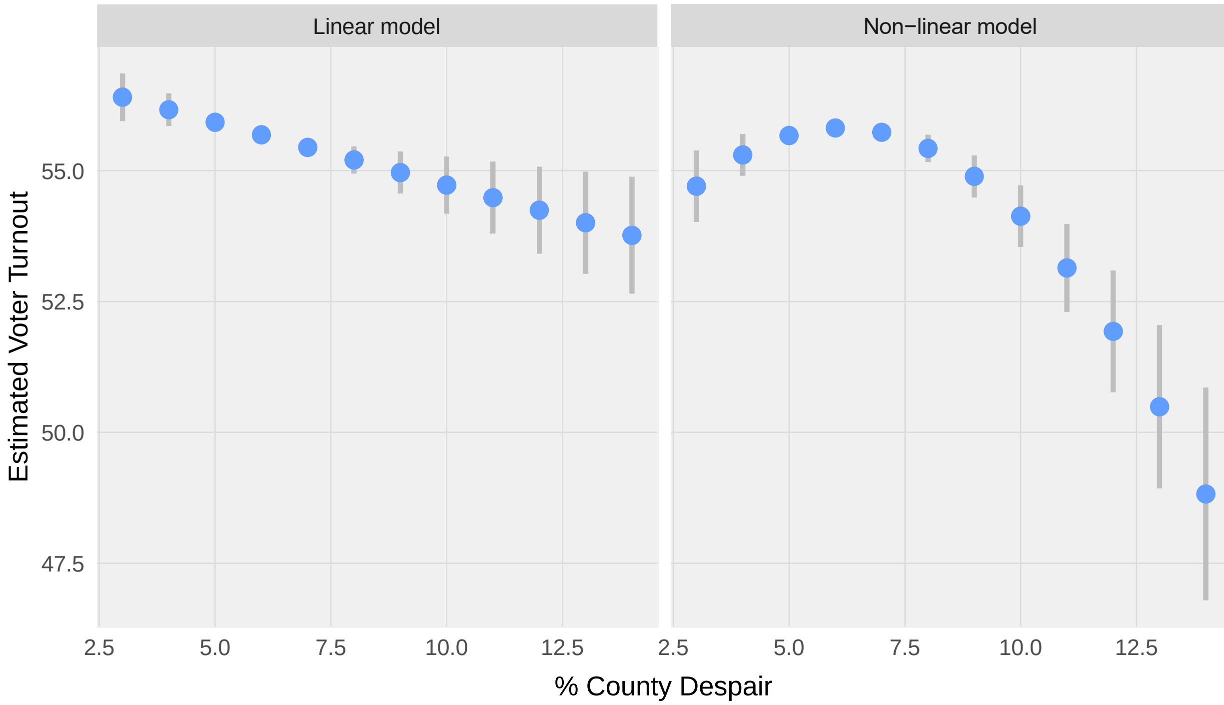
[14] Social Capital Project. 2019. Long-term trends in deaths of despair. SCP Report 4-19. https://www.jec.senate.gov/public/index.cfm/republicans/2019/9/long-term-trends-in-deaths-of-despair
[15] https://wonder.cdc.gov/mortSQL.html
[16] The database suppresses subnational statistics for reported figures of fewer than 10 deaths.

Figure A1. County-Level Despair Over Time, Full Sample and



Note: County-level estimates of despair created by the authors based on measure developed by Blanchflower and Oswald (2020). Data labeled "All counties" includes all counties with an estimate of despair in at least one time period. The group "Only counties with data in all periods" only includes counties that have estimates of despair in all five time periods.

Figure A2. Estimated Effect of County Despair on Voter Turnout, Linear and Non-Linear Model Results



Note: Estimated effects for the linear model are based on results from Table 2, model 2. The effects for the non-linear model are based on results from Appendix Table A4. Vertical lines represent 95% confidence intervals.

Table A1. The Effect of County Despair on County Despair Mortality Rates

	(1) Despair mortality rate	(2) Despair mortality rate, age adjusted	(3) Despair mortality rate	(4) Despair mortality rate, age adjusted
	b/se	b/se	b/se	b/se
Despair mortality rate$_{t-1}$	0.235***			
	(0.030)			
Despair mortality rate age adjusted$_{t-1}$		0.247***		
		(0.031)		
Despair$_t$	0.415**	0.415**	0.694***	0.724***
	(0.127)	(0.131)	(0.142)	(0.149)
Constant	15.134***	15.085***	19.494***	19.869***
	(1.081)	(1.119)	(0.824)	(0.866)
N	6138	6138	6698	6698
Time fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes

Note: County despair is calculated by the authors and discussed in the main text. County despair mortality rates (or "deaths of despair") are estimated using the CDC Compressed Mortality File and the coding scheme from the Social Capital Project (2019).

Table A2. Summary Statistics for County-Level Analysis

	Mean	Std. Dev.	Min	Max
Turnout	55.33	9.15	3.57	83.99
Despair	6.42	1.28	3.06	14.74
% Age 30-44	26.01	4.39	10.01	48.99
% Age 45-64	34.21	4.12	10.61	51.81
% Age 65 over	19.02	4.59	4.35	52.59
% Female	50.49	1.74	34.13	56.81
% Black	11.08	14.24	0.02	84.16
% Other races	3.55	6.33	0.11	90.27
% Hispanic	7.99	12.01	0.27	96.00
% Bachelor's degree	20.52	9.21	5.63	71.25
Per capita inc	32.84	9.63	12.07	190.22
Unemployment rate	6.45	2.49	1.40	30.60
Poverty rate	15.20	6.08	2.10	45.36

Table A3. The Effect of Despair on Voter Turnout in U.S. Counties, Models without Control Variables

	Two-way fixed effects models		Within-between random effects models	
	(1) b/(rob. se)	(2) b/(rob. se)	(3) b/(rob. se)	(4) b/(rob. se)
$Turnout_{t-1}$	0.347***	0.394***	0.888***	0.954***
	(0.018)	(0.020)	(0.007)	(0.007)
$Despair_t$	-0.012		-0.048	
	(0.064)		(0.067)	
$Despair_{t-1}$		-0.234**		-0.315***
		(0.080)		(0.078)
$Despair^B$			-0.285***	-0.136*
			(0.055)	(0.053)
Constant	33.969***	32.995***	-57.009***	-58.729***
	(0.957)	(1.068)	(2.694)	(3.032)
N	6280	4540	6280	4540

* p<0.05, ** p<0.01, *** p<0.001

Note: Entries are estimated coefficients with robust standard errors in parentheses. Two-way fixed effects models include fixed effects for counties and election years. Within-between random effects models include mean-centered variables over time within counties and variables representing the overall county averages (identified with superscript *B*). The within-between models also include time trend variables which are not reported in the table to preserve space.

Table A4. The Effect of Despair on Voter Turnout in U.S. Counties, Testing for Non-Linear Effects

	b	(rob. se)
Turnout $_{t-1}$	0.328***	(0.022)
Despair $_{t-1}$	1.389***	(0.274)
Despair^2 $_{t-1}$	-0.113***	(0.019)
% Age 30-44 $_t$	0.094	(0.100)
% Age 45-64 $_t$	0.172	(0.109)
% Age 65 over $_t$	0.110	(0.125)
% Female $_t$	1.010***	(0.285)
% Black $_t$	0.195*	(0.085)
% Other races $_t$	-0.337***	(0.094)
% Hispanic $_t$	-0.139*	(0.060)
% Bachelor's degree $_t$	0.097	(0.093)
Per capita inc $_t$	0.064*	(0.030)
Unemployment rate $_t$	0.442***	(0.056)
Poverty rate $_t$	0.085	(0.080)
Constant	-36.841**	(13.399)
N	4468	

* p<0.05, ** p<0.01, *** p<0.001

Note: Entries are estimated coefficients with robust standard errors in parentheses. The model includes fixed effects for counties and election years.

Table A5. The Association of Despair on Self-Reported Turnout in 2018, 2020, and 2022 using the Collaborative Midterm Survey and Individual Level Analyses (N=5,839) State Fixed Effects included but not shown								
		2018 Election			2020 Election			2022 Election	
		b/(rob.			b/(rob. se)			b/(rob.	
Despair		-0.3	#		-0.45	*		-0.2	
		0.18			0.22			0.15	
Occassional Depression		-0.2	*		-0.05			-0.2	*
		0.08			0.11			0.08	
SRHS		0.09	*		0.002			0.04	
		0.04			0.06			0.04	
Registered to vote		2.88	***		2.73	***		3.14	***
		0.18			0.12			0.24	
Some college or Associate Degree		0.34	***		0.41	**		0.11	
		0.1			0.13			0.1	
BA Degree or Higher		0.89	***		0.99	***		0.44	***
		0.11			0.16			0.1	
30-49 Years Old		0.82	***		0.22			0.23	#
		0.13			0.16			0.12	
50-64 Years Old		1.38	***		0.38	*		0.89	***
		0.13			0.16			0.12	
65+ Years Old		2.07	***		1.17	***		1.47	***
		0.15			0.19			0.13	
Female		-0.4	***		-0.31	**		-0.1	
		0.08			0.11			0.08	
Black, non-Hispanic		0.31	**		0.23			0.02	
		0.13			0.18			0.12	
Other, non-Hispanic		-0.3	*		-0.43	*		0.06	
		0.16			0.19			0.15	
Hispanic		-0.2			-0.04			-0	
		0.12			0.16			0.11	
Married		0.19	*		0.5	***		-0.1	
		0.09			0.12			0.08	
$40k-$99,999		0.23	*		0.36	**		0.3	**
		0.1			0.13			0.09	
$100k or higher		0.32	*		0.34	#		0.27	*
		0.13			0.18			0.12	
Strength of Partisan Identity		0.85	***		1.57	***		0.46	***
		0.09			0.12			0.08	
Constant		-4.5	***		-2.3	***		-5	***
		0.42			0.45			0.89	

Note: #p<.10, *p<.05, **p<.01, ***p<.001 with two-tailed significant tests.

Table A6. The Association of Despair on Administrative Turnout in 2020 and 2022 using the Collaborative Midterm Survey and Individual Level Analyses (N=3,472) State Fixed Effects included but not shown

		2020 Election			2022 Election	
		b/(rob. se)			b/(rob. se)	
Despair		-0.06			-0.04	
		0.21			0.24	
Occassional Depression		-0.29	**		-0.44	***
		0.1			0.1	
SRHS		-0.17	**		-0.18	**
		0.21			0.06	
Registered to vote		1.73	***		2.64	***
		0.25			0.35	
Some college or Associate Degree		0.13			0.2	
		0.13			0.14	
BA Degree or Higher		0.09			0.19	
		0.14			0.15	
30-49 Years Old		0.56	**		0.44	*
		0.17			0.19	
50-64 Years Old		1.36	***		1.48	***
		0.17			0.18	
65+ Years Old		2.22	***		2.42	***
		0.18			0.19	
Female		0.21	*		0.08	
		0.1			0.11	
Black, non-Hispanic		-0.37	*		-0.38	*
		0.16			0.18	
Other, non-Hispanic		-0.27			-0.06	
		0.19			0.2	
Hispanic		-0.48	**		-0.11	
		0.17			0.19	
Married		-0.22	*		-0.04	
		0.11			0.12	
$40k-$99,999		0.05			0.16	
		0.12			0.13	
$100k or higher		0.3	*		0.43	**
		0.15			0.16	
Strength of Partisan Identity		0.2	*		0.29	**
		0.1			0.1	
Constant		-3.92	***		-5.55	***
		0.61			0.7	

Note: #p<.10, *p<.05, **p<.01, ***p<.001 with two-tailed significant tests.