Who Wants Help? How Anxiety Shapes the Demand for Insurance After Economic Shocks*

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Abstract

Classic political economy models predict that income shocks increase demand for social insurance, but empirical findings are mixed. I argue that the effects of income shocks are conditional: They increase demand for insurance among individuals high in *trait anxiety* - a stable disposition to become anxious in response to adversity - but less or not at all among those low in trait anxiety. I test this claim using nationally representative panel data. I find that the average effect of losing a job is near zero, but that job loss increases support for unemployment insurance by twenty percentage points among the most anxious 20% of Americans. Demographic and socioeconomic variables do not show similar patterns of moderation, and a placebo test shows that trait anxiety is exogenous to unemployment. These results suggest that income shocks do affect insurance preferences, but only when individuals are predisposed to view them as consequential.

Keywords: economic policy, personality, panel data, anxiety, welfare, unemployment

Word Count: 6,026

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1 Introduction

> "[I]f unemployment is relatively painless, we have no puzzle to solve; there is no problem to be politicized" — Schlozman and Verba (1979, 26)

Do adverse economic experiences increase the demand for social insurance? Influential accounts in political economy imply that people should increase their support for unemployment insurance when they lose their jobs (Iversen and Soskice 2001; Moene and Wallerstein 2001; Sinn 1995; Hacker, Rehm, and Schlesinger 2013). Yet empirical findings are inconsistent: some studies detect attitudinal shifts following job loss, while others find weak or null average effects (e.g., Jæger 2006; Margalit 2013; Stegmueller 2013). These results pose a core question for research on public support for social welfare: Who responds to economic shocks, and why?

I propose a psychological mechanism - *anxiety* - that helps connect job loss to insurance preferences. Classic work on unemployment emphasizes the importance of stress for motivating political responses to economic hardship, but past research has not made the connection to psychology explicit (Schlozman and Verba 1979). Psychologists have shown that anxiety causes people to perceive negative events as more consequential and to update their plans accordingly (Carver and Scheier 1998; McNaughton and Gray 2024). A natural implication is that anxiety should increase people's sense of economic vulnerability, and hence their desire for insurance, by making adverse labor market experiences feel more damaging. Research shows that people vary in how easily they become anxious (Corr, DeYoung, and McNaughton 2013; Inzlicht, Bartholow, and Hirsh 2015) and that these differences are highly stable from adolescence to old age (Nivard et al. 2015). Thus, I argue that job loss increases support for unemployment insurance mainly among those high in *trait anxiety*. Calm individuals, in contrast, are less moved. This framework preserves the central insights of the insurance model of social preferences - namely, that risk matters - but adds a psychological layer that helps explain why only some people respond to economic shocks.

I test these expectations using The American Panel Survey (TAPS), a nationally representative panel of American adults. To identify effects of unemployment on attitudes, I use a nonparametric difference-in-differences estimator using matching and propensity score refinement (Imai, Kim, and Wang 2023). This design addresses common violations of fixed-effects panel estimators when prior outcomes predict future treatment or past treatments affect current outcomes (Imai and Kim 2019). I examine support for unemployment insurance as the focal, targeted policy; I also probe spillovers to broader stances (e.g., guaranteed jobs, ideology).

Three results stand out. First, the average effect of job loss on support for insurance is indistinguishable from zero. Second, consistent with the theory, effects are highly heterogeneous: among respondents in the top quintile of trait anxiety, unemployment increases support for insurance by roughly twenty percentage points; among the less anxious, effects are near zero. Third, the moderation is specific: I find no consistent effects on guaranteed jobs and limited evidence of broader ideological shifts; moreover, unemployment does not alter trait anxiety, supporting its role as a stable moderator rather than a post-treatment mediator. Demographic and socioeconomic attributes (age, sex, race, education, income) do not account for the heterogeneity. These findings help to make sense of mixed results in previous work by showing that the effects of job loss on preferences are conditional (cf. Margalit 2019). Theoretically, they refine political economic models of welfare state support by showing that public demand for insurance depends not only on objective risk but also on predispositions that govern whether risk is *experienced* as requiring protection (cf. Hacker, Rehm, and Schlesinger 2013).

2 Risk, Unemployment, and Public Demand for Insurance

Canonical theories of the welfare state say that people favor social insurance when they face a higher lifetime risk of losing their income, whether due to skill specificity, precarious employment, or poor health (Iversen 2005; Moene and Wallerstein 2001; Rueda 2005; Sinn 1995). In this framework, citizens should support the welfare state when they feel vulnerable and reject the welfare state when they feel secure. Cross-sectional research supports this view. For example, people in precarious employment or with greater perceived job insecurity often express stronger support for unemployment benefits and other safety net programs (Cusack, Iversen, and Rehm 2006; Iversen and Soskice 2001; Rehm 2009; Rehm, Hacker, and Schlesinger 2012; Rueda and Stegmueller 2019). And macro-level studies show that societies with higher income risk and fewer sources of informal social insurance tend to have more generous welfare states (Gingrich and Ansell 2012; Scheve and Stasavage 2006). Building on these findings, scholars have argued that "economic shocks have the potential to powerfully influence support for policies designed to reduce economic insecurity" (Hacker, Rehm, and Schlesinger 2013, 25).

However, showing that economic shocks causally affects people's social preferences has proven difficult. It is true that people's experiences with unemployment strongly correlate with their support for unemployment benefits (Hacker, Rehm, and Schlesinger

2013). Yet, as scholars have noted, this evidence is not dispositive. If politics are passed down within families or communities, material conditions could correlate with politics without causing them (Langsæther, Evans, and O'Grady 2022; O'Grady 2019). Consistent with this argument, studies that use panel data to identify within-person associations find much weaker associations between risk and insurance preferences. Some studies find that people respond to job loss by increasing their support for redistribution and social welfare (Emmenegger, Marx, and Schraff 2015; Margalit 2013; Martén 2019; Naumann, Buss, and Bähr 2016; Owens and Pedulla 2014), but others do not (Jæger 2006; Stegmueller 2013). More generally, research has shown that support for social welfare policy varies widely even among those with objectively similar levels of wealth, skills, and employment prospects (Rueda and Stegmueller 2019). This heterogeneity is difficult to reconcile with purely economic models of social preferences.

Some evidence suggests that the aggregate association between unemployment and insurance preferences is driven by a small but responsive minority (Margalit 2013, 2019). Existing theories would predict that this minority is the most economically precarious. However, studies that check whether responses to job loss depend on prior labor market experiences and expectations also yield mixed results (Alt, Barfort, and Lassen 2018; Margalit 2013; Wiertz and Rodon 2021). Thus, despite growing research in this area, there is little consensus on what might explain the variation between studies in the presence of unemployment effects, their magnitude, or the significance of moderators. In particular, the moderating effects of prior economic hardship remain elusive (Hacker, Rehm, and Schlesinger 2013; Margalit 2013; Schlozman and Verba 1979; Wiertz and Rodon 2021). In the following section, I lay out a theory of political responses to economic shocks that emphasizes individual differences in psychological processes that affect how people process and respond to negatively valenced information.

3 The Role of Anxiety

During the past few decades, political scientists have increasingly turned to the study of emotions to understand how people respond to information and make political decisions (Gadarian and Brader 2023; Neuman et al. 2007). Emotions are mental states that prepare the mind and body to accomplish goals by altering how we think and act in response to stimuli (Panksepp 1998). For example, when fear is active, people are more likely to scan their surroundings for possible threats and interpret ambiguous stimuli as threatening; at the same time, they are less likely to think about other goals such as food or sex. Researchers often invoke emotional processes to explain how people translate information into political attitudes and behaviors (Huddy, Feldman, and Cassese 2007; Marcus, Neuman, and MacKuen 2000).[1] Schlozman and Verba (1979) hint at the utility of this approach in studying responses to unemployment, arguing that people must perceive job loss as stressful for it to warrant a political response. However, while the idea that stress compels people to respond to economic shocks makes intuitive sense, this connection has not been developed theoretically.

When a person loses their job, they often do not know how long their unemployment will last, what its material impact will be, or whether they will lose another job in the future. Faced with this uncertainty, they must assess how vulnerable they are to future economic risks. Hacker, Rehm, and Schlesinger (2013) show that people's expectations of suffering economic setbacks in the future are related to how much they have struggled economically in the past. As these authors argue, experiencing job loss can "teach seminal 'lessons' about the prevalence and impact of economic instability that can shape expectations about the need for government help in the future" (2013, 25). However, their results also show that this relationship is not perfect. Although some people interpret job loss as important and damaging, others remain relatively optimistic (see also Margalit 2013; Schlozman and Verba 1979). These heterogeneous appraisals are likely shaped by anxiety. Anxiety's primary function is to increase the motivational salience of failure and harm, thereby spurring us to update our plans (Carver and Scheier 1998; McNaughton and Gray 2024). Therefore, losing a job should cause an anxious person to feel more vulnerable to future hardship and to anticipate that future hardship will be more painful than if they were less anxious.

One difficulty in testing this theory is that anxiety after job loss will partly reflect conscious appraisals, such as how good the job was, how difficult it will be to find a job of similar quality, and how far one's resources will stretch in the meantime (Hacker, Rehm, and Schlesinger 2013; Schlozman and Verba 1979). If people consciously choose how to respond to unemployment based on the severity of their circumstances,

[1] An influential paradigm in political psychology argues that anxiety causes people to rely less on existing beliefs and biases to make decisions (e.g., Brader 2006; MacKuen et al. 2010; Marcus et al. 2019; Valentino et al. 2008). However, a recent meta-analysis finds no evidence that experimentally induced anxiety increases the extent of information search (Funck and Lau 2024). This development suggests an alternative interpretation of the psychology literature: Rather than motivating a wider search for information and less biased cognitive processing, anxiety may simply increase the motivational salience of the aversive stimulus that sparked it. Consistent with this view, Gadarian and Albertson (2014) find that reading a threatening article about immigrants causes people to seek out and agree with other threatening articles about immigrants, but not non-threatening articles (see also Albertson and Gadarian 2015).

then the relationship between anxiety and updating could be spurious (cf. Ladd and Lenz 2008, 2011). However, this critique can be addressed by shifting focus away from the mediating role of within-person fluctuations in anxiety and instead focusing on the moderating role of stable individual differences in anxiety sensitivity. Unlike the level of anxiety that a person experiences from moment to moment, between-person differences in anxiousness that persist over a given period of time are unlikely to be downstream of within-person changes in material circumstances *during* that period of time. These stable differences in anxiety could still be endogenous to past economic hardship, but existing research finds that job loss does not increase the personality trait *neuroticism*, of which anxiety is a major component (Anger, Camehl, and Peter 2017; Boyce et al. 2015). Additionally, I test for endogeneity in a later section and find that job loss does not affect trait anxiety.

The literature on emotions and politics has largely treated anxiety as a product of situations and experiences rather than predispositions (for exceptions, see MacKuen et al. 2010; Marcus et al. 1995; Settle et al. 2017; Wolak and Marcus 2007). However, there is extensive evidence that people differ in the strength of negative feedback required to trigger anxiety and the intensity of anxiety responses to a given stimulus (Corr, DeYoung, and McNaughton 2013; Fowles 2001; Inzlicht, Bartholow, and Hirsh 2015; McNaughton and Gray 2024). In Appendix A, I report the results of a survey experiment testing whether people with higher levels of trait anxiety are more likely to feel vulnerable in response to stress. I measure trait anxiety at the beginning of the survey using the NEO PI-R Neuroticism-Anxiety facet scale (Costa Jr. and McCrae 1992). I induce stress by asking people to write about stressful (versus relaxing) memories. And I measure subjective vulnerability using a Likert item that asks "When it comes to your overall wellbeing, how secure or vulnerable do you feel?" The survey was fielded to a nationally representative sample by Bovitz in February 2025 ($N = 1,020$). Trait anxiety did not significantly moderate the treatment effect in an ordered probit model ($p = 0.176$). However, my quantity of interest is not the interaction term, but the treatment effect conditional on trait anxiety (King, Tomz, and Wittenberg 2000). To obtain this quantity of interest, I calculate first differences between treatment and control in the predicted probability of feeling vulnerable (versus feeling secure) for each respondent at each observed level of trait anxiety, averaging to obtain average marginal effects (Hanmer and Ozan Kalkan 2013). I show the results in Figure 1: People with low levels of trait anxiety are not affected by the anxiety induction, whereas the induction increased feelings of vulnerability among people with high levels of trait anxiety by 10 percentage points.

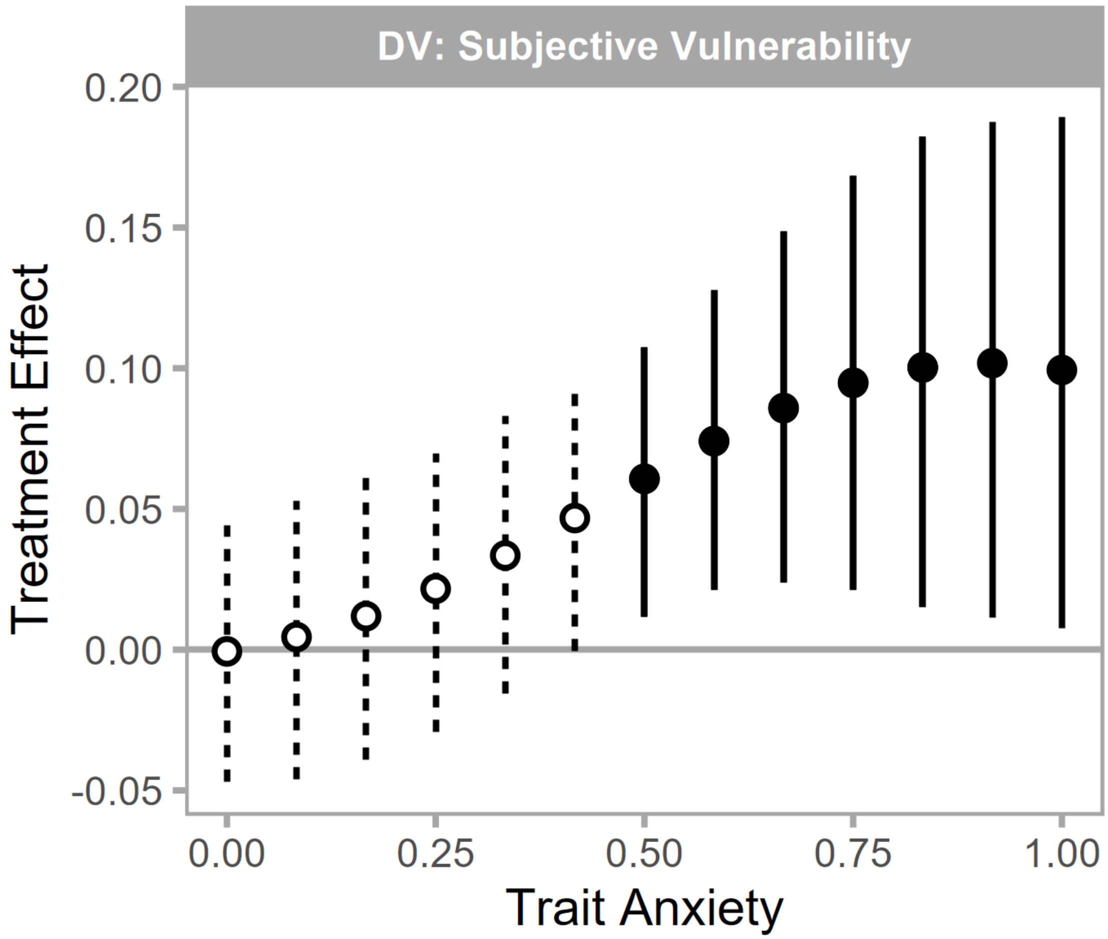

Figure 1: Anxiety induction increases feelings of vulnerability among people high in trait anxiety. *Note*: Estimates are average marginal effects of anxiety induction from an ordered probit regression (Hanmer and Ozan Kalkan 2013). The regression includes controls for all pairwise interactions between treatment and age, gender, race, education, income, and political interest (Blackwell and Olson 2022). Point estimates are direct transformations of maximum likelihood coefficients (Rainey 2024) and 95% confidence intervals are obtained using simulation (Gelman and Hill 2007).

4 Hypotheses

Based on the discussion above, I predict the following:

> Job loss will cause people with high levels of trait anxiety to increase their support for unemployment insurance, whereas job loss will have smaller or no effects on people with low levels of trait anxiety.

I focus on unemployment insurance because it provides a direct benefit to the unemployed and already operates in the United States, making the question more concrete than asking about a hypothetical program. It is less clear what to expect for hypothetical policies that are asked in surveys but with which citizens have no first-hand experience. For example, surveys often ask whether the government should guarantee every citizen a job. This idea should appeal to the unemployed. But it is also a relatively extreme example of government involvement in the economy that could strike otherwise sympathetic Americans as reminiscent of socialism (McCall 2013; McClosky and Zaller 1984). Moreover, there have been no serious attempts to provide universal employment in the US since the Works Progress Administration and the Civilian Conservation Corps were dissolved in the early 1940s (Tymoigne 2013). This lack of recent policy action may have made Americans skeptical that guaranteed employment is practical, much less a solution to their current unemployment. In contrast, many Americans will have directly benefited from unemployment insurance at some point before completing our surveys.

Although I mainly focus on support for unemployment insurance, some studies suggest that unemployment causes people to identify more with the political left (Wiertz and Rodon 2021). The psychological model laid out above suggests that this effect could be moderated by trait anxiety. If anxious people experience unemployment as dealing an especially large blow to their economic prospects, they may update in favor of political coalitions that lobby on behalf of the economically disadvantaged (i.e., liberals, Democrats).

5 Data and Methods

5.1 Data

I test my hypotheses using data from the American Panel Survey (TAPS). TAPS is a monthly internet survey that was fielded to a national probability sample of American adults between 2011 and 2018. TAPS panelists were recruited through a random stratified sampling process applied to the U.S. Postal Service's record of physical addresses, with fresh respondents added over time to compensate for attrition. In total, TAPS interviewed 4,200 people. I focus on 2,412 people who completed the relevant anxiety item at least once. TAPS provided panelists with free computers and internet access to ensure that economic constraints did not pose a barrier to participation.

5.2 Measurement

Unemployment. I measure job loss with items that ask panelists to pick one or more categories that describe their current employment status. I code panelists who indicate that they are (a) currently working for pay or (b) outside of the labor market – listing their occupations as homemaker, student, retiree, or permanently disabled – as untreated for that wave. I code people who indicate that they are neither working for pay nor in one of the above categories as treated for that wave. A drawback of this approach to measurement is that it lumps together instances where people are laid off or fired and instances where people quit their job voluntarily. However, to the extent that the switches from control to treatment are actually instances of voluntary quitting, this should depress both the overall effect of unemployment and the moderating role of anxiety. Voluntarily leaving a job suggests that a person is not concerned about running out of money in the short term and is reasonably confident that they will find other work in the long term. And the fact that this decision and its timing are planned means that anxiety should be less important, since it specifically motivates updating in response to unplanned events.

Outcome Variables. I measure support for unemployment insurance using an item that asks "Do you think it should be the government's responsibility to provide a decent standard of living for the unemployed?", to which panelists responded that it 'Definitely Should Be', 'Probably Should Be', 'Probably Should Not Be' or 'Definitely Should Not Be'. In Appendix D, I check whether unemployment affects support for guaranteed jobs, ideological identification, and partisan identification. Details of how these variables are measured are in Table D1. In the same section, I also use all available policy items to check whether unemployment shifts attitudes toward irrelevant policies. The exact wordings of these items are also provided in Table D1. I discuss the results for these alternative outcome variables below.

Personality. To measure trait anxiety, I use a an item from the Ten Item Personality Inventory (TIPI; Gosling, Rentfrow, and Swann Jr. 2003) that asks whether the respondent sees themselves as "Anxious, easily upset". Panelists answered on a seven-point scale ranging from "disagree strongly" to "agree strongly". In Appendix F, I check whether the broader trait of neuroticism, measured using the anxiety item and another (reverse-coded) item - "Calm, emotionally stable" - yields similar results. I also check whether the other four Big Five personality traits measured by the TIPI predict heterogeneity in the effect of job loss (John and Srivastava 1999). I discuss these results below. The TIPI was fielded nine times in TAPS between 2012 and 2016. For a detailed description of the structure of TAPS, see Appendix B.

5.2.1 Measuring Stable Individual Differences in Trait Anxiety

Research has shown that responses to anxiety-related personality items are influenced by chronic individual differences in anxiety sensitivity (Corr, DeYoung, and McNaughton 2013; Inzlicht, Bartholow, and Hirsh 2015). However, these responses are also affected by measurement error and daily fluctuations in people's emotional states. To get at the underlying trait, I use the TIPI anxiety item to estimate a Trait-State-Error (TSE) model (Kenny and Zautra 1995, 2001). Intuitively, this model can be thought of as saying that personality fluctuates around stable person-specific set points (Lykken and Tellegen 1996), where the set points represent people's thresholds for experiencing anxiety in response to stressors. Formally, the TSE model for individual $i \in [1, N]$ is

$$\begin{cases} y_{it} = T_i + O_{it} + \delta_{it}, & T_i \sim \mathcal{N}(\mu_T, \sigma_T^2), \quad \delta_{it} \sim \mathcal{N}(0, \sigma_\delta^2), \quad t = 1, \ldots, T, \\ O_{it} = \beta\, O_{i,t-1} + \varepsilon_{it}, & \varepsilon_{it} \sim \mathcal{N}(0, \sigma_\varepsilon^2), \quad t = 2, \ldots, T, \\ O_{i1} \sim \mathcal{N}(0, \sigma_O^2), & \rho_{O_{i1}, T_i} = 0. \end{cases} \tag{1}$$

where y_{it} is an observed response to the TIPI anxiety item, T_i is the time-invariant component of an individual's latent trait anxiety, O_{it} is the time-varying component of an individual's latent trait anxiety, and δ_{it} is random measurement error. In all but the first time period, O_{it} is a function of the individual's time-varying component at the previous time point ($O_{i,t-1}$) and a residual (ε_{it}). O_{i1} is exogenous. Lastly, β captures the degree of persistence in temporal fluctuations from one time to the next; I allow this parameter to vary to accommodate uneven intervals between TIPI administrations.

I estimate the TSE model using full information maximum likelihood in the `R` package `lavaan` (Rosseel 2012). The post-stratification sampling weights included in the public TAPS release are applied to ensure that the data approximate the characteristics of the US adult population. The TSE model displays an excellent fit (χ^2_{scaled}/df = 102788.842/25; $RMSEA_{robust}$ = .041; CFI_{robust} = .987; TLI_{robust} = .985; $SRMR$ = .048). Using the fitted TSE model, I obtain predicted values of stable trait anxiety for 2,412 TAPS panelists who completed the TIPI anxiety item at least once. For convenience, I omit the adjective 'stable' and refer to these scores simply as "trait anxiety" In Appendix C, I show that these stable individual differences account for approximately 40% of the variance in the TIPI anxiety item, with an additional 15% attributable to somewhat stable differences and the remainder attributable to wave-specific differences and error.

I report correlations between trait anxiety and a variety of demographic and socioeconomic characteristics in Table 1. The results are encouraging for my argument that trait anxiety is minimally endogenous to socioeconomic status. Most of the correlations are smaller than 0.1 and all but one - between trait anxiety and political interest - are smaller than 0.2. That said, people with higher levels of trait anxiety do tend to be younger, female, less educated, lower income, more likely to be unemployed, less likely to own a home, more likely to rent, less likely to be married, and less interested in politics. Although substantively small, these correlations could add up to explain apparent effects of trait anxiety. To address this possibility, I test whether these variables moderate the effects of job loss below. In general, I find that these demographic and socioeconomic characteristics do not moderate the effects of job loss. Those that do do not correlate closely enough with trait anxiety to explain much confounding.

5.3 A Matching Approach to Identifying Causal Effects of Unemployment

Studies examining the effect of job loss on political attitudes have used a wide array of methods, including lagged dependent variables, fixed effects, random effects, and first differences (Alt, Barfort, and Lassen 2018; Jæger 2006; Margalit 2013; Martén 2019; Naumann, Buss, and Bähr 2016; Owens and Pedulla 2014; Stegmueller 2013; Wiertz and Rodon 2021). Although these methods are preferable to cross-sectional analysis, they all rely on strong assumptions that are often violated in practice (Feldman et al. 2025; Imai and Kim 2019). To address the limitations of conventional panel data estimators, I use a nonparametric matching approach proposed by Imai, Kim, and Wang (2023; hereafter IKW). This method works by assembling a synthetic counterfactual outcome for each treated unit and calculating difference-in-differences within these matched sets. Specifically, for each unit i that is treated at time t and untreated at time $t-1$, the method identifies a set of control units i' that are untreated at both t and $t-1$ and share the same treatment history as i over the prior L waves. Once these matched sets are identified, they are refined to improve covariate balance between the treated unit and control units. Following IKW, covariate balancing propensity scores (CBPS; Imai and Ratkovic 2014) are used to assign greater weight

Table 1: Correlations between Trait Anxiety and Covariates

	r/ρ	p	n
Age	-.133	.000	2,366
Male	-.053	.009	2,412
Black	-.087	.000	2,412
Hispanic	.007	.740	2,412
Other Race	-.013	.535	2,412
Religious Attendance	-.072	.001	2,176
Education	-.116	.000	2,397
Household Income	-.134	.000	2,283
Own Home	-.137	.000	2,385
Renting	.131	.000	2,385
Occupy w/out Payment	.027	.192	2,385
Married	-.049	.021	2,181
Separated	.006	.771	2,181
Widowed	-.078	.000	2,181
Have Child Under 18	.013	.552	2,176
Homemaker	.021	.337	2,145
Retired	-.079	.000	2,145
Student	.008	.703	2,145
Disabled	.102	.000	2,145
Unemployed	.045	.035	2,145
Ideology (Liberal)	.013	.541	2,218
Party ID (Democratic)	.043	.081	1,644
Political Interest	-.208	.000	2,397

Note: Entries are correlations between covariates and trait anxiety with p-values and the number of valid observations used in estimation. For continuous and binary covariates, entries are Pearson product-moment/point-biserial correlations. For ordinal variables, entries are Spearman's rank correlations. Covariate data are from recruitment interviews completed before joining the TAPS panel.

to control units that more closely resemble the treated unit in observed characteristics that predict selection into unemployment. These characteristics include both time-varying and time-invariant variables such as age, gender, race, religious attendance, education, income, homeownership, marital status, whether the respondent has children, political ideology, partisanship, and political interest. After weighting, difference-in-differences are computed within each matched set such that the weighted average change in the outcome variable for units i' from time $t-1$ to time t is subtracted from the change in the outcome variable for unit i from time $t-1$ to time t. Finally, these individual estimated treatment effects are averaged across sets to yield the average treatment effect on the treated (ATT).

In theory, this matching estimator can recover causal estimates of the effects of unemployment by conditioning on treatment, covariate, and outcome histories. In practice, we cannot know whether these conditioning variables have captured all relevant confounders. Therefore, IKW rely on a modified version of the parallel trend assumption for identification. The assumption is that, had a treated unit remained untreated through time t, its outcome would have exhibited the same change from $t-1$ to t as the control, conditional on treatment, outcome, and covariate histories (Imai, Kim, and Wang 2023, 594, equation 10). This means that the characteristics that could cause a person to both lose their job and change their attitudes *cannot differ* in absolute levels or in trajectories between the person who lost their job and the weighted average of the people who had the same unemployment history and kept their jobs. The plausibility of this assumption hinges on whether the outcome variables and time-varying covariates exhibit similar trajectories among the treated and control units within each weighted matched set in the lead-up to the treatment period. Another factor that affects the plausibility of this assumption is whether time-invariant covariates differ significantly between treatment and control, since these differences could also be confounded with the treatment.

I construct matched sets using the `R` package `PanelMatch` (Rauh, Kim, and Imai 2025). I specify an L value of four, meaning that each treated unit is matched with control units that share the same employment history over the previous four waves. As Imai and colleagues note, there is not one correct lag value (Imai, Kim, and Wang 2023; Rauh, Kim, and Imai 2025). Larger values of L correspond to more waves of data used for matching, but fewer waves of data used for estimation. The unemployment insurance item can only accommodate up to four lags (see Figure 2). Therefore, I use $L = 4$ to minimize bias, though at the cost of decreased efficiency. After assembling the matched sets, I apply CBPS weights to the control units. These weights are generated using a broad range of potential confounders: age, gender, race, religious

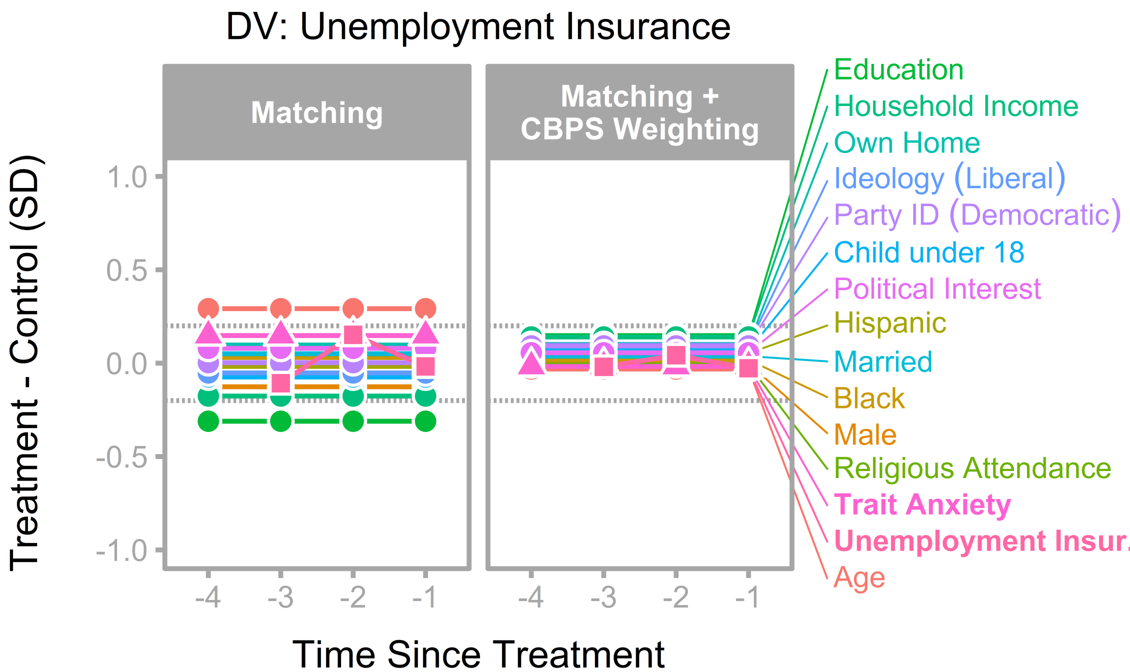

Figure 2: Covariate balance between treated and control units with and without weighting. Note: CBPS = Covariate Balancing Propensity Score. Covariate imbalances are shown as circles, outcome variable imbalances are shown as squares, and trait anxiety imbalances are shown as triangles. Dotted lines indicate 0.2 standard deviation imbalances.

attendance, education, household income, home ownership, marital status, presence of children in the household, political ideology, partisan identification, political interest, lagged values of the outcome variable, and trait anxiety scores.

To check whether the conditional parallel trend assumption is supported for the unemployment insurance item, I plot the standardized mean differences between treated units and their matched controls, both before and after applying CBPS weights to the matched sets, in Figure 2. As a rule of thumb, Imai and colleagues suggest that covariate imbalances should not exceed 0.2 standard deviations (Rauh, Kim, and Imai 2025). According to this criterion, the results in Figure 2 show that CBPS weighting successfully balanced the treated and control units on all observed covariates and lagged outcomes. Of particular importance are the squares indicating pretreatment trends in support for unemployment insurance. The weighted trend line is relatively flat and within 0.2 standard deviations of zero, indicating that the modified parallel trend assumption is met. Also notable are the triangles indicating that the treated and control units have comparable levels of trait anxiety after weighting. This is an important pre-requisite for the moderation analyses that I will conduct later.

6 Does Unemployment Increase Support for Unemployment Insurance?

I begin my analysis by estimating the the average treatment effect among the treated (ATT) for unemployment insurance. Using the `R` package `PanelMatch` (Rauh, Kim, and Imai 2025), I estimate an ATT at time t – the period when the treated unit enters treatment – as well as placebo ATTs at times $t-2$, $t-3$, and $t-4$. These placebo estimates serve as pre-trend checks: under the identifying assumptions, they should be statistically indistinguishable from zero, indicating no anticipatory or differential trends prior to treatment. Because the difference-in-differences at time t are taken with respect to the last untreated period $t-1$, placebos are reported with respect to $t-1$ from $t-2$ and earlier.

ATTs are plotted in Figure 3. All estimates are plotted with 95% confidence intervals, generated via block bootstrap to account for within-unit time dependence. The results show that unemployment did not cause average shifts among Americans who lost their jobs (null-centered p-value = 0.171). One potential explanation for this is that the assumptions of the fixed-effects regressions used in these studies are violated. Fixed effects regressions are biased when past results influence the probability of being treated at time t or when past treatments affect outcomes at time t, whereas the matching estimator used here can accommodate both of these scenarios (Imai and Kim 2019). Research suggests that both of these assumptions could be violated in the case of unemployment and politics; the former because changes in political attitudes are downstream of values that also influence selection into occupations (Ares and van Ditmars 2025), and the latter because prior job losses can have a cumulative effect on future risk tolerance (Hacker, Rehm, and Schlesinger 2013).

7 Does Trait Anxiety Moderate Political Responses?

To test whether trait anxiety moderates the effects of unemployment, I estimate conditional average treatment effects on the treated (CATT) stratifying by trait anxiety quintile.[2] In Figure 2, I showed that CBPS weighting successfully balanced the matched sets on trait anxiety. Because each treated unit already resembles the

[2]Currently, the `PanelMatch` package can only accommodate categorical moderators (Rauh, Kim, and Imai 2025).

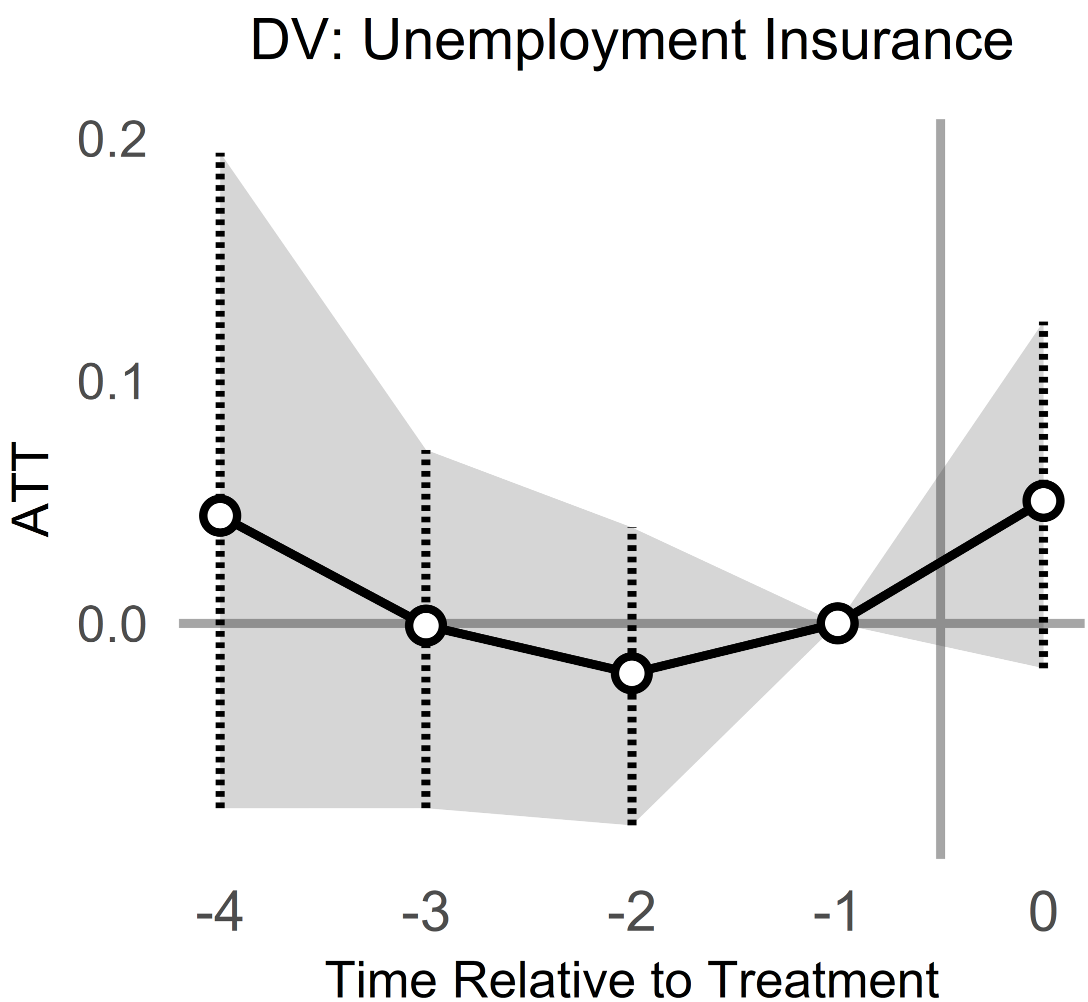

Figure 3: Causal effect of unemployment on support for unemployment insurance. Point estimates are average treatment effects on the treated (ATTs) with block bootstrapped 95% confidence intervals. The vertical gray line separates the pre-treatment periods (to the left) and the treatment period (to the right).

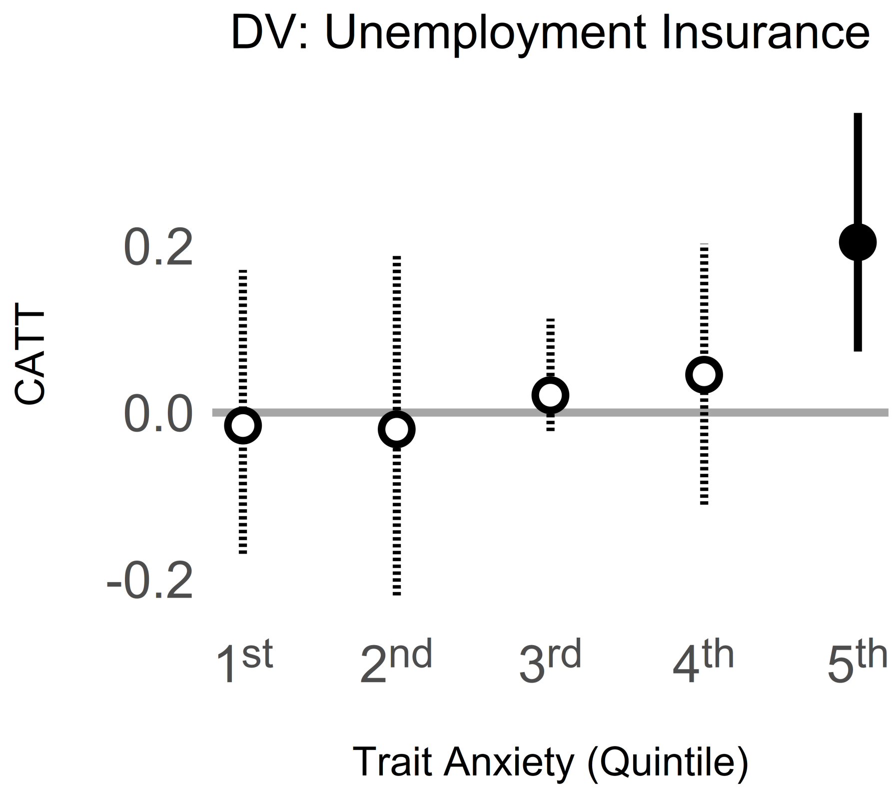

Figure 4: Trait anxiety predicts heterogeneity in the effects of unemployment. Point estimates are conditional average treatment effects on the treated (CATTs) at time t with block bootstrapped 95% confidence intervals. Alternative binning schemes are in Figure E1

control on trait anxiety, I can estimate conditional effects within bins defined by the treated units' trait anxiety scores. I report these results in Figure 4. To conserve space, I plot only the CATTs for time t. As in Figure 3, I report block-bootstrapped 95% confidence intervals.

According to my theory, job loss should cause people with high trait anxiety to update in favor of unemployment insurance. The results in Figure 4 show that they do. For the least anxious 80% of Americans, job loss has no effect on policy preferences. But among the most anxious 20% of Americans, job loss causes a 20.45 p.p. increase in support for unemployment insurance (CI = 7.54, 36.59). In substantive terms, this is like moving 60% of the way from answering "probably should not be" to "probably should be" in response to the question "Do you think it should be the government's responsibility to provide a decent standard of living for the unemployed?" In Appendix E, I show that these results are robust to dividing trait anxiety into two, three, four, six, or seven equally sized groups. In each case, Americans in the highest anxiety group shift by approximately 20 p.p. (Figure E1).[3] In Appendix F, I check whether the Big Five personality traits produce similar results (John and Srivastava 1999). Neuroticism shows a similar, albeit weaker pattern of moderation. This is a predictable result; neuroticism lumps anxiety with emotional volatility, which is less relevant for perceptions of vulnerability and avoidance of harm (Panish and Delton 2025). None of the other Big Five traits consistently moderate the effects of unemployment (Figure F1).

In Appendix D, I test whether trait anxiety moderates the effects of job loss on fourteen alternative political outcome variables. Thirteen of these tests produce null results or are uninterpretable due to failed placebo tests. In particular, I find that job loss has no effect on support for guaranteed jobs at any level of trait anxiety. As discussed above, there are several reasons why guaranteed jobs may not be as appealing a solution to unemployment as direct aid. In the United States, there is already a working system for providing aid to the unemployed, whereas the idea of universal employment has mostly disappeared from American politics since the New Deal (Tymoigne 2013). This lack of recent policy action may have made Americans skeptical that guaranteed employment is practical or even possible. In contrast, many unemployed Americans will have directly benefited from unemployment insurance by the time they complete the survey. Survey research also shows that Americans tend not to support government involvement in the economy that goes beyond providing a basic social safety net (McCall 2013).

In contrast, I do find that job loss causes people in the top quintile of trait anxiety to identify as more liberal by 17.82 p.p. (CI = 2.51, 34.24). Why should job loss affect ideological identification but not partisan identification? One possibility is that this result is driven by a subset of Americans whom Ellis and Stimson (2012) call 'conflicted conservatives', people who generally like the idea of social welfare programs but who associate the 'liberal' label with libertinism and lawlessness. These Americans' resistance to calling themselves liberal may ebb when their mind is on economic rather than cultural or racial issues. In contrast, partisan identities are less susceptible to this kind of framing (Green, Palmquist, and Schickler 2002).

These analyses show that the effects of unemployment are often stronger among people with higher levels of trait anxiety. However, this does not prove that trait anxiety

[3] However, all subgroups fail one or more placebo tests when splitting trait anxiety into more than six bins (Figure E1).

causes these effects (Bansak 2021). Other variables that are correlated with anxiety, such as income, gender, or political interest, could be their true drivers. Although I cannot entirely rule out this possibility with observational data, one step that I can take is to check whether these potential confounders produce similar patterns of conditional effects. If they do not, this provides some circumstantial evidence in favor of my argument that trait anxiety causes, rather than merely predicts, heterogeneity in the effects of unemployment. I check for similar patterns of moderation across eight variables that correlate with trait anxiety in Table 1: age, gender, race, education, household income, political interest, ideology, and party identification. As with the CATTs reported in Figure 5, it is straightforward to estimate conditional effects because the matched sets are already balanced on the relevant variables.

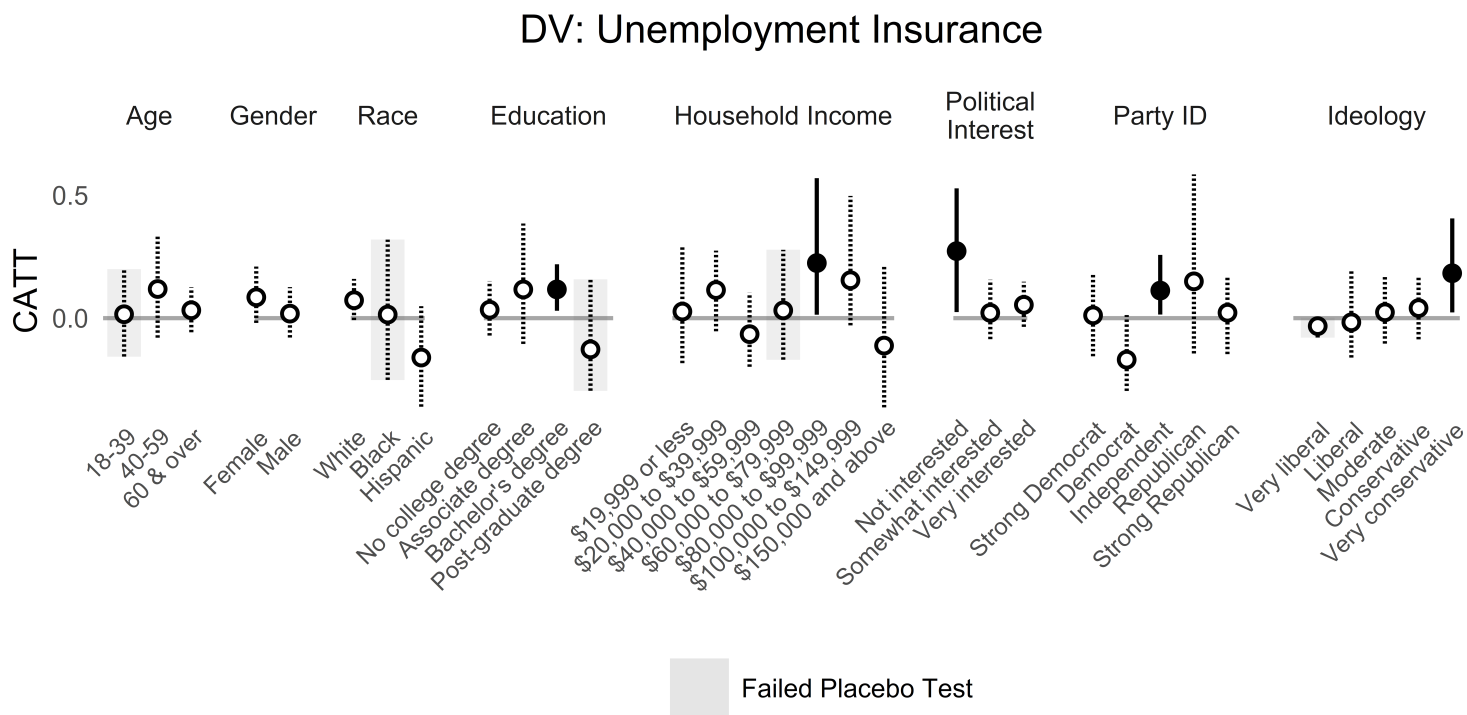

Figure 5: Alternative moderators. Point estimates are conditional average treatment effects on the treated (CATTs) with block bootstrapped 95% confidence intervals. The vertical gray lines separate the pre-treatment periods (to the left) and the treatment period (to the right). Shaded gray areas around point estimates indicate that one or more placebo tests failed for this CATT, suggesting that identifying assumptions are violated.

The results are shown in Figure 5. The effects of job loss on support for unemployment insurance are not moderated by age, gender, race. However, I find moderation by education, income, political interest, partisan identification, and ideology. Groups that are more likely to update include Bachelor's degree holders, those with annual household incomes between \$80,000 and \$99,999, the politically disinterested, Independents, and the very conservative. These results are somewhat consistent with previous studies, which found that Republicans, Independents, and right-wing identifiers responded more to job loss (Margalit 2013; Wiertz and Rodon 2021).[4] One reason for this pattern could be that the most extreme conservatives simply have more room to update in favor of left-wing policy than others. As Margalit (2013, 98-99) notes, a complementary explanation is that liberals who oppose social welfare programs must be particularly committed to these views if they have resisted the pressure to conform to liberal norms. In contrast, some people who identify as conservatives do so for non-economic reasons, so their stances on social welfare may be more malleable (see also Ellis and Stimson 2012).

While interesting, these results cannot explain the heterogeneity by trait anxiety shown in Figure 5. Bachelor's degree holders and those earning \$80,000 and \$99,999 per year are *less* likely to have trait anxiety scores in the top quintile (BA: $b = -0.025$, p = 0.003; 80k-99k: $b = -0.025$, p = 0.000), and neither Independents nor extreme conservatives are any higher or lower in trait anxiety than the average American (Independent: $b = -0.001$, p = 0.862; Very Conservative: $b = -0.001$, p = 0.881). However, the positive result for political interest could be an issue.[5] People who do not care about politics are more likely to score in the top quintile of trait anxiety ($b = 0.117$, p = 0.000). Could this mean that the apparent effect of trait anxiety is actually due to political disinterest? Probably not. Only 1.37% of the variance in belonging to the top quintile of trait anxiety is explained by membership in the lowest political interest group. Thus, while the effect of trait anxiety may be slightly inflated by anxious people's lack of interest in politics, it is unlikely that this will explain all or even most of the moderation. Why then should politically disinterested people respond so strongly to unemployment? At first, this might seem counterintuitive – shouldn't the most politically engaged be the first to connect their material circumstances to politics? In fact, research suggests that the opposite is true. Johnston, Lavine, and Federico (2017, 200-210) show that politically engaged

[4]Margalit (2013) reports in a footnote that conservative identifiers also shift more than liberal identifiers.

[5]In fact, political interest is the strongest moderator analyzed here. Whereas people who are more than minimally interested in politics do not respond to job loss, those who profess no interest respond by increasing their support for unemployment insurance by 27.28 p.p. (CI = 2.44, 52.79).

people are especially likely to prioritize symbolic, identity-based concerns rather than concrete benefits when evaluating policy.

8 Do Economic Shocks Increase Trait Anxiety?

So far I have focused on testing whether stable differences in trait anxiety moderate the effects of unemployment on political attitudes. However, recent work that focuses on within-person change raises the possibility that economic shocks themselves can influence personality traits (e.g., Mehra, Stopnitzky, and Alloush 2023). Thus, readers may question whether stable differences in trait anxiety are endogenous to prior unemployment. This is an important concern to address; if these prior, unobserved shocks are correlated with later shocks, then trait anxiety may be endogenous. In the worst-case scenario, stable differences in trait anxiety could be a mere index of past adversity that shapes political responses through nonemotional pathways.

To check whether trait anxiety is endogenous to unemployment, I switch from analyzing stable between-person differences in trait anxiety to analyzing within-person change. Using the IKW matching estimator, I first construct matched sets and refine them using CBPS weights generated from demographic and socioeconomic covariates, stable trait anxiety, and lagged values of time-varying trait anxiety. Unemployment and personality are only measured in close proximity four times, so I use the maximum feasible lag value of three. Otherwise, all specifications are the same as for the main results. As in the main analysis, I estimate difference-in-differences across the matched sets and aggregate them to produce ATTs, obtaining confidence intervals via block bootstrap. The results, plotted in Figure 6, show that unemployment does not influence trait anxiety. This may seem surprising given the popular intuition that adverse life events leave a mark on people's personalities. In fact, these null results are consistent with existing work that finds no effects of job loss on neuroticism, which encompasses trait anxiety (Anger, Camehl, and Peter 2017; Boyce et al. 2015).

9 Conclusion

Do people respond to economic shocks by changing their minds about policy? According to my results, the answer depends on whether these people are predisposed to become anxious. For most citizens, one spell of unemployment is apparently not enough to change minds. But for Americans high in trait anxiety, losing a job spurs a re-evaluation of where they stand on government aid for the unemployed. Interestingly, the type of factors that existing work argues should motivate political

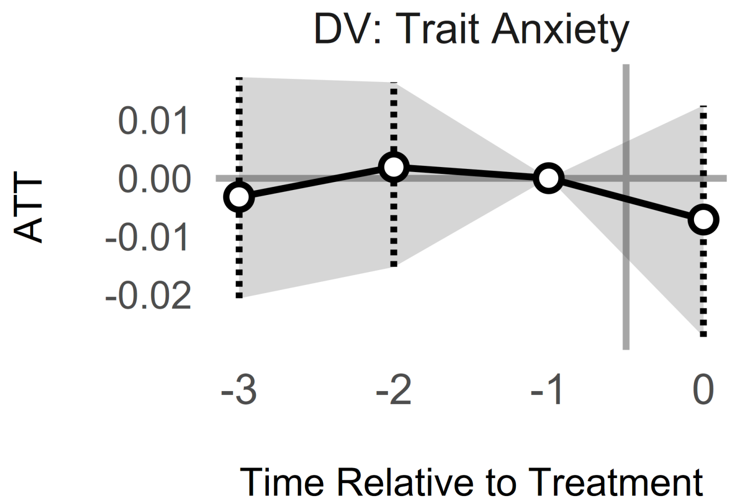

Figure 6: Job loss does not influence trait anxiety. Point estimates are ATTs with block bootstrapped 95% confidence intervals.

responses to unemployment, namely lower levels of education and income, do not predict sensitivity to shocks. Also notable is that those who did not express an interest in politics were more likely to respond politically to unemployment, consistent with work that argues that the politically engaged place less importance on material self-interest (Johnston, Lavine, and Federico 2017).

What do my results say about the theory that people support the welfare state because it insures them against economic risk (Iversen and Soskice 2001; Moene and Wallerstein 2001; Rehm 2009)? Contrary to a version of this theory that focuses exclusively on objective economic risk, I do not find an aggregate effect of job loss on support for unemployment insurance. Nor do I find that citizens' reactions to unemployment are shaped by existing economic risk as proxied by low levels of income and education. However, my results are consistent with a version of this theory that allows citizens' perceptions of risk to depart from their objective risk. They suggest that insurance preferences are not directly affected by objective risk, but by the interaction between objective risk and chronic sensitivity to anxiety. This finding helps reconcile the mixed evidence on whether job loss increases demand for unemployment insurance. More broadly, it suggests that emotions are an important source of public support for the welfare state.

My results also have implications for debates about the role of self-interest in public opinion (Sears et al. 1980; Citrin and Green 1990; Weeden and Kurzban 2017). I found that job loss caused the most anxious Americans to become more supportive of unemployment insurance, but not guaranteed jobs, public healthcare, government spending, the minimum wage, or other social welfare policies (Figure D2). This supports the argument that the effect of self-interest on political attitudes is real but circumscribed, acting only in cases where policies directly affect people's bottom lines (Chong, Citrin, and Conley 2001). In this sense, my results complement previous studies showing that lottery winners are particularly opposed to the estate tax (Doherty, Gerber, and Green 2006); that the poor are particularly supportive of redistributive taxes (Franko, Tolbert, and Witko 2013); that entrepreneurs are particularly opposed to regulation (Broockman, Ferenstein, and Malhotra 2019); and that homeowners are particularly opposed to loosening local zoning restrictions (Marble and Nall 2021).

However, not all of my results fit neatly within this framework. In Appendix D, I found that job loss causes the most anxious Americans to identify as more liberal (Figure D2). This result goes against the idea that the effects of material self-interest do not bleed over into general ideological stances. One possibility is that this result is driven by Americans who are open to social welfare programs but identify as conservatives for non-economic reasons (Ellis and Stimson 2012). These Americans may become more comfortable with the "liberal" label when their mind is on economic rather than cultural or racial issues.

In summary, this paper shows that objective indices of economic risk play a less important role in shaping political responses to economic shocks than is often assumed. Instead, only anxious citizens are more likely to want unemployment insurance when they lose their job. This finding suggests that the effects of material circumstances on politics are real, but they do not always occur automatically. Emotions do the leg work of motivating people to respond to setbacks by asking for help.

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Online Appendix for "Who Wants Help?"

A Anxiety Induction Experiment

In February 2025, I conducted a survey experiment designed to test the hypothesized mechanism connecting adverse experiences to political responses (Stony Brook IRB Approval: IRB2025-00027). According to my theory, people high in trait anxiety should feel more vulnerable in response to negative stimuli, wheres people low in trait anxiety should be unaffected.

Experiment I use the Autobiographical Emotional Memory Task (AEMT) to activate anxiety, in accordance with recommendations for inducing emotional states in political psychology (Albertson and Gadarian 2017; Searles and Mattes 2015). Specifically, I use a modified version of the AEMT text from Young (2019). Respondents in the **treatment group** read the following prompts:

> Next we're going to ask you to do a bit of writing.
>
> [*new page*] What are three to five things that make you feel anxious? Please write two to three sentences about each.
>
> [*new page*] Please describe in detail the one situation that has made you the most anxious you have been in your life. Try to describe it such that a person reading what you wrote would become anxious just from hearing about the situation.

Respondents in the **control group** read the following prompts:

> Next we're going to ask you to do a bit of writing.
>
> [*new page*] What are three to five activities that you like to do to relax and unwind? Please write two to three sentences about each activity.
>
> [*new page*] Now we'd like you to pick one of these relaxing activities and describe it in more detail. Try to describe the activity such that a person reading what you wrote would feel relaxed just from hearing about it.

Dependent Variable. Afterwards, respondents answered questions about a morality and humanitarianism that I analyze in a different project. At the very end of the survey, respondents were asked

> When it comes to your overall wellbeing, how secure or vulnerable do you feel?
>
> 1. Very secure
> 2. Secure
> 3. Somewhat secure

4. Somewhat vulnerable
5. Vulnerable
6. Very vulnerable

I use responses to this item to test whether trait anxiety indexes the propensity to feel vulnerable in response to adverse experiences.

Moderator. I measured *trait anxiety* at the beginning of the survey using the NEO PI-R Neuroticism-Anxiety facet scale (Costa Jr. and McCrae 1992). Respondents read the instructions "How well do the following statements describe you?" followed by a series of statements:

> Worry about things.
>
> Fear for the worst.
>
> Am afraid of many things.
>
> Get stressed out easily.

They rated each statement on the following scale:

1. Doesn't describe me well at all
2. Doesn't describe me very well
3. Describes me somewhat well
4. Describes me very well

I average responses to these items to get trait anxiety scores.

Sample Characteristics and Response Quality: I field the survey to a nationally representative sample of Americans through Bovitz in during February 21-28, 2025. I included two items designed to screen inattentive respondents and bots:

> We care about the quality of our survey data. For us to get the most accurate measures of your opinions, it is important that you read the questions and text carefully and provide thoughtful answers to each question in this survey. Do you commit to providing thoughtful answers to the questions in this survey?
>
> 1. I can't promise either way
> 2. Yes I will
> 3. No I will not
>
> The following question is to verify that you are a real person. Which of the following is a vegetable?
>
> 1. Salmon

2. Broccoli
3. Hamburger
4. Milk
5. Cheese
6. Egg

I drop one respondent who answered "I can't promise either way" and one who answered "No I will not" to the first question. I also drop six respondents who answered "Hamburger" and two who answered "Milk" to the second question. Lastly, I drop an additional 11 respondents who did not complete the survey. After dropping these 19 respondents, my final sample size is 1,009.

Analysis: To test whether the anxiety induction increases feelings of vulnerability conditional on trait anxiety, I estimate an ordered probit regression. In Table A1, I present two models. In the first, I interact a binary treatment indicator with trait anxiety but include only the direct effects of the control variables (age, gender, race, education, income, political interest). In the second model, I interact the treatment indicator with each of the control variables to control for omitted interaction bias (Blackwell and Olson 2022).

Table A1: Anxiety Induction Experiment Results

	DV: Subjective Vulnerability			
	Est. (SE)	p	Est. (SE)	p
Age	0.005(0.002)	0.031	0.007(0.003)	0.028
Male	-0.055(0.069)	0.429	-0.060(0.099)	0.547
Black	-0.119(0.100)	0.235	-0.183(0.144)	0.205
Hispanic	0.043(0.103)	0.675	0.041(0.154)	0.793
Asian	0.097(0.153)	0.527	0.221(0.238)	0.352
Native American	-0.400(0.340)	0.239	-0.387(0.491)	0.431
Other Race	0.076(0.216)	0.723	0.009(0.301)	0.977
Education	-0.026(0.156)	0.867	-0.152(0.224)	0.498
Household Income	-0.682(0.126)	0.000	-0.615(0.176)	0.000
Political Interest	-0.154(0.108)	0.157	-0.213(0.152)	0.161
Trait Anxiety	2.015(0.195)	0.000	2.017(0.201)	0.000
Stress Induction	-0.011(0.147)	0.938	0.039(0.344)	0.909
Age × Induction			-0.004(0.005)	0.348
Male × Induction			0.013(0.139)	0.925
Black × Induction			0.120(0.200)	0.549
Hispanic × Induction			0.000(0.208)	1.000
Asian × Induction			-0.222(0.311)	0.476
Native American × Induction			-0.075(0.682)	0.913
Other Race × Induction			0.148(0.433)	0.733
Education × Induction			0.254(0.313)	0.418
Income × Induction			-0.140(0.251)	0.576
Political Interest × Induction			0.123(0.218)	0.571
Trait Anxiety × Induction	0.356(0.263)	0.176	0.327(0.286)	0.253
Very secure | Secure	-0.677(0.186)	0.000	-0.666(0.233)	0.004
Secure | Somewhat secure	0.381(0.185)	0.039	0.393(0.231)	0.088
Somewhat secure | Somewhat vulnerable	1.254(0.187)	0.000	1.268(0.233)	0.000
Somewhat vulnerable | Vulnerable	2.017(0.191)	0.000	2.032(0.236)	0.000
Vulnerable | Very vulnerable	2.673(0.197)	0.000	2.689(0.242)	0.000
N	1009		1009	

Note: Entries are unstandardized probit coefficients. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

B Panel Structure

Before analyzing the TAPS data, I first coded the panel to ensure that data on outcome variables were available to allow for placebo tests. Figure B1 shows the structure of the TAPS panel. Closed circles indicate months when support for unemployment insurance was measured and open circles indicate months when employment status was measured. Shaded areas indicate chunks of data that are collapsed to create a single wave.

TAPS panelists usually completed the key economic policy items between 1 and 3 months after they indicated their employment status. The longest gap between the two is at the beginning of the panel, where the respondents indicated their employment status in February 2012 but did not complete the policy items until July. This 5-month gap would normally be cause for concern, but it is not an issue here. The IKW matching estimator does not use the outcome data from these early waves to estimate the effects of unemployment. Instead, it uses employment status data from earlier waves to match respondents and only uses responses to policy items to weight control units and conduct placebo tests.

The TIPI was administered to the US panel in February 2012, June 2012, October 2012, May 2013, September 2013, November 2013, March 2014, May 2015, and June 2016.

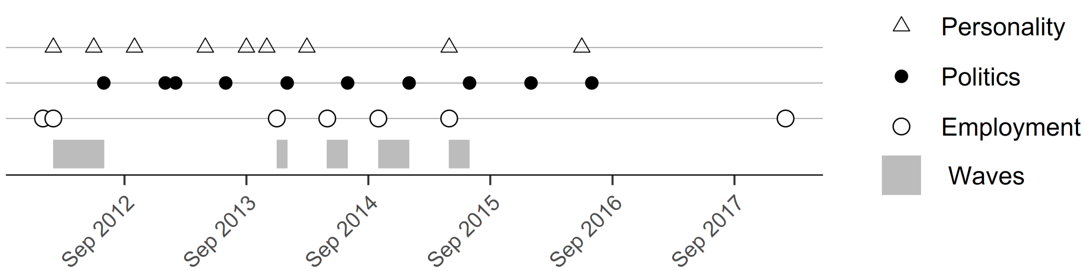

Figure B1: Structure of the TAPS dataset. Note: Open triangles indicates months when the TIPI anxiety item was fielded. Closed circles indicate months when the unemployment insurance item was fielded. Open circles indicate months when the employment status items were fielded. Shaded areas indicate chunks of data that are collapsed to create a single wave.

C Variance Decomposition of Trait Anxiety

Figure C1 shows the variance components of trait anxiety from the TSE model. The occasion-specific/measurement error component accounts for roughly 45% of the variance in the TIPI anxiety item across time points. This aligns with Alwin's (2007, 158-60) conclusion that measurement error accounts for 40 to 50% of the variance in individual survey items. Meanwhile, of the roughly 55% of the TAPS variance that can be confidently attributed to trait anxiety, about 40% is perfectly stable over 4.5 years and about 15% is somewhat stable. If we assume, following Alwin, that the proportion of error variance in the TAPS panel is 40%, then the true proportion of perfectly stable variance in trait anxiety is about 67% and the proportion of somewhat stable variance is 25%.[6]

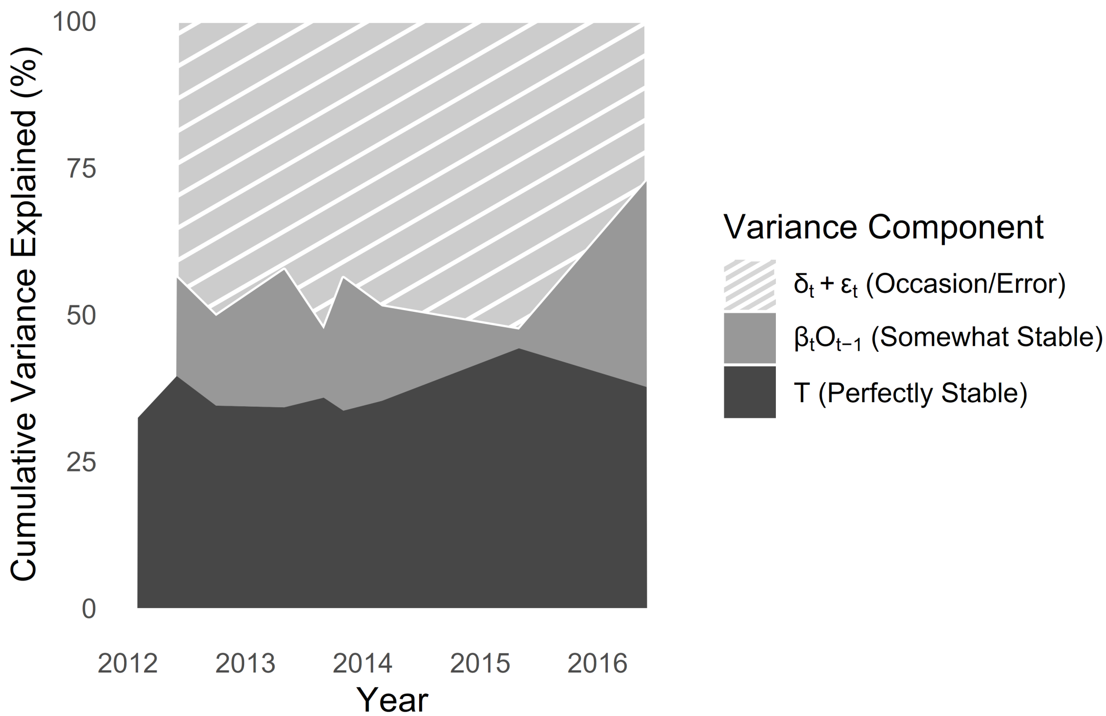

Figure C1: Variance decomposition of trait anxiety. Only T can be estimated for the first round because O_{i1} is exogenous.

[6] $\frac{40}{100-40} = 0.\overline{6}, \qquad \frac{15}{100-40} = 0.25$

D Alternative Outcome Variables

Table D1: Question Wording, Response Options, and Fielded Waves

Item Label	Item Text	Response Options	Waves
Unemployment Insurance	Do you think it should be the government's responsibility to provide a decent standard of living for the unemployed?	definitely should be; probably should be; probably should not be; definitely should not be; DK	8, 14, 15, 20, 26, 32, 38, 44, 50, 56
Guaranteed Jobs	Do you think it should be the government's responsibility to provide a job for everyone who wants one?	definitely should be; probably should be; probably should not be; definitely should not be; DK	8, 14, 15, 20, 26, 32, 38, 44, 50, 56
Public Healthcare	Do you think it should be the government's responsibility to provide health care for the sick?	definitely should be; probably should be; probably should not be; definitely should not be; DK	8, 14, 15, 20, 26, 32, 38, 44, 50, 56
Income Equality	Do you think it should be the government's responsibility to reduce income differences between the rich and poor?	definitely should be; probably should be; probably should not be; definitely should not be; DK	8, 14, 15, 20, 26, 32, 38, 44, 50, 56, 62, 66, 70
Government Spending	Which actions are you in favor of and which are you against?: Cuts in government spending.	strongly favor; favor; neither favor nor against; against; strongly against	8, 14, 15, 20, 26, 32, 38, 44, 50
Care for Elderly	Do you think it should be the government's responsibility to provide a decent standard of living for the old [elderly]?	definitely should be; probably should be; probably should not be; definitely should not be; DK	8, 14, 15, 20, 26, 32, 38, 44, 50, 56
Minimum Wage	Do you think it should be the government's responsibility to require a minimum wage for workers?	definitely should be; probably should be; probably should not be; definitely should not be; DK	8, 14, 15, 20, 26, 32, 38, 44, 50, 56
Tax the Rich	Indicate your level of agreement with each statement: Federal personal income taxes for individuals with incomes higher than $250,000 should be raised.	Strongly Agree; Agree; Neither Agree nor Disagree; Disagree; Strongly Disagree	3, 7, 13, 14, 18, 28, 34, 48, 58, 64, 70, 71

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Table D1 (continued)

Item Label	Item Text	Response Options	Waves
Limit CEO Pay	Do you think it should be the government's responsibility to place limits on executive pay?	definitely should be; probably should be; probably should not be; definitely should not be; DK	8, 14, 15, 20, 26, 32, 38, 44, 50, 56
Abortion	We want to know whether you strongly agree, agree, neither agree nor disagree, disagree, or strongly disagree with each statement: Federal programs that provide health care benefits should allow funding for abortions	Strongly Agree; Agree; Neither Agree nor Disagree; Disagree; Strongly Disagree	1, 3, 7, 13, 14, 18, 28, 34, 48, 58, 64, 70, 71
Gun Control	Indicate your level of agreement with each statement: Federal law should ban the possession of handguns except by law enforcement personnel.	Strongly Agree; Agree; Neither Agree nor Disagree; Disagree; Strongly Disagree	1, 3, 13, 14, 18, 28, 34, 48, 58, 64, 70, 71
Immigration	Indicate your level of agreement with each statement: The government should find a way to allow people who are in the U.S. illegally to stay in the U.S.	Strongly Agree; Agree; Neither Agree nor Disagree; Disagree; Strongly Disagree	1, 3, 8, 13, 14, 18, 28, 34, 48, 58, 64, 70, 71
Same-Sex Marriage	Indicate your level of agreement with each statement: The federal government should recognize the validity of a same-sex marriage where state law does.	Strongly Agree; Agree; Neither Agree nor Disagree; Disagree; Strongly Disagree	1, 3, 13, 14, 18, 28, 34, 48, 58, 64, 70, 71
Party ID	Generally speaking, do you usually think of yourself as a [Democrat, a Republican,/Republican, a Democrat,], an independent, or what? If Democrat/Republican: Would you call yourself a strong [Democrat/Republican] or a not very strong [Democrat/Republican] If Independent: Do you think of yourself as CLOSER to the Republican Party or to the Democratic Party? If Refused or Other: Do you lean more toward the Democrats or the Republicans?	Democrat; Republican; Independent Strong; not very strong Democratic Party; Republican Party Democrats; Republicans	1, 5, 7, 10, 11, 12, 17, 18, 20, 25, 28, 31, 34, 36, 38, 44, 46, 50, 51, 54, 61, 64, 66, 70

Continued on next page

Table D1 (continued)

Item Label	**Item Text**	**Response Options**	**Waves**
Ideology	In terms of your political views, do you think of yourself as...	Very liberal; Liberal; Slightly liberal; Moderate; Slightly conservative; Conservative; Very conservative; DK	1, 6, 10, 12, 24, 25, 31, 35, 36, 40, 42, 46, 51, 61, 63, 64

Figure D1: Causal effects of unemployment. Point estimates are average treatment effects on the treated (ATTs) with block bootstrapped 95% confidence intervals. The vertical gray lines separate the pre-treatment periods (to the left) and the treatment period (to the right).

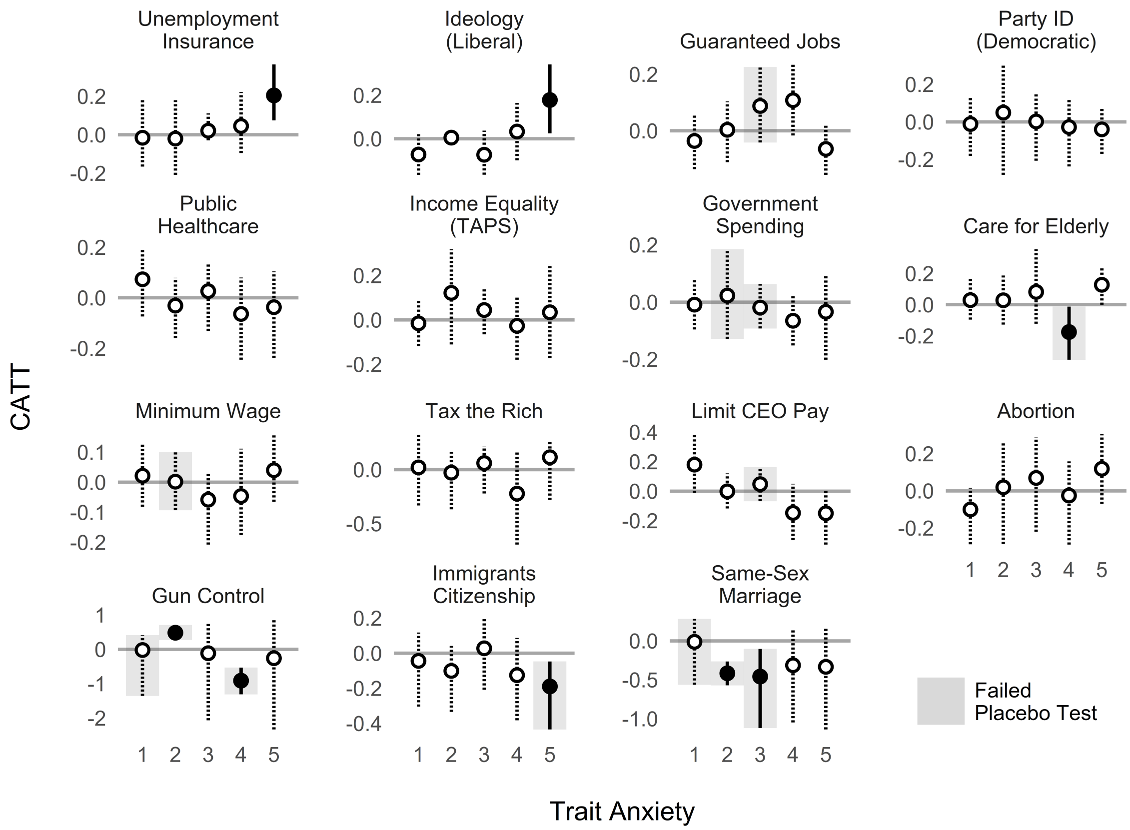

Figure D2: Heterogeneity by trait anxiety. Point estimates are conditional average treatment effects on the treated (CATTs) at time t with block bootstrapped 95% confidence intervals.

E Alternative Moderator Binning

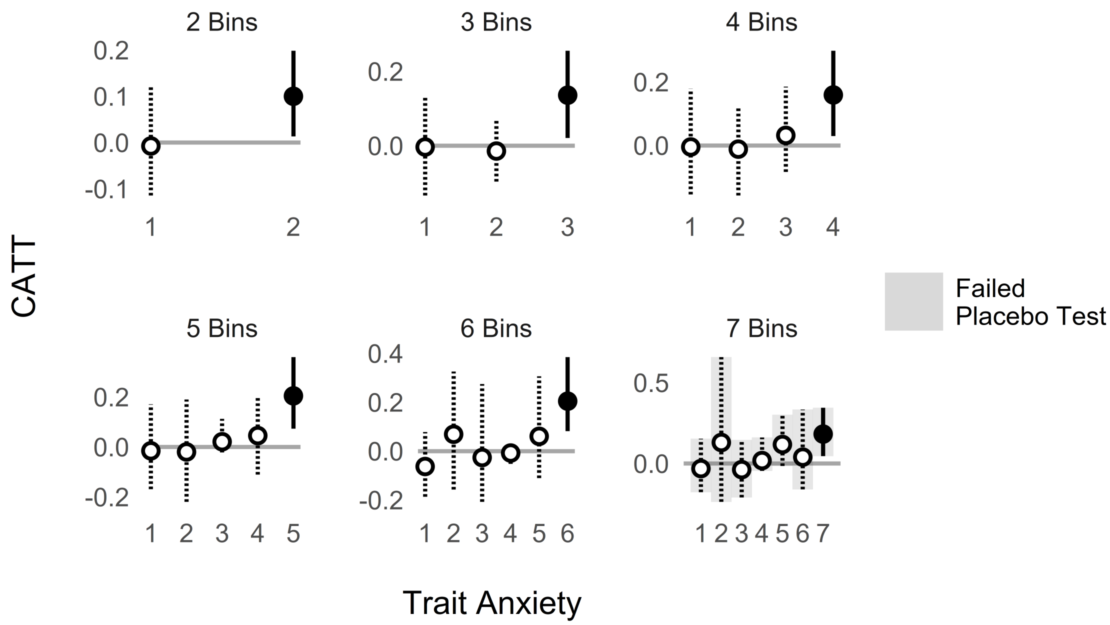

Figure E1: Heterogeneity by trait anxiety with alternative binning. Point estimates are conditional average treatment effects on the treated (CATTs) at time t with block bootstrapped 95% confidence intervals.

F Heterogeneity by Big Five Personality Traits

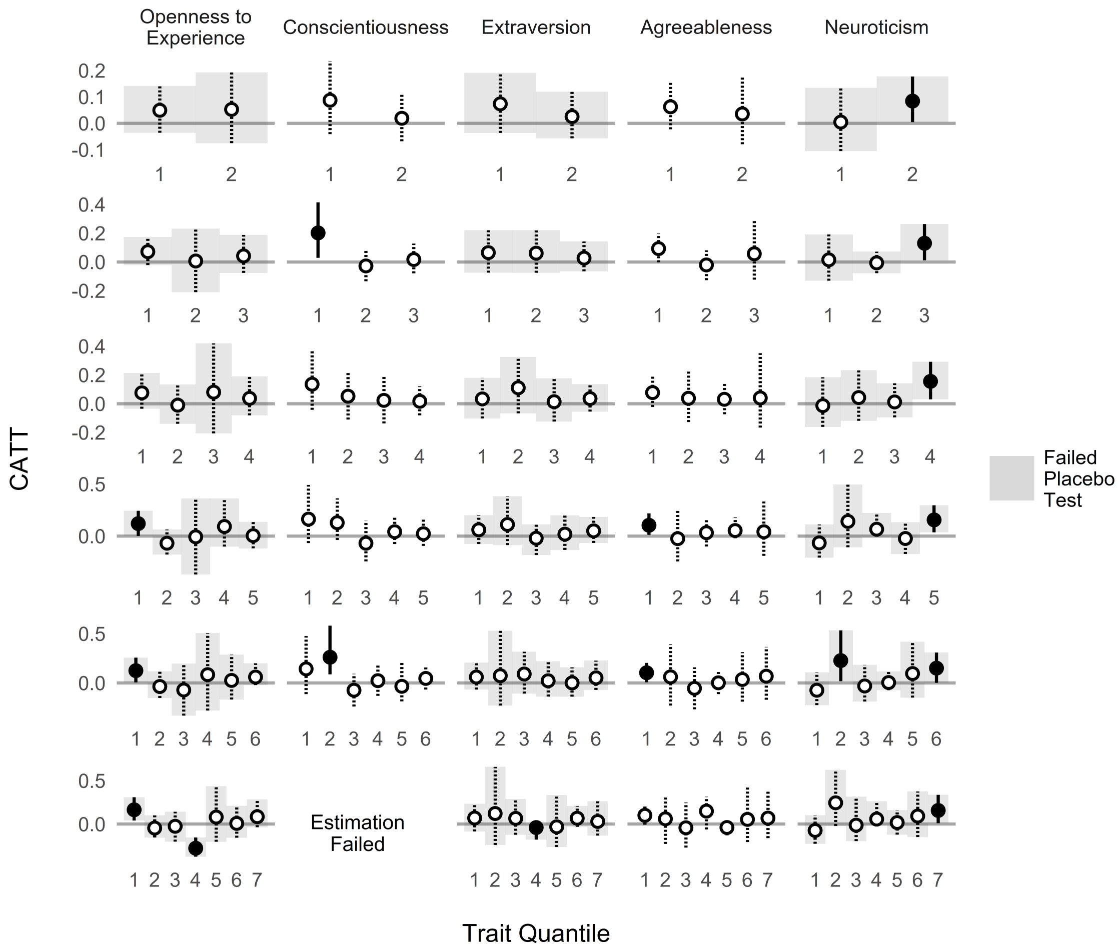

Figure F1: Heterogeneity by Big Five personality traits. Point estimates are conditional average treatment effects on the treated (CATTs) at time t with block bootstrapped 95% confidence intervals.