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Mental Health and Employment: The SAD Story

Nathan Tefft^a

^aDepartment of Economics, Bates College, 4 Andrews Road, Lewiston, ME 04240,
nathan.tefft@bates.edu, phone: 207-786-6069, fax: 207-786-8337

Abstract

This paper explores the relationship between health-related quality of life (HRQOL) measures and employment status in light of a constructed index related to Seasonal Affective Disorder that depends only on latitude and day of year. In models including demographic covariates and indicators for state, year, and quarter, more hours of darkness is associated with poorer HRQOL, which in turn is associated with a lower likelihood of employment. The relationships between the darkness index and HRQOL measures are stronger overall for women than for men. Inclusion of both the darkness index and the HRQOL measures in models of employment status determinants provides some evidence that the former operates through the latter in predicting a lower likelihood of employment. When specifying the darkness index as an instrument for HRQOL, each additional day of poor mental health per month leads to a 0.76 percentage point increase in the probability of unemployment among women.

Keywords

Mental Health; Employment; Seasonal Affective Disorder

1. Introduction

In recent years, researchers have combined new empirical methods with greater data availability to demonstrate that mental health plays a significant role in the development of health and human capital and their consequent outcomes. For example, Currie and Stabile (2006) examine the effects of Attention Deficit Hyperactivity Disorder, the most common mental health diagnosis among children, on test scores and schooling attainment. They find significant negative effects on each, and they argue that mental health conditions are important determinants of economic outcomes. Kessler et al (2005a,b) find that the 12-month and lifetime prevalence of all mental disorders in the U.S. are 26.2% and 46.4%, respectively. However, Kessler et al (2007) estimate that only 20.9% of individuals with 12-month major depressive disorder received adequate treatment. Because of the relatively low concomitant treatment utilization there is reason to believe that the effects of mental disorders are underappreciated.

We explore the relationship between mental health and employment using data drawn from the Behavioral Risk Factor Surveillance System (BRFSS) and the Current Population Survey (CPS). The analysis focuses on health-related quality of life (HRQOL) measures

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related to mood disorders that occur within approximately one month prior to respondent interviews. The overall goal of this paper is to inform research on the short term effects of mental health symptoms on employment status. To this end, associations between an index of darkness (as a measure of daylight length) hypothesized to be related to HRQOL measures through Seasonal Affective Disorder (SAD), as well as the association between the darkness index and employment status, are estimated. In addition, use of the darkness index as an instrumental variable in employment status models is explored. Overall, the results are consistent with the hypothesis that short-term negative shocks to mental health caused by SAD have a detrimental effect on employment outcomes.

Section 2 discusses previous studies that have explored the relationship between mental health and employment. Next, the SAD epidemiology literature is outlined and the connection between SAD and the question at hand is detailed. Section 3 describes the empirical strategy, both for constructing the darkness index and for the estimation procedures. Section 4 describes the data used in the analysis, and Section 5 presents the results. In Section 6, the results and conclusions are discussed.

2. Background

2.1. Mental Health and Employment

There is a large literature examining the relationship between mental health and employment. Many studies focus on mechanisms that may account for what is generally observed to be the adverse effect of poor mental health on employment outcomes. In the labor market, mental health may first of all influence the job matching process since, for example, a depressed individual may be unable to enter the job market in the first place. After securing an interview, an individual with impaired mental health may be less likely to attend or perform well at the interview. Hamilton et al (1997) find beneficial effects of good mental health on employability. Slade and Salkever (2001) find that, among adults diagnosed with schizophrenia, negative symptoms (in this context, those indicating deficits in personality characteristics), and symptoms of depression are negatively related to employment.

Individuals with poor mental health may require more sick leave, thus reducing their total production. Also, hourly productivity may be lower among individuals with poor mental health through direct performance effects or insofar as they devote more attention to symptom management at work. Berndt et al (1998) find that a reduction in the severity of depression improves perceived work performance. Zuvekas and Hill (2000) find that drug and alcohol dependence and abuse among the homeless are associated with fewer work hours. Productivity effects may slow wage growth or hasten termination. Catalano et al (1999) explore whether individuals with severe mental illness are at greater risk of layoff than other workers when the economy contracts, but they find no strong evidence for this. Mullahy and Sindelar (1996) find that alcohol abuse and dependence decrease the probability of employment and increase the probability of unemployment. An arguably contrary association regarding bipolar disorder and productivity, however, is that persons with bipolar illness are more likely to work in creative occupations and engage in creative activities on the job (Tremblay, Grosskopf, and Yang, 2010).

However, causation may operate in the opposite direction in the sense that employment experiences can affect mental health. A new job or increased responsibility may raise stress and anxiety. An involuntary increase in work hours at the expense of leisure time may reduce protective time investment in mental health, thereby increasing the likelihood of the onset of depression or anxiety disorders. In some cases, the increased stress of work could trigger more severe forms or episodes of mental disorders. The varying effects of job

environments is evident in research showing that mental health outcomes differ by occupation among women (Llena-Nozal et al, 2004). On the other hand, increased income due to employment may partially offset mental health effects since the individual will be able to purchase more or higher quality mental health care.

The process of ending employment, either voluntarily or involuntarily, may affect mental health. These effects are ambiguous since the individual will likely have lower income but may endure lower stress levels. Especially in the case of involuntary unemployment, the loss of income may dominate, leading to worse mental health outcomes. In either case, individuals who view work as providing daily structure may experience a decline in mental health after becoming unemployed. Björklund (1985) shows mixed evidence with respect to the effects of unemployment on mental health. Theodossiou (1998) finds that unemployed individuals experience greater declines in mental health outcomes, even compared to individuals with low-paid employment. Dave et al (2006) show that retirement is associated with significant declines in both physical and mental health.

In addition to examining the reciprocal causation between mental health and employment, other studies have addressed the issue that unobserved characteristics may affect both outcomes. Using Finnish panel data Böckerman and Ilmakunnas (2009) find that persons who already have poor self-assessed health have a higher likelihood of unemployment, thus yielding no observed effect of an episode of unemployment on self-assessed health. On the other hand, Chatterji, Alegria, and Takeuchi (in press) find that when accounting for selection on unobservable factors the presence of psychiatric disorder is negatively associated with labor force participation and employment. Bivariate probit methods have also been used to model jointly determined outcomes related to mental health and employment (Alexandre and French, 2001; Chatterji et al, 2007). A specific, often unobserved characteristic that has been studied and that can have direct effects on both unemployment and mental health is job displacement in the form of mass-layoffs. Browning et al (2006) study the relationship between unemployment and hospitalization for stress-related disease in the context of plant closings. Classen and Dunn (2011) use data on mass-layoffs to separate the effects of job loss from unemployment duration on suicide risk.

Evidently, the relationship between mental health and employment status operates through many channels, and endogeneity is an important concern. Previous attempts to address this relationship in the context of an instrumental variables (IV) strategy have estimated decreases in the probability of employment due to mental disorder (Ettner et al, 1997) and self-reported mental health (Alexandre and French, 2001). In a related study, Marcotte et al. (2000) demonstrate a negative impact of psychiatric disorder on earnings. These studies use family history of mental illness as an instrument for a respondent's mental health. This paper is therefore one of the first attempts to identify a natural experiment that can be leveraged in the context of mental health's effects on employment status.

2.2. Seasonal Affective Disorder (SAD)

SAD is a condition that can be characterized as a susceptibility to the onset of depressive episodes or related symptoms according to a seasonal pattern. The seasonal pattern most often peaks in the fall and winter. It is estimated that up to 10 million persons in the United States each year have symptoms that satisfy the clinical classification of SAD (Sohn and Lam, 2005). However, it is believed that up to 25 percent of the population may suffer from significant seasonality, or what is known as "subsyndromal SAD." A similar incidence exists in other countries. Sohn and Lam (2005) also discuss a physiological basis for the disorder, which is understood to be a set of responses triggered by seasonal environmental cues. Clinically, SAD is defined as a "seasonal pattern specifier" of major depressive episodes that occur in major depressive disorder or bipolar disorder. In other words, SAD is a designation

applied to the subset of major depressive episode diagnoses which are best explained by seasonal patterns. Symptoms associated with SAD include, in addition to symptoms of depression, a weakened immune response, increased sleeping, overeating, weight gain, and a craving for carbohydrates. See American Psychiatric Association (2000) for a full discussion of the clinical characteristics of SAD.

Researchers have investigated the determinants of SAD with the goal of identifying environmental cues that account for the onset of SAD. The disorder has been strongly associated with the fall and winter months, and it has also been identified as more prevalent at greater latitudes. These observations suggest that daylight length (photoperiod) is a likely explanatory factor, but its strong correlation with other environmental variables requires further analysis.¹ Some of these potentially confounding variables include direct sunshine in winter, temperature, and total light exposure from the sun or other sources.² Perhaps the most direct evidence for photoperiod's role is in assessments of SAD treatments. The most effective SAD treatment has been found to be light therapy, where an individual exposes himself to high intensity light, often in the morning or outside the range of normal daylight hours.³

3. Empirical Strategy

3.1. The Darkness Index

The darkness index is a measure that reflects the daily number of hours without sunlight that an individual experiences at a given place and date. It is constructed in a similar manner to that implemented by Kamstra et al (2003) except where differences are noted below. More specifically, for a given date (day of year) and latitude the index is calculated as the negative photoperiod deviation from 12 (which is the overall mean photoperiod, or hours of light per day, across a year). In other words, the negative photoperiod deviation can be expressed as the number of hours of darkness relative to the mean (12 hours) during a 24 hour period. In contrast to the index constructed here, Kamstra and coauthors also restrict the darkness index to be equal to zero during the spring and summer months and include a dummy variable for the fall months because of evidence suggesting that SAD effects are greatest in the fall and winter months.⁴ However, Kelly and Meschke (2010) explain that this specification is equivalent to including both a dummy variable for fall/winter and a second dummy for fall only, and they show that the model may then suffer from an “overlapping dummy variables” bias that can generate spurious results. Therefore, the approach taken here is a more straightforward application of the unrestricted negative photoperiod deviation. The primary empirical specifications include quarter dummy variables to control for unobserved factors that vary across seasons and affect mental health symptoms, in addition to the darkness index.

In order to calculate the darkness index for each respondent, the sun's declination angle is first calculated for each interview date, which is the angle between the earth's axis and a ray from the center of the sun passing through the center of the earth (Kamstra et al, 2003). For the northern hemisphere this is,

¹For a recent discussion of the currently active literature with respect to SAD and latitude, see Magnusson and Partonen (2005). Issues that have yet to be resolved include the stronger latitude effects measured in the U.S. than in Europe, differing results between self-diagnoses and clinical assessments, differences between ethnic groups (in particular, those who may have acclimated to SAD over time), and issues of selection in epidemiological studies.

²Examples of studies that explore these relationships include Molin et al (1996), who use stepwise regression techniques to identify length of day as having the largest correlation with SAD onset, and Young et al (1997), who study the onset of SAD across locations within a year and across years within a location.

³See Golden et al (2005) for a meta-analysis of the efficacy of light therapy.

⁴Young et al (1997) note that only 10 percent of SAD cases are known to occur prior to the fall equinox (also known as “summer SAD”), so there appears to be a diminished relationship between photoperiod and SAD during the spring and summer months.

$$declination_t = 0.4102 * \sin \left[\frac{2\pi}{365} (day_t - 80.25) \right].$$

Here, day_t is the number of the day of the year corresponding to the interview date, which varies between 1 and 365 (366 in leap years). Next, the number of hours of darkness on the given interview date for a respondent's county c (determined by the given county's latitude l) is,

$$hrs_{ct} = 12 - 7.72 * \arccos \left[\frac{2\pi l}{360} \tan(declination_t) \right].$$

The hrs_{ct} equation can be motivated as first using the sun's declination angle to determine the solar terminator (defined as the boundary between the half of the earth in sunlight and the shadowed half), next calculating the proportion of time in the earth's rotation that a point on the given latitude is in sunlight, and finally scaling this to hours and subtracting from 12 (Kamstra et al, 2003). The final darkness index d_{ct} is then calculated as an unweighted average of hrs_{ct} across the lag i relevant to the variable of interest.⁵ This is given by,

$$d_{ct} = \frac{1}{i} \sum_{j=(t-i)}^t hrs_{cj}.$$

3.2. Empirical Framework

The analysis is conducted using two general models. The first, which describes the association between the darkness index and the BRFSS symptom measures, is implemented using linear and probit models of the following general form:

$$g(E(m_{ict})) = \beta_0 + d_{ct}\beta_d + z_{ct}\beta_z + x_{ict}\beta_x + \lambda_t + \delta_s. \quad (1)$$

When m_{ict} is an indicator of whether the number of symptom days is above or below a given threshold, a probit model is used (such that the link function g above is the inverse normal cumulative distribution function). Otherwise, when m_{ict} is a count of the number of symptom days, simple linear regression models are used (such that the link function is the identity function). The general model includes vectors d_{ct} and z_{ct} that vary by county and time (here, the darkness index and weather variables, respectively), and a vector of characteristics x_{ict} that varies by individual and time (including demographic characteristics such as age, sex, race, ethnicity, and education). Also, λ_t is a vector of indicator variables by year and quarter and δ_s is a vector of indicator variables by state.

The second general model refers to an analysis of the association between the darkness index or mental health, and employment status. It is:

$$g(E(y_{ict})) = \beta_0 + m_{ict}\beta_m + d_{ct}\beta_d + z_{ct}\beta_z + x_{ict}\beta_x + \lambda_t + \delta_s. \quad (2)$$

⁵The symptom measures are coded for specific durations, in each case thirty days prior to the interview date. In order to most accurately capture the effects of photoperiod on the measure in question, an average of the negative photoperiod deviation is calculated across the appropriate lag prior to the interview date.

Since y_{ict} is specified as an indicator of employment status, probit models are estimated for equation (2). In addition to the covariates included in equation (1), equation (2) also specifies the mental health measures as covariates since they are included in some of the employment regressions (while d_{ct} is omitted in some). The reported coefficients for the probit models are calculated marginal effects at the means of the covariates.

The final set of regressions involves estimates of two-stage least-squares (2SLS) models. In these cases, equation (1) (with the identity link function) is first estimated using OLS, and the predicted values of the endogenous variable m_{ict} are calculated. Next, these predicted values are substituted into a regression of equation (2) (with the identity link function) except with d_{ct} omitted. The coefficient estimates from this second-stage regression are reported as the 2SLS results, and they are interpreted as linear probability marginal effects.

4. Data

The main analysis uses data from the 1994 to 2009 waves of the Behavioral Risk Factor Surveillance System (BRFSS).⁶ BRFSS is a repeated cross-section survey that is conducted annually by state and U.S. territory health departments with support from the Centers for Disease Control. Because BRFSS includes a large number of respondents distributed across the nation and its territories, it offers a comprehensive look at overall patterns of health. Table 1 shows population weighted summary statistics for the subset of BRFSS response variables used in the analysis (as well as additional merged variables).

The analysis is restricted to respondents between the ages of 18 and 65 living in the 50 U.S. states and the District of Columbia in order to focus on the population most likely to be attached to the labor market. Also, a potential source of bias in the models specified above is through behavioral responses such as migration. If individuals who are most strongly affected by SAD seek to ameliorate their situation by relocating, there could be a migration trend towards lower latitudes induced by SAD.⁷ However, it is possible that only some individuals, such as those most successful in the labor market, are willing to pay the monetary and psychic costs of relocation. In any case, this issue supports excluding individuals older than retirement age when estimating the relationship between the darkness index and HRQOL since retirees may be more able or motivated to relocate across latitudes.

Individuals without county identifiers are dropped because the latitude of each county's center of population is used to calculate the darkness index. Counties with missing data on monthly mean temperature and total precipitation are dropped.⁸ After excluding observations with missing demographic information, the final remaining sample consists of 1,456,199 observations.

BRFSS provides data on general questions regarding employment. Respondents are asked, "Are you currently [employment status]?" where [employment status] can take on the values "Employed for wages"; "Self-employed"; "Out of work for more than 1 year"; "Out of work

⁶See <http://www.cdc.gov/BRFSS/> for more details.

⁷Magnusson (2001) shows evidence for differences in susceptibility between ethnic groups and suggests that these differences may have occurred due to genetic or cultural selection towards acclimatization at higher latitudes. Since many ethnic groups are more dispersed in the United States than in Europe, this could partially explain the stronger evidence for latitude effects that has been found in the United States, as discussed by Mersch (2001). By the same token, sorting on SAD susceptibility may be less of a concern in U.S. data.

⁸Following the epidemiology literature, precipitation and temperature are believed to have separate effects on mental health status, but they are correlated with photoperiod (and total light exposure). Weather data were acquired from the National Climatic Data Center (NCDC). The data sets used were the Summary of the Month Cooperative Data, #DSI-3220, from 1994–2009. County information is incomplete, however. Thus, in order to assign temperature and precipitation values to a given county, I calculated the average climate variable value across the five closest weather stations located within a 50 mile radius, weighted by the square of the station's great circle distance from the center of population.

for less than 1 year"; "A homemaker"; "A student"; "Retired"; or "Unable to work." These responses are aggregated into more relevant categories, namely "employed", "unemployed", or "out of the labor force." "Employed for wages" and "Self-employed" are combined in "employed", "Out of work for less than 1 year" in "unemployed", and all other responses in "out of the labor force." It is unlikely that these map directly to employment categories as defined by the Bureau of Labor Statistics, however, so later in the analysis data from the Current Population Survey (CPS) are considered in part to present clearer employment relationships.

BRFSS includes several HRQOL measures including the core Healthy Days measures.⁹ The primary Healthy Days question asks, "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?" (hereafter and in the tables noted as "unhealthy" days). That it refers to symptoms in the 30 days prior to the interview date is advantageous. This time frame is large enough to calculate the proportion of time that an individual experiences a symptom in the short-term, but it is small enough such that using averages of the darkness index over the time period of 30 days does not overly dampen its variation.

The Healthy Days questions also include measures that are related to more specific mental health symptoms, all of which are based on the same temporal structure as the "unhealthy" days question. Summary statistics for these measures are also reported in Table 1. They include questions about feeling "sad, blue, or depressed" (noted as "blue" days); feeling "worried, tense, or anxious" (noted as "stressed" days); and feeling "very healthy and full of energy" (noted as "energy" days).^{10,11} Since these more specific questions are included in optional modules, they are selected for survey inclusion by fewer states and in fewer years within the sample period, so the sample sizes available for estimation are considerably smaller than for the "unhealthy" days question.¹²

5. Results

5.1. Healthy Days Results

Tables 2 through 4 report results from an investigation of the relationship between the darkness index and the Healthy Days survey questions that are related to mental health (and more specifically, mood disorder symptoms). Table 2 includes the main results for the overall sample while Tables 3 and 4 explore specific subgroups of interest based on findings from epidemiological studies of SAD.

Table 2 reports OLS coefficient estimates of the determinants of the Healthy Days measures, which are coded as the number of days the respondent experienced a particular symptom in the last 30 days.¹³ The models also include indicator variables for states (to control for unobserved differences across states that are fixed over time), years (to control for unobserved differences across years that are fixed over geographic regions), and quarter (to

⁹See CDC (2000) for a full discussion of the HRQOL measures included in BRFSS.

¹⁰Questions about activity limitations due to "physical, mental, or emotional problems" and the number of days that the respondent "did not get enough rest or sleep" were not considered in the analysis because of their less direct relevance to SAD.

¹¹For the sample of individuals who responded to all of the considered Healthy Days questions, the pairwise correlations between the "unhealthy", "blue", and "stress" questions were between 0.55 and 0.65 while the correlations between the "energy" question and the other three were between -0.35 and -0.38.

¹²The pattern of selection is not obviously different from a random selection of states and years. For example, respondents are drawn from over two-thirds of all states at some point during the sample period, and all regions of the U.S. are numerous represented. Sample response frequencies by state and year are available on request.

¹³Probit models were also estimated where the dependent variable was coded as an indicator for whether the number of days reported was greater than zero. The results are broadly and qualitatively consistent with the results presented in Tables 2 through 4 and are available upon request.

in part control for broad differences in mental health across the year).¹⁴ The identification of changes in the Healthy Days measures therefore arises from within-state, within-quarter variation in the darkness index. With respect to location and time, there may be a wide range of mental disorder treatments that vary across states according to regional treatment practices or differences in the stigma associated with mental disorder treatment, as well as changes across the sample period for the entire U.S. such as increasing penetration of anti-depressant medication utilization. The models include heteroskedasticity-robust standard errors clustered at the state level.

Column (1) of Table 2 shows the estimated coefficients when the “unhealthy” days measure is the dependent variable. Here, the darkness index coefficient is positive and significant at the 1% level. The magnitude and sign of the coefficient are expected in the sense that a higher darkness index predicts more “unhealthy” days. More specifically, an increase of one hour of darkness per day is associated with an increase in the average number of days per month in which overall mental health is “not good” (by 0.041 days). The coefficient estimates on the weather variables, namely monthly mean temperature and total precipitation, are also significantly different from zero in this model. As suggested by the epidemiology literature previously noted, there appears to be an association between weather and HRQOL measures independent of that with photoperiod.¹⁵ Coefficient estimates for demographic variables generally show that, conditional on the covariates, “unhealthy days” a) are fewer in number for men than for women, b) increase at a decreasing rate with age, c) are fewer in number for whites and blacks than for other race groups, d) are fewer in number for Hispanics than for other ethnic groups, and e) increase with an increasing education level.

The remaining Healthy Days measures considered here are reported in Columns (2) through (4) of Table 2. As mentioned earlier, the number of observations available for estimation with respect to these Healthy Days measures is substantially smaller than for the “unhealthy” days measure. As is clear from the signs of the coefficients on the demographic covariates in comparison with those in Column (1) the “blue” and “stress” questions in Columns (2) and (4) tend to measure adverse outcomes while the “energy” question measures an advantageous outcome. This is reflected in the darkness index coefficients, since an increase in hours of darkness is associated with an increase, albeit insignificant, in the number of days of feeling “blue” and “stressed” and a decrease in the number of days with “energy”. Although the Healthy Days measures are not specific diagnostic criteria and the identified associations are relatively small in magnitude, the overall pattern is suggestive that hours of darkness are associated with symptoms that include depression and low energy.¹⁶

Table 3 investigates a common finding in the epidemiology literature, namely that women tend to be more affected by SAD than men (Magnusson and Partonen, 2005). Panels 1 and 2 divide the sample into men and women, respectively, and the darkness index and weather

¹⁴The magnitudes and statistical significance of the SAD index coefficients are similar when the primary models are estimated with state-by-quarter fixed effects (in order to allow for the possibility that seasonal patterns of employment vary across the U.S.). The results are available on request.

¹⁵It is perhaps surprising that temperature is positively associated with the number of unhealthy days, but previous studies have found the relationship to be complex. For example, Denissen et al (2008) explain that the response varies by season, where mood may respond positively to increasing temperature in the spring but negatively to increasing temperature in the summer. Denissen et al (2008) additionally argue that controlling for sun exposure or, equivalently, cloud cover (which are not included in this analysis) can alter or even flip the sign of the temperature coefficient.

¹⁶The 2003–2004 National Health and Nutrition Examination Survey includes both the Healthy Days measures and results from the Composite International Diagnostic Interview. Mean estimates for the number of poor overall mental health days for persons with and without an implied diagnosis of depression are 12.46 and 3.22, respectively. A t test that the means are equal is rejected at the 1% level.

coefficients for the same empirical models estimated in Table 2 are reported. The evidence offers mixed support for findings in the epidemiology literature. But the strongest result, namely that the coefficient on the overall “unhealthy” days measure for women is significant and larger than that for the overall sample, is consistent with women being more strongly affected by daylight exposure than are men. While the other coefficients for women vary in their magnitude relative to the coefficients for the overall sample, they are not significantly different from zero. Overall, there is no significant detectable relationship for men with respect to the darkness index, although higher total precipitation is associated with more “unhealthy” and “blue” days.

The analysis in Tables 2 and 3 restricts the linear relationship between the darkness index and the number of symptom days to be equal across the entire distribution of symptom days. This may not be appropriate if the darkness effect varies according to initial mental health. In addition, the association between mental health and employment may in turn vary according to initial mental health. For an example of a previously studied category, CDC (2000) examines the determinants of and associations with “frequent mental distress”, defined as equal to a response of 14 or greater to the “unhealthy” days question. Another important threshold to consider is whether any days of a given symptom are reported because an individual may first decide whether to report any “unhealthy” days and next decide how many to report. To explore the margins on which daylight is operating, Table 4 reports the darkness index coefficients for probit models where the dependent variable indicates whether the number of reported days exceeds 0, 5, 10, 15, 20, or 25 days (each coefficient and standard error pair is reported from a separate regression model).

The results in Table 4 are broadly consistent with the findings in Tables 2 and 3 in the sense that the signs of all significant coefficients are expected. The darkness index coefficients for the “unhealthy” days models are greater than zero for all thresholds, although the strength of the relationship appears to decline as the threshold increases. The zero threshold model coefficient for the “blue” question is relatively large and significant compared to the other thresholds for the question, suggesting that much of the relationship is on the extensive margin of “blue” days. The thresholds for the “energy” question that yield significant coefficients are not clustered near 0 or 25 (perhaps due to the fact that the question asks about advantageous, instead of adverse, day characteristics), while there are no significant coefficients for the “stress” question. Overall, these findings suggest that the daylight effect can vary across the distribution of HRQOL questions, and the variation can differ across questions.

5.2. Employment Results

This sub-section is devoted to exploring the relationships between the darkness index, the Healthy Days measures, and employment status. As discussed earlier, there is a large literature relating mental health to employment outcomes, so the aim is to investigate whether the darkness index may play a role in this relationship. Although the results that follow may represent meaningful effects of daylight and/or mental health on employment status, they should be viewed with caution due to the potential issues of endogeneity and reverse causality, as discussed earlier.

First, the analysis is supplemented using data from the Current Population Survey (CPS), collected by the Bureau of Census for the Bureau of Labor Statistics.¹⁷ Table 5 reports summary statistics of data drawn from the CPS Monthly Basic data set for the years 1994–2009, merged with the same weather and darkness index data that were collected and

¹⁷See <http://www.bls.gov/cps/> for more details.

constructed for the initial analysis. Because the original CPS data set contained over 7 million observations, thus making calculation of marginal effects for the full sample prohibitive with respect to available computational capability, a random sample of 100,000 observations was drawn and used for the 18 Analogous demographic characteristics were extracted in order to provide as close a comparison as possible to the initial estimation results.

Table 6 reports associations between the darkness index and employment status. The reported coefficients are the marginal effects (calculated at the mean of the covariates) for probit models where the dependent variable is an indicator for whether the respondent is employed (unemployed). For both the CPS and BRFSS models, indicator variables for state, year, and quarter are included and heteroskedasticity-robust standard errors, clustered by state, are reported in parentheses. CPS data are used to examine the darkness index and its relationship to employment status since the questions used in the survey are used by the Bureau of Labor Statistics to report employment data information. The BRFSS employment status variables, by contrast (and as discussed earlier), are approximations of employment status as defined in the CPS.

Columns (1) and (2), and separately (5) and (6) compare equivalent models for the CPS and BRFSS data for employment and unemployment, respectively. The darkness index has expected relationships with employment and unemployment. More specifically, the CPS models suggest that a one hour per day increase in darkness is associated with a reduction in the probability of employment by 0.57 percentage points (with no significant relationship to unemployment) while the BRFSS models suggest that a one hour per day increase in darkness is associated with an increase in the probability of unemployment by 0.06 percentage points (with no significant relationship to employment). Overall, this is consistent with the earlier discussion regarding mental health and employment, in the sense that a worsening of mental health may in the short term influence employment status. It is unclear what the differences are between the two models that yield the differences in emphasis, but at least in part this may be due to the difference in the definitions of employment and unemployment. Coefficient estimates for the covariates are included for comparison, and they appear to be broadly similar.

Next, Columns (3), (4), (7) and (8) of Table 6 explore how the inclusion of the Healthy Days measures as covariates affects the relationship between the darkness index and employment status. Columns (3) and (7) add only the “unhealthy” days measure so as not to markedly reduce the sample size to allow for a direct comparison with columns (2) and (6), while columns (4) and (8) include the full set of studied HRQOL questions.¹⁹ The signs of the coefficients on the Healthy Days measures, with the exception of the “stress” coefficient in the employment model, are consistent with the idea that adverse mental health in the short term is associated with worse employment status. After including these measures, the darkness index coefficients are no longer significant, so it is plausible that the darkness index relationship operates in part through mental health outcomes associated with the Healthy Days measures. Unfortunately, the CPS data include no similar measures of HRQOL or other mental health symptoms so this relationship cannot be directly compared across data sets.

¹⁸A size of 100,000 was chosen to approximate the size of the smallest comparison sample in the results that follow.

¹⁹The analysis reported in columns (4) and (8) of both Tables 6 and 7 was repeated using the unweighted average of the number of “unhealthy”, “blue”, and “stress” days and 30 minus the number of “energy” days instead of including each measure as a separate covariate. The signs and significance levels of the coefficients were the same as those in columns (3) and (7) where only “unhealthy” days was included.

For a comparison similar to that between Tables 2 and 3, Table 7 reports employment model results when estimated separately for men and women to allow for comparison with Table 6. Again consistent with findings from the epidemiology literature, the darkness index has a significant and expected relationship with both employment and unemployment for women in the CPS sample. The magnitudes of the marginal effects for women, implying a reduction in the probability of employment by 0.84 percentage points and an increase in the probability of unemployment by 0.15 percentage points, are larger than those for the entire sample. When not controlling for the HRQOL measures, none of the darkness index marginal effects are significant for men. Similar to the results in Table 6, the darkness index is no longer significant after controlling for the HRQOL measures in all cases except for the unemployment regression for men in column (8). While this is somewhat surprising, the result taken together with the marginal effect of 0 (at least, not statistically different from 0) from the employment regression for men in column (4) implies an increase in the number of men out of the labor force (the omitted dependent variable category). It may be that the HRQOL measures are not picking up all of the variation in mental health related to the darkness index in this case.

5.3. 2SLS Results

Tables 8 and 9 present a comparison of probit, OLS, and 2SLS estimates of the effect of the “unhealthy” days measure on employment status for the entire sample and for men and women separately.²⁰ The darkness index is a valid instrument for the “unhealthy” days measure if it is uncorrelated with the unobserved determinants of employment status, so validity cannot be directly tested. Although the finding that the darkness index is no longer significant after controlling for the HRQOL measures in Tables 6 and 7 (with one exception) suggests that its relationship to employment status is only through the “unhealthy” days measure, this result could also arise if the instrumental variable is invalid and its coefficient estimate is biased. Therefore, these results should be taken as merely suggestive with respect to the validity of the instrumental variable. As discussed in the following, the darkness index also passes weak instrument tests for the entire sample and for women.²¹

First, probit and OLS coefficient estimates in columns (1), (2), (4), and (5) of Table 8 are reported in order to provide information about how the implementation of a linear probability specification influences the IV results. Although the “unhealthy days” coefficients estimated in the probit models tend to be somewhat smaller in magnitude than in the OLS models, they are similarly significant in all of the models in both Tables 8 and 9.²² A comparison of the OLS and 2SLS coefficients for employment in columns (2) and (3) suggests that although a linear regression model yields a highly significant negative relationship between “unhealthy” days and employment status, the effect is no longer significant in a 2SLS context (although the sign does not change and the magnitude of the coefficient increases). Regarding “unhealthy” days and the likelihood of unemployment in column (6), there remains a significant positive effect after instrumenting for the endogenous variable. The magnitude is over six times that of the OLS estimate, implying a

²⁰IV models were also estimated using Newey’s (1987) two-step probit model with endogenous regressors, but since it is not possible to directly compare the two-step coefficients with standard probit coefficients (or calculate marginal effects) the coefficients are not reported. However, results from these models are descriptively compared to the presented linear model results in the text with regard to statistical significance. Maximum likelihood estimation of the probit model with endogenous regressors was also attempted, but as is common for this model with many regressors (in this case fixed effects) the coefficient estimates fail to converge.

²¹For example, according to Stock and Yogo (2002), if the coefficient on the instrumented endogenous variable has an estimated significance level of 5%, the coefficient could have an actual significance level of at most 10% if the F statistic is at least 19.93, and 15% if the F statistic is at least 11.59.

²²It is not surprising that the proportional difference in coefficient estimates is greater for the unemployment models than for the employment models because the mean value of the unemployed variable is 0.059. This is closer to the bounds of the support of the inverse normal probability distribution than is the mean of the employed variable (0.718).

relatively large 1.37 percentage point increase in the probability of unemployment due to an increase of one day out of thirty of poor mental health. Results from auxiliary regressions using Newey's (1987) two-step probit estimator (not reported) similarly show no significant employment effect and a positive and significant unemployment effect. But the fact that the F statistic in the first stage only narrowly passes a weak instrument test urges some caution in interpreting these results. The remaining coefficients for the covariates are relatively consistent between the OLS and 2SLS models, although perhaps the most noticeable difference is the weakened effect of education status on the likelihood of unemployment in the 2SLS model.

Finally, Table 9 shows the probit, OLS, and 2SLS comparisons separately for men and women. Most notably, the darkness index unquestionably fails weak instrument tests when the sample is restricted to men only, so the estimated significance levels for the male sample must be viewed with a great degree of caution. For females, though, the instrument is rather strong. Similar to the full sample, the change in the likelihood of employment is no longer significant and in this case is smaller in absolute value than the OLS estimate. But for women, the 2SLS estimate implies that there is a 0.76 percentage point increase in the probability of unemployment due to an extra day of poor mental health. This is more than three times the estimated relationship in OLS models. The auxiliary two-step model results reveal no statistically significant results for the "unhealthy" days coefficients, although the coefficient in the unemployment regression for women is positive with a p-value of 0.142.

6. Discussion & Conclusion

In models that include indicators for state, year, and quarter in addition to demographic covariates, an increase in short-term health-related quality of life (HRQOL) measures related to adverse mental health outcomes is associated with a) more hours of darkness and b) worsening employment status. The relationships between the darkness index and HRQOL measures are stronger overall (larger in absolute value and more often significantly different from zero) for women than for men. Among women, one more hour of darkness is associated with 0.07 more "unhealthy days" (specifically referring to mental health) per month, and an extra "unhealthy day" per month is in turn associated with a decrease in the probability of employment by 0.6 percentage points. Inclusion of both the darkness index and the HRQOL measures in regression analyses provides some evidence that the former operates through the latter in predicting worse employment status. Finally, the darkness index is found to be a strong instrument for the effects of short-term changes in mental health on employment status, particularly among women.²³ For example, results from a two-stage least-squares analysis implies that one more "unhealthy day" per month increases the probability of being unemployed by approximately 0.8 percentage points for women. This is a substantial finding when compared with the national U.S. unemployment rate of 9.1% in July, 2011.²⁴

These results contribute to understanding the relationship between mental health and employment. Because virtually all experiences modify and are modified by mental health, it is challenging to identify causal relationships when examining observational data. This is in part due to the fact that individuals readily adjust their behavior in response to and in anticipation of situations in which they expect their mental health to be compromised. In spite of these challenges, this paper identifies a source of exogenous variation in mental health that may be used to study changes in employment status.

²³In these models the first stage F statistic is 30.54.

²⁴The most recent national unemployment rate estimate is published by the United States Department of Labor, Bureau of Labor Statistics at <http://www.bls.gov/cps/> (last accessed August 21, 2011).

A compelling feature of darkness as an instrumental variable is that it represents a phenomenon that "casts a shadow" on every corner of the earth. Barring complete isolation from the outside world, everyone is to some degree aware of the changes in daylight across the year. However, it is possible that only a fraction of the population actually presents measurable effects in terms of mental health responses. Variation in mental health measures among individuals suffering from subsyndromal SAD may be picked up by the darkness index. Mersch (2001) discusses evidence that even individuals who are not diagnosed with SAD show seasonal variation on continuous mood measures, so 25 percent may represent a lower bound on the proportion of individuals for whom the "unhealthy days" measure is sensitive. Nevertheless, the fact that the data do not allow for a direct SAD diagnosis forces a consideration of only the overall population mean effect, which may in fact underestimate relationships for the subset of the population with SAD.

The issue of instrument validity is a concern when considering the 2SLS results. In part to address questions about validity along the dimension of time, the inclusion of year and quarter dummy variables control for seasonal and other cycles in labor markets. Similarly, state fixed effects (and, in alternative specifications not reported, state-by-quarter fixed effects) control for unobservable labor market conditions and differences in the simultaneous determination of mental health and employment status as they vary across states. These covariates are likely to account for unobserved correlates that could bias the relationship between mental health and employment and raise questions about instrument validity.

That the HRQOL measures in BRFSS do not directly reflect clinical diagnostic criteria for mental disorders requires a careful interpretation of the results. Since most discussions of mental health are couched in clinical classifications, clear interpretation requires translation between the given HRQOL measures and more widely used clinical classifications. The HRQOL measures used here likely suggest meaningful variation in clinical classifications because they represent categories of symptoms related to SAD and depression. It is likely that the estimated relationship with employment status is appropriately viewed as at least an approximation of, say, the relationship between depression and employment status. It may be that the results presented here in fact underestimate the relationship between depression and employment status because SAD symptoms are, by definition, present only in the short-term. From another perspective, the effects of clinically diagnosed depression on employment would perhaps not be as precisely interpreted temporally as are the employment effects of the HRQOL measures used here.

From a societal perspective, intervention may be warranted. If the darkness index association with employment is causal, the fact that photoperiod changes are the same for everyone in a given county may imply that everyone is either adversely affected or at best unaffected with respect to employment status. A detectable net increase in unemployment may be viewed as evidence that SAD is not simply changing who has jobs, where some lose and some gain. And even if this is not the case, further research could explore whether specific efforts to improve mental health are more cost-effective in improving employee retention and productivity than paying hiring transaction or training costs. Although it is beyond the scope of this paper to draw specific conclusions regarding the welfare effects of interventions, the findings presented here support previous findings that poor mental health adversely affects employment status.

- An index of darkness (measuring daylight length) is constructed and hypothesized to be related to Seasonal Affective Disorder.

- The darkness index as a potential instrument for health-related quality of life measures is explored.
- More hours of darkness is associated with poorer HRQOL, which in turn is associated with a lower likelihood of employment.

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Table 1

Summary statistics, BRFSS

	Mean	Std. Dev.	Min	Max	Obs
Darkness Index	-0.188	1.818	-4.086	3.834	1,456,199
Mean Temperature	58.287	15.699	-4.738	97.130	1,456,199
Total Precipitation	3.083	2.484	0.000	31.801	1,456,199
Unhealthy Days	3.504	7.448	0	30	1,383,002
Blue Days	3.147	6.540	0	30	92,140
Energy Days	18.457	10.331	0	30	91,416
Stress Days	5.496	8.563	0	30	91,923
Employed	0.718	0.450	0	1	1,456,199
Unemployed	0.059	0.236	0	1	1,456,199
Male	0.499	0.500	0	1	1,456,199
Age	39.799	12.939	18	65	1,456,199
White	0.794	0.404	0	1	1,456,199
Black	0.103	0.304	0	1	1,456,199
Hispanic	0.156	0.363	0	1	1,456,199
High School Grad	0.564	0.496	0	1	1,456,199
College Grad	0.326	0.469	0	1	1,456,199

Notes: The sample includes the 1994–2009 waves of the Behavioral Risk Factor Surveillance System (BRFSS). The darkness index is calculated using day of year and the latitude of the center of population of the respondent's county. County level mean temperature and total precipitation are calculated using data drawn from the National Climatic Data Center's Summary of the Month data files. Health-related quality of life (HRQOL) measures are part of the BRFSS Healthy Days optional modules, selected for inclusion by some states in some years. See text for more details.

Table 2

Darkness index associations with Healthy Days measures

	(1)	(2)	(3)	(4)
Healthy Days Measures:	Unhealthy	Blue	Energy	Stress
Darkness Index	0.041*** (0.011)	0.029 (0.030)	-0.139 (0.083)	0.041 (0.048)
Mean Temperature	0.005*** (0.002)	0.002 (0.005)	-0.007 (0.011)	0.005 (0.006)
Total Precipitation	0.017*** (0.004)	0.017 (0.012)	0.010 (0.024)	0.030* (0.017)
Male	-1.338*** (0.026)	-1.123*** (0.044)	1.764*** (0.076)	-1.532*** (0.070)
Age	0.115*** (0.009)	0.119*** (0.017)	-0.087*** (0.023)	0.195*** (0.021)
Age ²	-0.002*** (0.000)	-0.001*** (0.000)	0.001*** (0.000)	-0.003*** (0.000)
White	-0.105 (0.064)	-0.079 (0.129)	0.147 (0.189)	0.444*** (0.138)
Black	-0.088 (0.108)	0.252 (0.192)	0.555*** (0.190)	-0.436** (0.206)
Hispanic	-0.792*** (0.117)	-0.139 (0.180)	1.220*** (0.268)	-0.704** (0.277)
High School Grad	-1.934*** (0.126)	-2.321*** (0.170)	2.393*** (0.224)	-2.060*** (0.239)
College Grad	-3.421*** (0.147)	-3.545*** (0.177)	3.533*** (0.294)	-3.204*** (0.249)
Observations	1,383,002	92,140	91,416	91,923
R-squared	0.026	0.030	0.022	0.025

Notes: Each column represents a separate OLS regression model. Heteroskedasticity-robust standard errors, clustered by state, are in parentheses. Each model also includes dummy variables for state, year, and quarter. See Table 1 for other variable details.

significant at 1%,

**
significant at 5%,

*
significant at 10%.

Table 3

Darkness index associations for men and women

	(1)	(2)	(3)	(4)
Healthy Days Measures:	Unhealthy	Blue	Energy	Stress
1) Men Only				
Darkness Index	0.001	0.032	-0.183	0.025
	(0.013)	(0.048)	(0.112)	(0.063)
Mean Temperature	0.001	0.006	-0.013	0.006
	(0.002)	(0.006)	(0.014)	(0.008)
Total Precipitation	0.020***	0.037*	-0.011	0.047
	(0.004)	(0.019)	(0.033)	(0.029)
Observations	559,339	37,867	37,616	37,737
R-squared	0.017	0.020	0.013	0.017
2) Women Only				
Darkness Index	0.070***	0.026	-0.107	0.053
	(0.013)	(0.037)	(0.090)	(0.068)
Mean Temperature	0.008***	0.000	-0.002	0.004
	(0.002)	(0.005)	(0.011)	(0.007)
Total Precipitation	0.015***	0.003	0.025	0.019
	(0.005)	(0.013)	(0.027)	(0.020)
Observations	823,663	54,273	53,800	54,186
R-squared	0.021	0.026	0.020	0.021

Notes: Each column in each panel represents a separate OLS regression model. Heteroskedasticity-robust standard errors, clustered by state, are in parentheses. Each model also includes dummy variables for state, year, and quarter. See Table 1 for other variable details.

significant at 1%,

**
significant at 5%,

*
significant at 10%.

Table 4

Darkness index associations by varying days thresholds

	(1)	(2)	(3)	(4)
Healthy Days Measures:	Unhealthy	Blue	Energy	Stress
Indicator for Days > 0	0.0015 [*]	0.0062 [*]	-0.0024 [*]	0.0035
	(0.0008)	(0.0033)	(0.0014)	(0.0046)
Pseudo R ²	0.0298	0.0281	0.0441	0.0363
Indicator for Days > 5	0.0018 ^{***}	0.0012	-0.0040 [*]	0.0013
	(0.0005)	(0.0018)	(0.0023)	(0.0027)
Pseudo R ²	0.0287	0.0312	0.0215	0.0202
Indicator for Days > 10	0.0016 ^{***}	0.0004	-0.0049	0.0016
	(0.0004)	(0.0012)	(0.0033)	(0.0020)
Pseudo R ²	0.0307	0.0362	0.0133	0.0203
Indicator for Days > 15	0.0012 ^{***}	0.0000	-0.0043	0.0011
	(0.0004)	(0.0010)	(0.0037)	(0.0018)
Pseudo R ²	0.0310	0.0408	0.0133	0.0226
Indicator for Days > 20	0.0012 ^{***}	0.0001	-0.0074 [*]	0.0011
	(0.0004)	(0.0009)	(0.0039)	(0.0016)
Pseudo R ²	0.0325	0.0464	0.0175	0.0266
Indicator for Days > 25	0.0010 ^{***}	0.0005	-0.0043	0.0009
	(0.0003)	(0.0008)	(0.0041)	(0.0015)
Pseudo R ²	0.0331	0.0480	0.0221	0.0283
Observations	1,383,002	92,140	91,416	91,923

Notes: Each coefficient and standard error pair represents a separate probit model, and each coefficient is the marginal effect of the darkness index (at the mean of the covariates). Heteroskedasticity-robust standard errors, clustered by state, are in parentheses. Each model also includes dummy variables for state, year, and quarter. See Table 1 for other variable details.

significant at 1%,

**
significant at 5%,

*
significant at 10%.

Table 5

Summary statistics, Current Population Survey

	Mean	Std. Dev.	Min	Max
Darkness Index	-0.123	1.883	-6.930	6.635
Mean Temperature	58.784	16.264	-1.210	96.700
Total Precipitation	2.812	2.823	0.000	31.410
Employed	0.740	0.439	0	1
Unemployed	0.038	0.191	0	1
Male	0.484	0.500	0	1
Age	40.273	12.872	18	65
White	0.811	0.392	0	1
Black	0.094	0.292	0	1
Hispanic	0.166	0.372	0	1
High School Grad	0.502	0.500	0	1
College Grad	0.367	0.482	0	1

Notes: $N = 100,000$ (a random sample of the original data set). The sample includes the years 1994–2009. The darkness index is calculated using day of year and the latitude of the center of population of the respondent's county. County level mean temperature and total precipitation are calculated using data drawn from the National Climatic Data Center's Summary of the Month data files. See text for more details.

Table 6

Darkness index associations with employment status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employed			Unemployed				
	CPS	BRFSS			CPS	BRFSS		
Darkness Index	-0.0057** (0.0027)	-0.0004 (0.0010)	-0.0000 (0.0099)	0.0029 (0.0020)	0.0011 (0.0010)	0.0006** (0.0003)	0.0004 (0.0003)	-0.0008 (0.0009)
Unhealthy Days			-0.0072*** (0.0002)	-0.0016*** (0.0004)			0.0015*** (0.0000)	0.0001 (0.0001)
Blue Days				-0.0057*** (0.0003)				0.0012*** (0.0001)
Energy Days				0.0022*** (0.0002)				-0.0001 (0.0001)
Stress Days				0.0006** (0.0003)				0.0005*** (0.0001)
Mean Temperature	-0.0004 (0.0003)	0.0001 (0.0001)	0.0001 (0.0001)	0.0003 (0.0003)	0.0001 (0.0001)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0003*** (0.0001)
Total Precipitation	0.0009 (0.0007)	-0.0003 (0.0002)	-0.0001 (0.0002)	-0.0003 (0.0007)	-0.0000 (0.0003)	0.0002** (0.0001)	0.0002** (0.0001)	0.0003 (0.0003)
Male	0.1435*** (0.0071)	0.1388*** (0.0042)	0.1314*** (0.0044)	0.1339*** (0.0066)	0.0066*** (0.0009)	0.0009 (0.0007)	0.0030*** (0.0008)	-0.0028 (0.0024)
Age	0.0417*** (0.0006)	0.0536*** (0.0007)	0.0552*** (0.0007)	0.0523*** (0.0014)	-0.0021*** (0.0004)	-0.0004*** (0.0002)	-0.0007*** (0.0002)	-0.0001 (0.0004)
Age ²	-0.0005*** (0.0000)	-0.0007*** (0.0000)	-0.0007*** (0.0000)	-0.0007*** (0.0000)	0.0000*** (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)
White	0.0422*** (0.0103)	0.0423*** (0.003)	0.0412*** (0.0060)	0.0303*** (0.0096)	-0.0027*** (0.0019)	-0.0141*** (0.0019)	-0.0136*** (0.0017)	-0.0105*** (0.0025)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Employed				Unemployed			
CPS	BRFSS	CPS	BRFSS	CPS	BRFSS	CPS	BRFSS
Black	-0.0196* (0.0106)	0.0119* (0.0068)	0.0184* (0.0092)	0.0193*** (0.0020)	0.0132*** (0.0017)	0.0133*** (0.0016)	0.0118*** (0.0023)
Hispanic	0.0076 (0.0086)	0.0028 (0.0045)	-0.0079 (0.0053)	0.0024 (0.0018)	0.0005 (0.0013)	0.0024* (0.0013)	0.0017 (0.0026)
High School Grad	0.1327*** (0.0058)	0.1554*** (0.0046)	0.1177*** (0.0062)	-0.0125*** (0.0013)	-0.0235*** (0.0012)	-0.0200*** (0.0011)	-0.0219*** (0.0021)
College Grad	0.2276*** (0.0071)	0.2483*** (0.0067)	0.1761*** (0.0080)	-0.0262*** (0.0021)	-0.0500*** (0.0015)	-0.0431*** (0.0014)	-0.0382*** (0.0034)
Observations	100,000	1,452,690	76,961	100,000	1,452,690	1,379,724	76,961
Pseudo R ²	0.0999	0.1128	0.1267	0.0439	0.0384	0.0506	0.0550

Notes: Each column represents a separate probit model. Heteroskedasticity-robust standard errors, clustered by state, are in parentheses. Each model also includes dummy variables for state, year, and quarter. See Tables 1 and 5 for other variable details.

*** significant at 1%,

** significant at 5%,

* significant at 10%.

Table 7

Darkness index associations with employment status for men and women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employed			Unemployed				
	CPS		BRESS	CPS	BRESS			
1) Men Only								
Darkness Index	-0.0024 (0.0021)	-0.0011 (0.0010)	-0.0006 (0.0011)	0.0051 (0.0040)	0.0006 (0.0013)	0.0006 (0.0004)	0.0003 (0.0004)	-0.0033** (0.0016)
Unhealthy Days			-0.0084*** (0.0001)	-0.0027*** (0.0003)		0.0017*** (0.0000)		0.0003** (0.0001)
Blue Days				-0.0052*** (0.0005)				0.0011*** (0.0002)
Energy Days				0.0025*** (0.0002)				-0.0002* (0.0001)
Stress Days				0.0001 (0.0003)				0.0004** (0.0002)
Observations	48,389	587854	557970	31663	48,389	587854	557970	31663
Pseudo R ²	0.1252	0.1543	0.1825	0.1974	0.0497	0.0461	0.0613	0.0727
2) Women Only								
Darkness Index	-0.0084* (0.0048)	0.0001 (0.0012)	0.0005 (0.0013)	0.0010 (0.0038)	0.0015* (0.0009)	0.0005* (0.0003)	0.0004 (0.0003)	0.0012 (0.0016)
Unhealthy Days			-0.0063*** (0.0002)	-0.0009 (0.0005)		0.0014*** (0.0000)		-0.0000 (0.0001)
Blue Days				-0.0058*** (0.0003)				0.0013*** (0.0002)
Energy Days				0.0017*** (0.0001)				-0.0001 (0.0001)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Employed			Unemployed				
	CPS		BRFSS		CPS		BRFSS	
Stress Days				(0.0002)			(0.0001)	
				0.0008**			0.0003**	
				(0.0003)			(0.0001)	
Observations	51,611	864836	821754	45298	51,611	864836	821754	45298
Pseudo R ²	0.1252	0.1543	0.1825	0.1974	0.0497	0.0461	0.0613	0.0727

Notes: Each column represents a separate probit model. Heteroskedasticity-robust standard errors, clustered by state, are in parentheses. Each model also includes dummy variables for state, year, and quarter. See Tables 1 and 5 for other variable details.

*** significant at 1%.

** significant at 5%.

* significant at 10%.

Table 8

Probit, OLS, and 2SLS estimates of unhealthy days effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed			Unemployed		
	Probit	OLS	2SLS	Probit	OLS	2SLS
Unhealthy Days	-0.0072 *** (0.0002)	-0.0074 *** (0.0002)	-0.0105 (0.0218)	0.0015 *** (0.0000)	0.0021 *** (0.0001)	0.0137 ** (0.0067)
Mean Temperature	0.0001 ** (0.0001)	0.0001 ** (0.0001)	0.0001 *** (0.0000)	-0.0001 *** (0.0000)	-0.0001 *** (0.0000)	-0.0001 *** (0.0000)
Total Precipitation	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0004)	0.0002 ** (0.0001)	0.0002 ** (0.0001)	-0.0000 (0.0002)
Male	0.1314 *** (0.0045)	0.1128 *** (0.0045)	0.1087 *** (0.0280)	0.0030 *** (0.0008)	0.0041 *** (0.0008)	0.0195 ** (0.0090)
Age	0.0552 *** (0.0007)	0.0555 *** (0.0006)	0.0558 *** (0.0027)	-0.0007 *** (0.0002)	-0.0012 *** (0.0002)	-0.0025 *** (0.0007)
Age ²	-0.0007 *** (0.0000)	-0.0007 *** (0.0000)	-0.0007 *** (0.0000)	0.0000 (0.0000)	0.0000 *** (0.0000)	0.0000 ** (0.0000)
White	0.0412 *** (0.006)	0.0375 *** (0.0054)	0.0372 *** (0.0060)	-0.0134 *** (0.0017)	-0.0162 *** (0.0022)	-0.0150 *** (0.0020)
Black	0.0104 (0.0064)	0.0080 (0.0060)	0.0078 (0.0063)	0.0133 *** (0.0016)	0.0212 *** (0.0023)	0.0222 *** (0.0024)
Hispanic	-0.0043 (0.0041)	-0.0038 (0.0041)	-0.0062 (0.0181)	0.0024 * (0.0013)	0.0041 ** (0.0020)	0.0132 ** (0.0060)
High School Grad	0.1422 *** (0.0041)	0.1524 *** (0.0046)	0.1465 *** (0.0430)	-0.0200 *** (0.0011)	-0.0316 *** (0.0018)	-0.0093 (0.0128)
College Grad	0.2226 *** (0.0060)	0.2226 *** (0.0064)	0.2122 *** (0.0764)	-0.0431 *** (0.0014)	-0.0531 *** (0.0021)	-0.0136 (0.0228)
Observations	1,379,724					

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed			Unemployed		
	Probit	OLS	2SLS	Probit	OLS	2SLS
(Pseudo) R ²	0.1267	0.1484		0.0505	0.022	
Kleibergen-Paap F stat			14.93			14.93

Notes: Each column represents a separate regression model. Heteroskedasticity-robust standard errors, clustered by state, are in parentheses. Each model also includes dummy variables for state, year, and quarter. See Table 1 for other variable details.

- *** significant at 1%,
- ** significant at 5%,
- * significant at 10%.

Table 9

Probit, OLS, and 2SLS estimates of unhealthy days effects for men and women

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed			Unemployed		
	Probit	OLS	2SLS	Probit	OLS	2SLS
1) Men Only						
Unhealthy Days	-0.0084*** (0.0001)	-0.0097*** (0.0002)	-0.1107*** (0.0024)	0.0017*** (0.0000)	0.0027*** (0.0001)	0.0361*** (0.0010)
Observations	557,970					
(Pseudo) R ²	0.1825	0.1929		0.0613	0.0272	
Kleibergen-Paap F stat	0.001					
2) Women Only						
Unhealthy Days	-0.0063*** (0.0002)	-0.0062*** (0.0002)	-0.0010 (0.0167)	0.0014*** (0.0000)	0.0019*** (0.0001)	0.0076* (0.0039)
Observations	821,75					
(Pseudo) R ²	0.0866	0.1100		0.0459	0.0198	
Kleibergen-Paap F stat	30.54					

Notes: Each column represents a separate regression model. Heteroskedasticity-robust standard errors, clustered by state, are in parentheses. Each model also includes dummy variables for state, year, and quarter. See Table 1 for other variable details.

significant at 1%,

**
significant at 5%,

*
significant at 10%.