The Light of Life: The Effects of Sunlight on Suicide*

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January 2023

Abstract

This study examines the causal effects of sunlight exposure on suicide. The analysis relates solar insolation to suicide rates at the county-by-month level between 1979 and 2004 in the U.S. We find that suicide increases by 6.99% as sunlight decreases by one standard deviation, and such effects exhibit limited adaptation across space and time. We find consistent evidence between sunlight and mental well-being measured by Google searches containing depressive language. These estimates suggest that proposed solar geoengineering can result in 1.26–3.18 thousand excess suicides by reducing incoming sunlight to keep the temperature rise below 1.5°C between 2030 and 2100.

*We thank Tamma Carleton, Ujjayant Chakravorty, Steve Cicala, Molly Elder, Hiromasa Furufu, Mesay Gebresilasse, Cynthia Kinan, Kazuki Motohashi, Elizabeth Setren, Hitoshi Shigeoka, Elizabeth Spink, Eric Zou, and seminar participants at Osaka University, Tufts University, and Japan-Tokyo Resource and Environmental Economics for helpful discussions and comments.

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I. Introduction

The so-called "Deaths of Despair" (Case and Deaton 2020) phenomenon attributes the rising rate of premature deaths and declining life expectancy among certain demographic groups in the U.S. to an increase in the rate of suicide. Since suicide has most often been linked to individual, social, and economic factors (Hamermesh and Soss 1974, Ruhm 2000, CDC 2022c), policy and program interventions have tended to address the issue accordingly. Yet, by and large these efforts have failed to stem the recent rising trend in the rates of suicide—by 30% between 2000 and 2018 and more than twice higher among younger people (CDC 2022a)—making it the only leading cause of deaths that is on the rise in critical need of a new approach. New research is calling into question whether environmental changes, e.g., temperature (Carleton 2017; Burke et al. 2018) and air pollution (Braithwaite et al. 2019, Marcotte and Persico 2022), portend a substantial change in the suicide rate.

We conduct the first large-scale, causal investigation of how sunlight exposure affects our mental health by focusing on suicide as an outcome. We first quantify the effects of solar insolation on suicide rates using novel datasets at the county-by-month level between 1979 and 2004 from the U.S. We then explore potential adaptation to sunlight exposure in suicidal behavior by assessing whether the effects of sunlight on suicide differ by county characteristics or over decades. To uncover potential mechanisms, we assess whether sunlight exposure affects mental well-being among a general population by investigating whether the number of searches containing or related to depressive language on Google is related to the sunlight patterns. Lastly, we project, to the best of our knowledge, the first estimates of the impacts of proposed solar radiation management geoengineering by assessing the excess suicides due to the negative radiative forcing required to keep the temperature rise below 1.5 °C between 2030 and 2100.

This study contributes to addressing three distinct economic questions that remain largely unanswered. First, determining factors that contribute to suicide risk merits close attention as suicide imposes substantial economic costs worldwide. Globally, more people die from suicide every year than major diseases such as HIV, malaria, or breast cancer, or conflicts and other types of violence (WHO 2021). In the U.S., an estimated 12.2 million American adults had serious thoughts about suicide, 3.2 million planned an attempt, and 1.2 million attempted suicide, and nearly 46,000 people, or one person every 11 minutes, died in 2020 (CDC 2022b). The economic costs of medical and work-loss alone as a result of suicide and suicide attempts amount to $70 billion annually in the U.S. (CDC 2019).

Second, the potential effects of sunlight exposure on mental health, and on suicide in particular, remain surprisingly poorly understood. Insufficient sunlight exposure during wintertime has been hypothesized to explain Seasonal Affective Disorder, a type of depression that peaks in wintertime, because of disrupted sleep, impeded neurotransmissions of serotonin, vitamin D deficiency, and the overproduction of melatonin (Benedetti et al. 2001; Berk et al. 2007; Kim et al. 2021). In contrast, suicide rates typically peak in late spring to early summer and decline in wintertime (Figure A.1). This apparently paradoxical seasonal pattern in the suicide rate has been cited as discrediting the sunlight-suicide relationship.

In addition, determining whether or not sunlight exposure affects the rate of suicide has an important policy implication, as the growing awareness worldwide of the adverse effects of Sun's ultraviolet (UV) rays, such as skin cancer, amplified by public campaigns to reduce excessive exposure to sunlight (CDC 2022d), has resulted in people spending increasing amounts of time indoors. On the other hand, there is increasing evidence that insufficient sunlight exposure can also be hazardous. For example, the worldwide vitamin D deficiency (about 40% of population in the U.S. and Europe (Forrest and Stuhldreher 2011; Cashman et al. 2016)) due to increased time indoors has been linked to increased mortality from chronic diseases such as cancer, cardiovascular diseases, and metabolic syndrome, resulting in an estimated 340,000 deaths in the U.S. and 480,000 deaths in Europe each year (Alfredsson et al. 2020).

Third, the sunlight-suicide relationship provides an important policy implication for new climate geoengineering technologies. Despite the worldwide efforts to curb the temperature rise and combat climate change, culminating in the Paris Agreement, progress in reducing pollution emissions is insufficient, and key mechanisms to accomplish the goal of keeping global warming to less than 1.5 °C remain to be developed. In this light, there is increasing interest in employing solar radiation management, which reflects sunlight back into space by using orbiting mirrors or spraying aerosol particles into the outer atmosphere (Crutzen 2006; National Research Council 2015; National Academies of Sciences, Engineering, and Medicine 2021). While the low financial cost and high availability of relevant technologies enable solar geoengineering to be implemented within a couple of years, resulting in a rapid reduction in global temperatures (Robock et al. 2009), the substantial uncertainties that remain concerning the impacts of solar geoengineering on both the natural environment and human health and well-being have given rise to controversies among scholars and policymakers regarding its deployment (MacMartin et al. 2016; Proctor et al. 2018; Trisos et al. 2018; Irvine et al. 2019; Abatayo et al. 2020; Keith 2021; Aldy et al. 2021).

Our empirical approach involves two novel features. First, sunlight exposure is measured by solar insolation, which is the amount of incident solar radiation energy received from the Sun per unit surface of the Earth over a specified period. Many factors determine how much sunlight reaches the surface, such as the solar zenith angle, the variable distance from the Earth to the Sun, day length, weather conditions, levels of atmospheric aerosols, and solar activity. Thus, solar insolation measures the intensive margin of sunlight exposure to humans much more precisely than the duration of daylight, the metric most widely used in the existing literature, which measures only the extensive margin of sunrise and sunset. Because the conventional use of daylight duration allows for little variation after controlling for the month effects, most studies have concluded that there is no relationship between sunlight and suicide (Kadotani et al. 2014; White et al. 2015; Gao et al. 2019; Makris et al. 2021; Papadopoulos et al. 2005; Vyssoki et al. 2014). Further, the more direct measure of sunlight exposure provided by solar insolation is necessary to project the impacts of geoengineering-driven reductions in sunlight on suicides.

Second, our longitudinal dataset with substantial cross-sectional and temporal coverage, along with our novel use of a direct measure of solar insolation, offers a unique opportunity to plausibly isolate the effects of sunlight exposure on suicide from a large set of other potential impacts on the suicide patterns by local monthly seasonality effects, such as daylight duration and school calendar, as well as local time-varying shocks, such as economic conditions, agricultural production, poverty rates, and gun ownership. In contrast, a handful of studies using solar insolation or irradiation as the exposure measure have relied exclusively on time-series data and showed a positive association with suicide (Papadopoulos et al. 2005), which we show is likely to be driven by other local seasonal patterns in meteorological, social, and economic factors.

Our main findings suggest that suicide rates increase by 6.99% (95% CI: 3.86, 10.13) as sunlight in a given and previous months decreases by one standard deviation, which is almost equivalent to the difference in sunlight between the lowest (Vermont) and highest (Arizona) state-level averages. We find few heterogeneities in the sunlight-suicide relationship by county characteristics or over time, suggesting limited adaptation to sunlight exposure in suicidal behavior. Our additional analysis indicates that sunlight is negatively related to the volume of internet searches for depressive language on Google, highlighting individuals' mental well-being as a suggestive mechanism linking sunlight and suicide. Our projection suggests that reducing solar radiation to keep the global temperature rise below 1.5 °C, as targeted by the Paris Agreement, can result in 1.26–3.18 thousand additional suicides in the 95% confidence interval (CI) between 2030 and 2100, which can more than offset the averted suicides by temperature reductions.

The rest of the paper is organized as follows. Section II describes data and empirical strategies. Section III presents empirical results. Lastly, Section IV concludes.

II. Empirical Framework

A. Data

Our data on suicide comes from Burke et al. (2018), which reports the age-adjusted suicide rates at the county-month level based on the Multiple Cause of Death Mortality Data from the National Vital Statistics System between 1968 and 2004.[1] The data also included the monthly average temperature and total precipitation from PRISM.[2]

We combine the suicide data with average daily solar insolation data at the county-by-month level in kilojoules per square meter (KJ/m^2) from the North America Land Data Assimilation System Daily Sunlight data compiled by the U.S. Centers for Disease Control and Prevention (CDC) (CDC 2012). Solar insolation is the amount of incident solar radiation energy received from the Sun per unit surface of the Earth over a specified period of time. Many factors determine how much sunlight reaches the surface, such as the solar zenith angle, the variable distance from the earth from the sun, day length, weather conditions, atmospheric aerosols levels, and the solar activity. The original data cover the 48 contiguous states plus the District of Columbia from 1979 to 2011. Thus, the resulting data after merging sunlight and suicide information span the period from 1979 to 2004 across (unbalanced) 3,107 counties in the 48 contiguous states and the District of Columbia.

To explore the potential heterogeneities in the effects of sunlight on suicide rates by various county characteristics, we draw annual county income data from the U.S. Bureau of Economic Analysis, deflated by the GDP deflator, data on the state-level average adoption of air conditioning between 1979 and 2004 from Barreca et al. (2016), and state-level gun ownership data from Okoro et al. (2005). The suicide rates by gender and methods of suicide are from Burke et al. (2018).

We analyze the impacts of sunlight exposure on the volume of searches made on Google using Google Trends. Google Trends reports the search data at several geographical levels, and two sets of the regions useful in our context are the state and Designated Marketing Area (DMA), whereas the county data are unavailable. A DMA is a geographically delineated media market, in which people receive the same television and radio options. There are 210 DMAs in total across the U.S. Google Trends reports normalized search interests, rather than raw search volumes, on a scale of 0 to 100, by comparing the search volumes in the respective time and region relative to the highest point under the selected condition. For example, an

[1] The data contain all counties until 1988 and counties with more than 100,000 residents after 1989. The data period necessarily ended in 2004 because county identifiers were not reported in the public-use data after 2004.

[2] See more details on how these variables were constructed in Burke et al. (2018).

index of 50 at a given time (e.g., month, week, or day) represents half the volume of searches with the index value of 100 at the same time.

Given the restrictions on the number of regions and keywords that can be included for each search, and because the data date back to 2004, each round of our data collection involves the words "depression" and one other keyword from the list of depressive language below for 2004–2011 by each region.[3] The set of depressive language follows Burke et al. (2018) and includes: addictive, alone, anxiety, appetite, attacks, bleak, depress, depressed, depression, drowsiness, episodes, fatigue, frightened, lonely, nausea, nervousness, severe, sleep, suicidal, suicide, and trapped. We sum up Google Trends values for all these keywords at the region-by-year-by-month level and again normalize them to the highest value within the region with a scale of 0 to 100 to construct the overall normalized search interests in depressive language. Note that while the constructed Google Trends values are not comparable across regions, e.g., 100 in region A is not comparable to 100 in region B, the inclusion of region fixed effects addresses this issue.

B. The effects of sunlight exposure on the suicide rate

The main analysis estimates the following distributed lag models that includes the lags and leads of each environmental factor, using ordinary least squares:

$$Y_{csmt} = \alpha + \sum_{l=k}^{K} \left[\beta_l \ln(Sunlight)_{c(m+l)t} + \gamma_l T_{c(m+l)t} + \lambda_l P_{c(m+l)t} \right] + \mu_{cm} + \tau_{st} + \varepsilon_{csmt}, \quad (1)$$

where the main outcome variable is the suicide rate in county c in state s in month m of year t. The main independent variable of interest, $\ln(Sunlight)$, is the log of average daily solar insolation (in $\mathrm{KJ/m^2}$), T denotes the monthly average temperature, and P denotes the monthly precipitation. The county-by-month fixed effects, μ_{cm}, control for unobserved seasonality effects at the county-month level, such as the daylight duration or the school calendar, whereas the state-by-year fixed effects, τ_{st}, account for any time-varying factors common across counties within a given state, such as economic conditions, agricultural production, poverty rates, and gun ownership. Thus, the parameters of interest, β_l's, are estimated based on the random variation in the amount of sunlight between, for example, August 2000 in a particular county and August 2001 in the same county. Following the convention, the regressions are weighted by county population, as the suicide rate is more precisely estimated with

[3] For example, we select "depression" and "suicide" as search terms, 2004–2011 as the time range, and California as the location. We select the word "depression" as the reference word because this yields greater search volumes than most other keywords, and in this way the Google Trends values for each keyword are comparable within each region.

a larger population. Further, we cluster the standard errors at the county level to correct heteroskedasticity in the error term, ε_{csmt}, and allow for correlations between observations within clusters. We also test alternative levels of clustering, such as the state level and two-way clustering at the county and year level, to account for spatial correlation in sunlight and show that the results are virtually the same (Table A.4).

The identification assumption is that such within-county-month variation in the amount of sunlight is uncorrelated with any other factors that affect the suicide rate. Such assumption is plausible because the amount of sunlight is determined by random fluctuations in climatic and meteorological conditions, after adjusting for factors related to sunlight itself, such as temperature, precipitation, the average sunlight in a given county-by-month, and year-specific shocks common within a given state. Thus, our estimates are not confounded by the permanent heterogeneities across counties or state-specific within-year fluctuations in sunlight and suicide rate. For example, individuals with higher incomes may be at a lower risk of suicides and may be inclined to live in areas with sunnier climates; or state-level annual average suicide rates may be lower in years with greater sunlight and greater agricultural production. Air pollution may be another environmental factor that is related to both sunlight and suicides. Unfortunately, reliable data on air pollution is available only for recent years, e.g., after 2000 (van Donkelaar et al. 2019). As a robustness check, we confirm that the estimated effect of sunlight is unchanged with and without controlling for the $PM_{2.5}$ concentrations in ambient air in 2000–2004, the period during which we have both air pollution and suicide data (Table A.5).

The distributed lag models allow us to examine whether insufficient sunlight exposure caused excess suicides or simply hastened suicides that would have occurred later anyway, the so-called harvesting effect. Each parameter, $\omega_l \in (\beta_l, \gamma_l, \lambda_l)$ for $l \in [k, K]$, can be interpreted as the effects of sunlight, temperature, and precipitation, respectively, in each month with lags and leads of l. For example, ω_0 indicates the effect of a given month's environmental factor, ω_{-1} the previous month's factor, and ω_1, the following month's factor. A finding of $\beta_l < 0$ for $l < 0$ indicates the lagged impacts of sunlight exposure in the previous l month on the current suicide rate, whereas a finding of $\beta_l > 0$ for $l < 0$ indicates a displacement effect, where insufficient sunlight in a particular month hastened suicides that would have occurred anyway in a $-l$ month later. Thus, the overall effect of sunlight in a given month is given by $\sum_{l=k}^{0} \beta_l$. We expect $\omega_l = 0$ for $l > 0$ as a placebo test since a future amount of sunlight should not have a causal impact on the incidence of suicide in a given month.

Since the main model is the level-log model, the interpretation of the coefficient is that a 1% increase in sunlight increases the suicide rate by $\beta_l/100$. To allow for potential non-linear effects of sunlight, we also consider a 3rd order polynomial function of average daily sunlight, where the main independent variable is replaced with $\sum_{l=k}^{K}[\beta_{1l}Sunlight_{cs(m+l)t} + \beta_{2l}Sunlight_{cs(m+l)t}^2 + \beta_{3l}Sunlight_{cs(m+l)t}^3]$.[4] As a further robustness check, we also consider a nonparametric binned model, where the main independent variable is replaced with $\sum_{l=k}^{K}\sum_{b=1}^{10}\beta_l^b \times \ln Sunlight_{cs(m+l)t} \times D_b$, where D_b is an indicator variable for each decile bin b. Based on the results from the main analysis and to ensure greater statistical power, we consider $l \in [-1, 0]$, whereas extending the period does not alter the conclusion.

A concern may arise about the endogeneity of temperature to sunlight, making it a "bad control" (Angrist and Pischke 2009). However, our main model includes temperature as a control for two reasons. One is that our goal is to estimate the effects of sunlight itself free from the effects of temperature. Because increased sunlight raises temperature, a model that does not control for temperature would estimate the overall impacts of sunlight on suicides resulting from two offsetting channels; reductions in suicides due to increased sunlight itself and increases in suicides due to higher temperatures. Thus, the inclusion of temperature as a control helps us isolate the impacts of sunlight on suicides net to temperature effects. Indeed, a model that does not control for temperature understates the effects of sunlight itself on suicides (Table A.6). Second, the effect of sunlight on temperature is small, rendering the problem of endogeneity negligible. For example, the county-by-month and state-by-year fixed effects explain 97.27% of the overall variation in temperature, whereas precipitation only accounts for an additional 0.01 percentage point explanatory power, and sunlight adds 0.03 percentage points (Table A.7). We also show that a one standard deviation decrease in sunlight leads to a 0.144 standard deviation decrease in temperature. Thus, the overall variation in temperature that is explained by sunlight is small.

C. Heterogeneities in the effects of sunlight

To estimate the potential heterogeneous effects of sunlight exposure on the suicide rate by various county- or state-level characteristics, i.e., sunlight, temperature, income, air conditioning ownership, and gun ownership, we first compute the population-weighted county- or state-level median characteristics and run a regression for each characteristic:

[4] The temperature and precipitation are included as a linear function based on evidence presented by Burke et al. (2018).

$$
\begin{aligned}
Y_{csmt} =& \sum_{l=k}^{K} \Big[\beta_l^A \ln(Sunlight)_{c(m+l)t} + \gamma_l^A T_{c(m+l)t} + \lambda_l^A P_{c(m+l)t}\Big] \times D \\
& \sum_{l=k}^{K} \Big[\beta_l^B \ln(Sunlight)_{c(m+l)t} + \gamma_l^B T_{c(m+l)t} + \lambda_l^B P_{c(m+l)t}\Big] \times (1-D) \\
& + \mu_{cm} + \tau_{st} + \varepsilon_{csmt},
\end{aligned} \tag{2}
$$

where D is an indicator variable for being above the median characteristics. Then, β_l^A indicates the effects of sunlight in counties with above-median characteristics and β_l^B indicates the effects for counties with below-median characteristics.

D. Adaptation over time

We explore how individuals adapt to variations in sunlight over time. Given that increasing public awareness of the harmful effects of sunlight exposure (e.g. skin cancer) has caused people increasingly to avoid such exposure, we would expect to see the suicide effects of sunlight lessen in more recent years. We first apply a model comparable to the main analysis by interacting each environmental factor with a dummy variable for the respective year.

$$
Y_{csmt} = \sum_{t=1979}^{2004} \sum_{l=k}^{K} \Big[\beta_l \ln(Sunlight)_{c(m+l)t} + \gamma_l T_{c(m+l)t} + \lambda_l P_{c(m+l)t}\Big] \times D_t + \mu_{cm} + \tau_{st} + \varepsilon_{csmt}, \tag{3}
$$

where D_t is an indicator variable for each year t. Based on the results from the main analysis and to ensure greater statistical power, we consider $l \in [-1, 0]$, whereas extending the period does not alter the conclusion.

E. Sunlight and depressive language in Google Trends

We estimate the effects of monthly sunlight on Google searches containing depressive language by regressing the following fixed-effects model using the ordinary least squares:

$$
Y_{rmt} = \alpha + \sum_{l=k}^{K} \Big[\beta_l \ln(Sunlight)_{r(m+l)t} + \gamma_l T_{r(m+l)t} + \lambda_l P_{r(m+l)t}\Big] + \nu_r + \mu_m + \tau_t + \varepsilon_{rmt}. \tag{4}
$$

where Y_{rmt} is the Google Trends index in region $r \in (state, DMA)$, month m, and year t. Based on the results from the main analysis and to ensure greater statistical power, we consider $l \in [-1, 0]$, whereas extending the period does not alter the conclusion. The regressions are weighted by regional population, and the standard errors are clustered at the regional level. Since the time framework for Google Trends data does not overlap with that of the main analysis, we additionally obtain population data from the U.S. Census. We also obtain the temperature and precipitation information from NOAA's Global Historical Climatology Network - Daily.

As robustness checks, we include a set of alternative fixed effects. For example, with the DMA-level data, we include state-by-year and state-by-month fixed effects or state-by-month and state-specific trends, as in the main analysis. Note that many DMAs cross multiple states. In such a case, we select the state that is referenced in the DMA name as the primary state of affiliation.

As further robustness checks, we estimate the same models for a different subset of depressive language terms and find similar results (Table A.9).

F. Projected impacts of solar geoengineering

The estimated effects of sunlight on suicides thus far include both the effects of an anticipated shift in sunlight over time, i.e., climate effects, and the effects of an unanticipated shock to sunlight exposure, i.e., weather shocks. For example, individuals in areas with greater sunlight may shelter themselves from the increased harms of sunlight exposure due to, for instance, ozone depletion, by shifting their work from outdoors to indoors over time, whereas current daily activities, such as work and school, are less responsive to day-to-day fluctuations in sunlight. In this case, the marginal effects of an unanticipated shock are likely to outweigh the marginal effects of an anticipated shift over time (Gammans 2020), with the result that the projected impacts of solar geoengineering based on weather shocks overstate the actual impacts of the climate effect. Thus, we adopt a model that explicitly disentangles these two effects as follows:

$$
\begin{aligned}
Y_{csmt} =& \alpha + \sum_{l=k}^{K} \Bigg\{ \beta_l \underbrace{\ln(\overline{Sunlight})_{c(m+l)}}_{\text{climate effect}} \\
& + \delta_l \underbrace{\left[\ln(Sunlight)_{c(m+l)t} - \ln(\overline{Sunlight})_{c(m+l)} \right]}_{\text{weather effect}} \\
& + \gamma_l T_{c(m-+)t} + \lambda_l P_{c(m+l)t} \Bigg\} + \nu_c + \mu_m + \tau_{st} + \varepsilon_{csmt},
\end{aligned} \tag{5}
$$

where we separately control for the county-month average sunlight in our study period, $(\overline{Sunlight})_{cm}$, and the difference between the observed sunlight and long-term average sunlight for each county and month. Since the county-by-month fixed effects would be multicollinear with the county-month's average sunlight, we separately control for county fixed effects, ν_c, and month fixed effects, μ_m. The county fixed effects control for permanent differences in county characteristics that affect the suicide rate, whereas the month fixed effects control for seasonality patterns across months in the suicide rate. Additionally, we control for state-by-year fixed effects to control for transitory shocks to the suicide rate that are common within a particular year of the state.

The effect of an anticipated sunlight shift over time is captured by the $\sum_{l=k}^{K} \beta_l$ coefficients, which are identified from within-county variation in the average sunlight in each month, after controlling for national seasonality. For example, sunlight may be stronger in August than in July in County A much more so than in County B, leading people in County A to spend more time indoors than those in County B. In contrast, the effects of an unanticipated sunlight shock in a given month of a particular year is captured by the $\sum_{l=k}^{K} \delta_l$ coefficients, which are identified from a transitory deviation from the anticipated level of sunlight in a specific month.

Then, using the parameter based on the climate effect, we project how the reduction of sunlight due to solar radiation management will affect the incidence of suicide between 2030 and 2100. We assume that the cumulative CO_2 emissions in 2030 would be 700 Gt (Benveniste et al. 2018) and would grow at the rate of 47 Gt/year under a business-as-usual scenario thereafter (Lawrence et al. 2018).[5] Temperature is already set to be above 1 °C from preindustrial times in 2015 (Schurer et al. 2018) and is projected to increase by 1 °C for every 1,300 Gt CO_2 emissions (Lawrence et al. 2018). Thus, the cumulative CO_2 emissions must stay at 650 Gt from 2015 onward to keep the temperature rise below 1.5 °C or 1,300 Gt for the temperature to be below 2° C. The equivalent radiative forcing amount

[5] As robustness checks, we also consider other emission reductions scenarios in each year.

is taken from the equilibrium climate sensitivity of approximately 0.8 °C/(W/m^2) (IPCC 2013). Together, these parameters imply the amount of radiative forcing that is required to offset the temperature rise due to 1 Gt of CO_2 is 9.6×10^{-4} (W/m^2)/Gt(CO_2) (Lawrence et al. 2018).

Using these parameters, the cumulative number of excess suicides due to the reduction in sunlight required to meet the goal of keeping global temperature rise below 1.5 °C between 2030 and 2100 can be obtained by:

$$\sum_{t=2030}^{2100} pop_t \times \beta \times \Delta \ln(Sunlight)_t, \tag{6}$$

where pop_t is the projected U.S. population in year t in hundred thousand from United Nations (UN 2022), β is the estimated climate impact of sunlight on the suicide rate ($\beta = -0.078$, 95%CI: $-0.112, -0.044$) from Table A.10 Column (1), and $\Delta \ln(Sunlight)$ is the log point change of the implied negative radiative forcing gap to achieve the temperature limit in each year from the mean (set to be zero if the radiative forcing gap is positive since radiative forcing need not be increased to meet the temperature limit). For example, in 2030, the cumulative CO_2 emissions will already exceed the remaining CO_2 budgets of 650 Gt by 50 Gt to keep the temperature rise below 1.5 °C. The implied negative radiative forcing gap is then 0.048 W/m^2 ($= 50 \times 9.610^{-4}$). This is equivalent to a 4.4172 KJ/m^2 reduction in the daily solar insolation, which is a 0.0002526 log point reduction from its mean, i.e., an approximately 0.025% reduction in daily solar insolation. Finally, to arrive at the annual increase in suicides, we multiply the number by the projected population and by 12 months.

Since reduced temperature has been shown to reduce suicides (Burke et al. 2018), we incorporate suicides "averted" by temperature fall to arrive at the net impacts of solar geoengineering on the incidence of suicides. We conduct a similar analysis to compute averted suicides due to reduced temperature to meet the global temperature rise between 2030 and 2100 by:

$$\sum_{t=2030}^{2100} pop_t \times \gamma \times \Delta T_t, \tag{7}$$

where ΔT_t is the change in temperature from the business-as-usual scenario to achieve the temperature limit (again set to be zero if the temperature is below the limit). For example, in 2030, the temperature will exceed the 1.5 °C limit by 0.038 °C. We then multiply 0.038 by the estimated impacts of temperature in a given and previous month on the suicide rate ($\gamma = 0.00134$ (95% CI: 0.000287, 0.00248) from Gammans (2020)) to obtain the averted suicide rates.[6] To arrive at the annual reductions in suicides, we multiplied the number by the projected population and by 12 months.

To compute the net effects of sunlight and temperature on the incidence of suicides, we randomly draw β and γ from its estimated distribution and projected their cumulative impacts in 2100. We repeat the process by 10,000 times to arrive at the 95% CI.

III. Results

A. The effects of sunlight on the suicide rate

We find that insufficient sunlight significantly increases the suicide rate. The results of the distributed lag model show that the contemporaneous effect is negative and statistically significant ($\beta_0 = -0.049$; 95% CI: $-0.092, -0.006$) (Table A.2). We additionally find a statistically significant and larger in magnitude effect of sunlight from the previous month ($\beta_{-1} = -0.085$; 95% CI: $-0.132, -0.038$), suggesting that the sunlight-suicide relationship is a dynamic one in which the trajectory of depression leading to suicide can develop over months (Ballard et al. 2020). In contrast, the effect of sunlight in the second previous month is negligible ($\beta_{-2} = -0.003$; 95% CI: $-0.046, 0.040$), indicating that the cumulative effects span two months. As placebo evidence, we find that the effect of sunlight in the following month has no impact on the suicide rate in this month (β_1=0.010; 95% CI: $-0.037, 0.057$). The overall impact of sunlight is thus given by $\beta_0 + \beta_{-1}$, which is -0.134 (95% CI: $-0.194, -0.074$, p-value = 0.000, N = 444,861).

These estimates suggest that a one standard deviation decrease in population-weighted sunlight, 6,449.2 KJ/m^2, from the population-weighted mean value of 16,422.9 KJ/m^2, leads to a 6.99% (95% CI: 3.86, 10.13) increase in the suicide rate. This amount of change in sunlight is approximately equivalent to the difference in the average state-level sunlight between Vermont at the lowest level of sunlight and Arizona at the highest level of sunlight during our study period of 1979–2004. The estimated size of the effect is nearly comparable to the effect of a one standard deviation increase in temperature on the suicide rate (Table A.2).

We test the robustness of these estimates in several ways. First, we use different, and often more granular, fixed effects, such as county-by-month and county-by-year fixed effects, and cubic polynomial models. Figure 1 illustrates the estimated cumulative effects based on these alternative models. The shaded area represents the 95% CI of the baseline model with

[6] We take the temperature effects from Gammans (2020) because our unbalanced data do not allow us to compute the county-month average temperature in our study period. Nonetheless, the estimated effects using the county-month average temperature within our data produce very similar impacts.

county-by-month and state-by-year fixed effects. We find that all estimated effects from the alternative models are quantitatively similar to each other. Second, we find similar results using various other dependent variables and a count model (Table A.3). Third, we explore temporal displacement effects over a longer period, showing consistent evidence that the months before the second previous month have no impact on the suicide rate in a given month (Figure A.4).

Let us compare our estimated impact of sunlight on the suicide rate with the impacts of other interventions in previous studies. Figure 2 describes the amount of changes in sunlight in both percentage and standard deviation that brings about the equivalent impacts by other factors such as air pollution (Braithwaite et al. 2019), temperature (Burke et al. 2018), firearm regulations (Okoro et al. 2005), national suicide prevention programs (Matsubayashi and Ueda 2011), celebrity suicides (Ueda et al. 2014), a higher unemployment rate (Stuckler et al. 2009), and COVID-19 (Tanaka and Okamoto 2021). For example, a 0.34 standard deviation, or 13.3%, decrease in sunlight brings about the equivalent effect of a 10-$\mu g/m^3$ increase in PM_{10} on suicide. Overall, we find that a 1 to 2 standard deviation change in sunlight generates the equivalent impact of other interventions, revealing sunlight as a major risk factor in the incidence of suicide.

B. Heterogeneities in the effects of sunlight

We now explore potential heterogeneities in the sunlight-suicide relationships by county characteristics (Figure 3). We find that the effects of sunlight are virtually identical between counties with above- or below-median sunlight. The results from the nonparametric approach that explores the effects in each decile of historical sunlight exposure provide consistent results, although the highest decile appears to have a slightly stronger effect (Figure A.2). We also find that the effects in each month are quantitatively in the similar range (Figure A.3). These results suggest that the effects of sunlight exposure do not vary by the baseline levels of sunlight exposure. We also find similar impacts of sunlight on the suicide rate across county temperature, indicating that the effect of sunlight on the suicide rate is independent from that of temperature. It is worth noting that while the log of sunlight is positively correlated with the monthly temperature, temperature is significantly and positively associated with the suicide rate. Using the county-level income data, we find a larger effect of sunlight in counties with above-median income, whereas the estimated effect among below-median income counties is not statistically different from zero. We also find no heterogeneities in the effects of sunlight by the state-level adoption rate of air conditioning, although people with air conditioning may stay indoors on warm days and avoid sunlight exposure. Further, we find no heterogeneities by state-level gun ownership rate, although over 50% of suicides involved a firearm in 2020 (CDC 2020). Lastly, we find no heterogeneities by method of suicide among men, whereas the estimated effects are smaller for women, particularly using violent methods.

C. Adaptation over time

Existing studies find mixed evidence regarding the extent of adaptation to changes in the environment. For example, while the effects of temperature on all-cause mortality have lessened over time in the U.S. due to the adoption of air conditioning (Barreca et al. 2016), the effects of temperature on suicide have been stable over decades in the U.S. and Mexico (Burke et al. 2018).

In contrast, existing evidence offers no insight into the sunlight-suicide relationship. Increasing evidence regarding the role of ultraviolet radiation in skin cancer has led to reduced time spent outdoors over the past decades, which has potentially reduced the effects of sunlight on suicide over time. We find that the effects of sunlight on the suicide rate have been quantitively similar over our study period (Figure 4). Overall, these findings point to limited adaptation to sunlight exposure in suicidal behavior.

D. Sunlight and depressive language on Google Trends

Our findings thus far demonstrate a strong relationship between sunlight and suicide, while the underlying mechanism remains unclear. Building upon Burke et al. (2018), we seek to uncover the mechanism by examining the possibility that sunlight exposure is related to mental well-being. We measure mental well-being by the patterns of internet searches for or using depressive language among the general population, in anticipation that they vary in accordance with sunlight. To test this, we obtain the monthly internet search results using depressive language on Google using Google Trends between 2004 and 2011.[7]

Using a similar fixed-effects model, we find evidence consistent with the main analysis that sunlight in given and previous months has significantly negative impacts on the number of searches employing depressive language (Figure 5). In particular, we find that a one standard deviation decrease in the amount of monthly sunlight (6,532.7 KJ/m^2) at the state level leads to a 4.33% (95% CI: 3.26, 5.40, p = 0.000, N = 4,655) increase in the search volumes for depressive language. We also find similar effects with the Designated Marketing Area (DMA)-level of observations with various fixed effects (Figure 5). We further find comparable effects

[7] The study period is bounded by the initial year when Google Trends is available and the last year for which the sunlight data is available.

with subsets of the entire list of depressive language (Table A.9).

The mechanism through which sunlight affects mental well-being may well be biological and/or behavioral. Biologically, insufficient sunlight is known to cause disrupted sleep, impeded neurotransmissions of serotonin, vitamin D deficiency, and the overproduction of melatonin levels (Benedetti et al. 2001; Berk et al. 2007; Kim et al. 2021), all or some of which may adversely affect mental health and increase suicide risk. The behavioral component may stem from the association of greater sunlight with more physical activity and more social interactions, both of which can reduce feelings of sadness and isolation. Such a behavioral linkage is likely for individuals in places with low levels of sunlight who would spend more time outdoors on sunnier days (holding temperature constant). On the other hand, individuals in places with high levels of sunlight would spend more time indoors when sunlight is greater (Graff Zivin and Neidell 2014), which would lead to a positive association, or at least a weaker negative association, between sunlight and suicides. Thus, such a behavioral mechanism contradicts our finding that the effect is strongest in the top decile areas. In addition, the substantial cumulative impacts from the previous month suggest the mechanism leading to a suicide attempt is a dynamic process over months. In contrast, temperature and air pollution have immediate effects on suicides, as aggressive emotions or inflammation of the nervous system trigger self-harm attempts (Cianconi et al. 2020).

E. Projected impacts of solar geoengineering

We project the first estimates of how reduced incoming sunlight by solar radiation management will affect the suicide rate. We first disentangle the effects of an anticipated shift in sunlight (climate effect) and an unanticipated shock to sunlight exposure (weather effect). Since the future impacts depend solely on the anticipated climate effect, we project the future impacts of sunlight shift by solar geoengineering using the parameters for the climate effect (Gammans 2020).

Overall, our estimates suggest that solar insolation needs to be reduced by up to 1.69% in 2100 under the business-as-usual scenario, which will cause cumulative 2.23 (95% CI: 1.26 3.18) thousand additional suicides by 2100 (Figure 6, Table A.12). In contrast, temperature is projected to rise by 4 °C in 2100 under the business-as-usual scenario. By reducing the temperature rise by about 2.5 °C to achieve the goal of a 1.5 °C temperature rise, we project that 5.75 (95% CI: 1.23 10.69) thousand suicides will be averted. Thus, the effects of insufficient sunlight will offset about 38.8% (95% CI: 27.8, 163.5) of the suicides averted by temperature fall. The resulting net reduction in the cumulative suicides by 2100 will be 3.52 (95% CI: −0.781, 7.72) thousand (Table A.12). Thus, solar geoengineering can indeed increase the incidence of suicides when the effects of insufficient sunlight more than offset the effects of temperature (Figure A.5). The results are consistent with an alternative goal of a 2.0 °C temperature rise and with other pollution emission reductions scenarios (Table A.12).

IV. Conclusion

This study assesses whether and to what extent sunlight exposure affects the suicide rate and the implications for solar geoengineering. Our main findings suggest that suicide rates increase by 6.99% as sunlight in a given and previous months decreases by one standard deviation. We find few heterogeneities in the sunlight-suicide relationship by county characteristics or over time, suggesting limited adaptation to sunlight exposure in suicidal behavior. The findings should still be carefully interpreted for generalizability, especially for places at extremely high or low latitudes. Our additional analysis indicates that sunlight is negatively related to the volume of internet searches for depressive language on Google, highlighting individuals' mental well-being as a suggestive mechanism linking sunlight and suicide. Future research is warranted to discover the precise underlying mechanism(s) at work.

Our projection suggests that reducing solar radiation to keep the global temperature rise below 1.5 °C, as currently targeted by the Paris Agreement, can result in 1.26–3.18 thousand additional suicides (95% CI) between 2030 and 2100, and the net of the temperature reduction effects is projected to cause 0.781 to −7.72 additional suicides by 2100. Thus, solar geoengineering can indeed increase the incidence of suicides when the effects of insufficient sunlight more than offset the effects of temperature. From a distributive justice perspective, future research would also be useful to explore potential differences in the effects of solar geoengineering between developed and developing countries.

This study has important policy implications for two distinct fields. First, most research on sunlight has focused on adverse health consequences such as skin cancer, resulting in the widespread awareness and current public health advice to reduce sunlight exposure. However, our findings suggest that it is vital for public health policies to evaluate and attempt to balance the potential benefits and harms of sunlight exposure, incorporating benefits of sunlight exposure on preventing suicide and improving mental health along with other health benefits.

Second, our findings show that climate policy remedies, such as geoengineering, can have adverse impacts on human well-being, offering key insights that accompanying supplemental policy remedies, such as suicide prevention programs or mental health assistance programs, may be beneficial to mitigate some of the adverse impacts of solar geoengineering.

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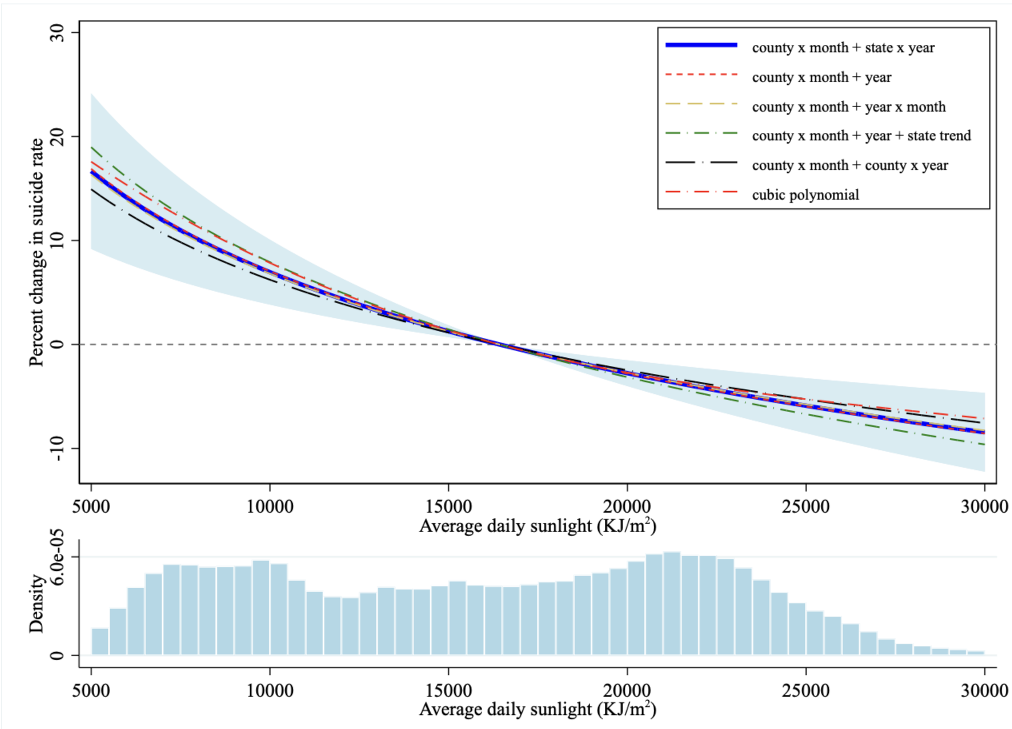
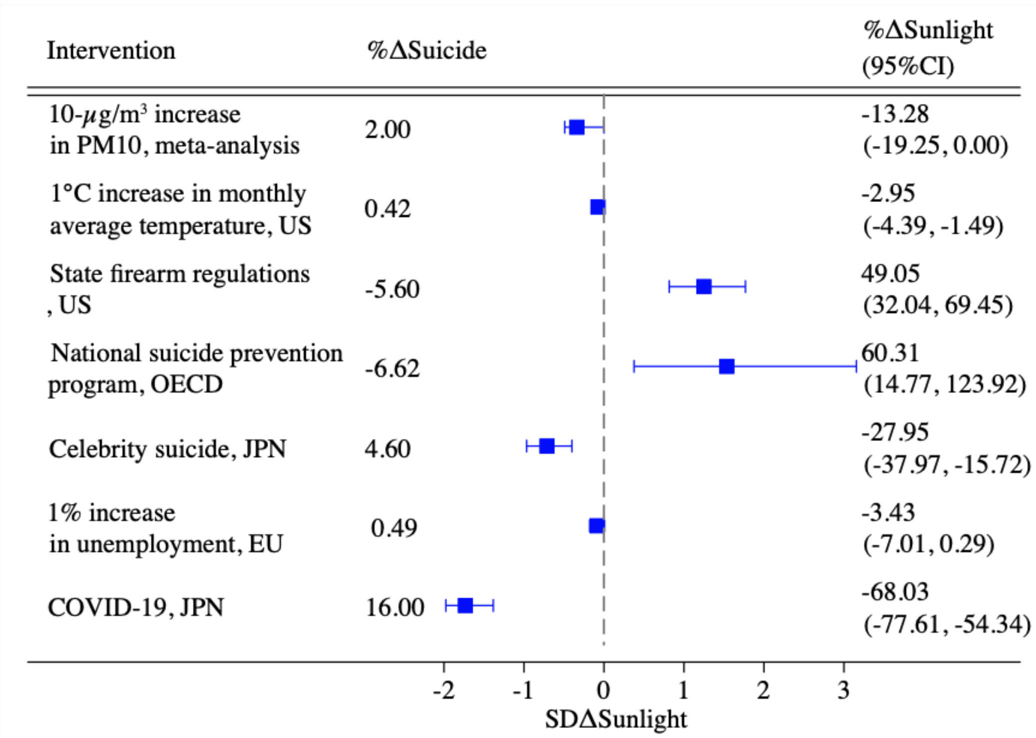
Figures

Figure 1: Effects of Sunlight on the Suicide Rate



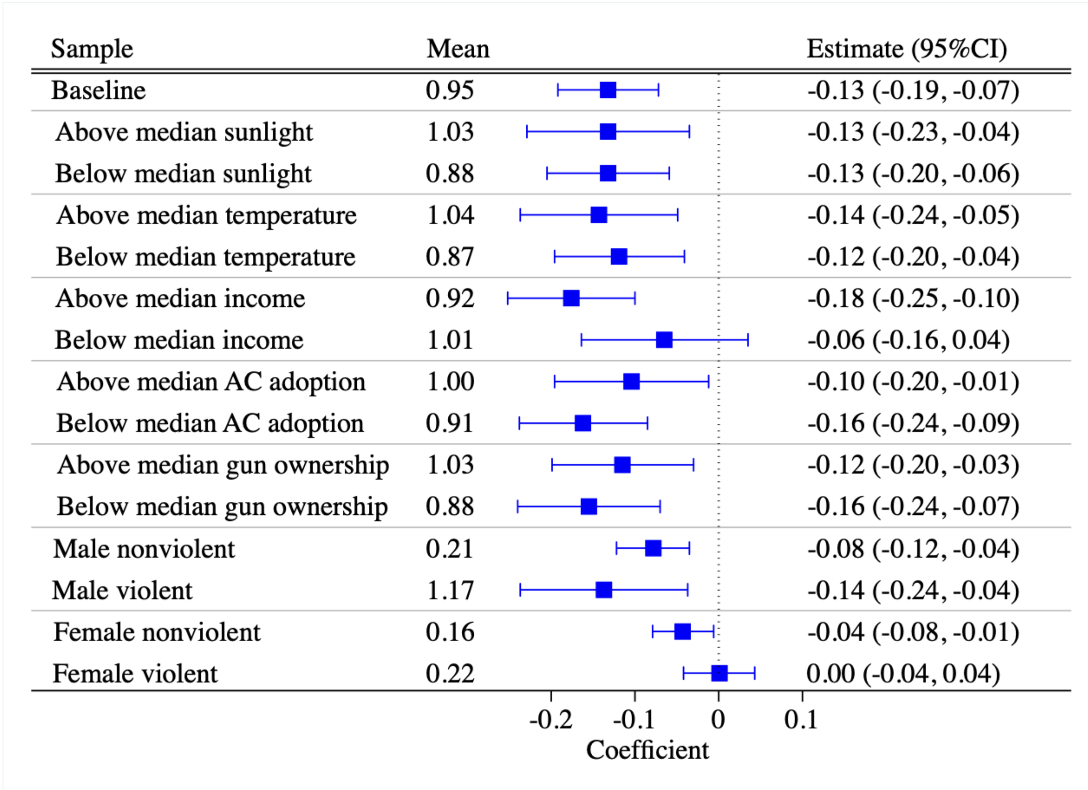
Notes: The top panel plots the estimated cumulative effects of sunlight in given and previous months on the percentage change in the suicide rate with various time effects and models as specified by the labels. The intercepts are adjusted to allow all curves to show no change in the suicide rate at the mean sunlight level. The blue shaded area represents the 95% confidence interval of the elasticity estimated from the baseline model with the county-month and state-year fixed effects. All regressions additionally include the mean temperature and precipitation in the given and previous months. The underlying coefficients are presented in Table A.2. The bottom figure plots the distribution of average monthly sunlight in our sample. The average monthly suicide rate weighted by county population is 0.955 per 100,000 population. The mean of average daily sunlight weighted by county population is 16,422.91 KJ/m^2.

Figure 2: Changes in Sunlight Required to Achieve the Equivalent Impacts of Other Interventions



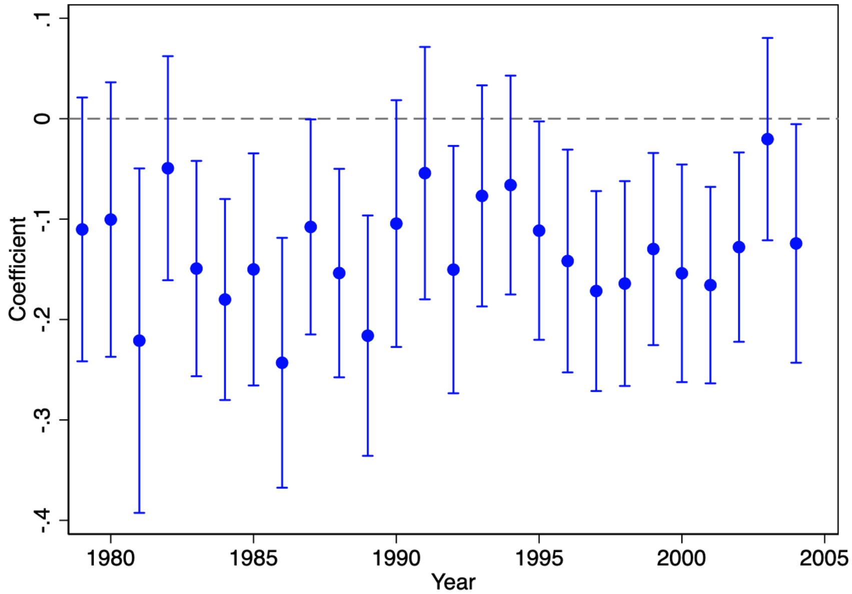
Notes: This figure describes the amount of changes in sunlight in both percentage and standard deviation (SD) that is required to achieve the equivalent impacts of other interventions estimated in previous studies (Braithwaite et al. 2019; Burke et al. 2018; Okoro et al. 2005; Matsubayashi and Ueda 2011; Ueda et al. 2014; Stuckler et al. 2009; Tanaka and Okamoto 2021). "Intervention" describes the type of intervention, "%Δ*Suicide*" describes the percentage change in the suicide rate by the intervention, each dot describes the change in the standard deviation of sunlight that is required to achieve the same magnitude of the impact as the intervention, along with its associated 95% CI, and "%Δ*Sunlight*" indicates the percentage change in sunlight that is required to achieve the same magnitude of impact as the intervention. The underlying parameters are reported in Table A.11.

Figure 3: Heterogeneous Effects of Sunlight



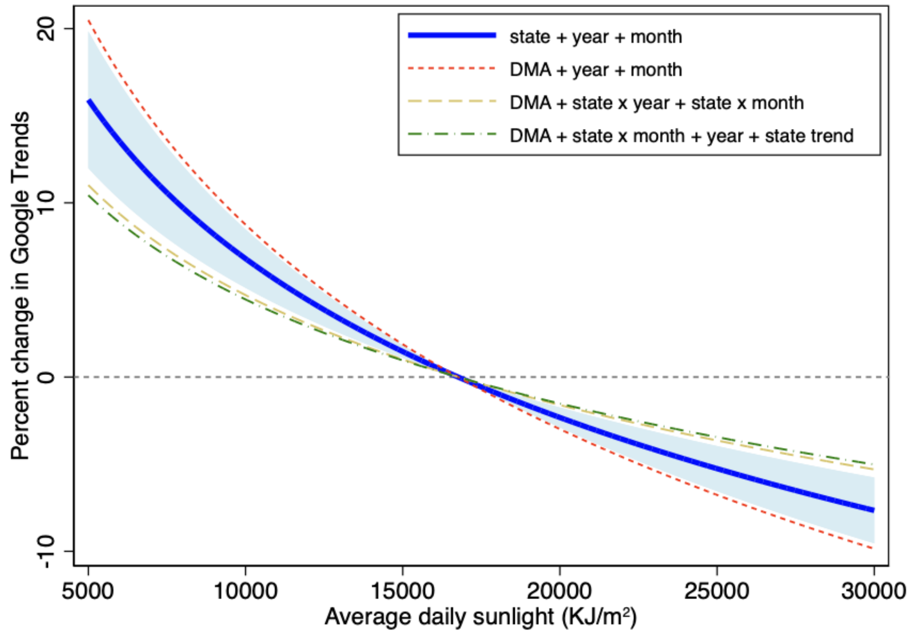
Notes: This figure plots the cumulative effect of sunlight in given and previous months, as given by $\beta_0 + \beta_{-1}$ and its 95% confidence interval based on Equation (2).

Figure 4: Effects of Sunlight on the Suicide Rate across Years



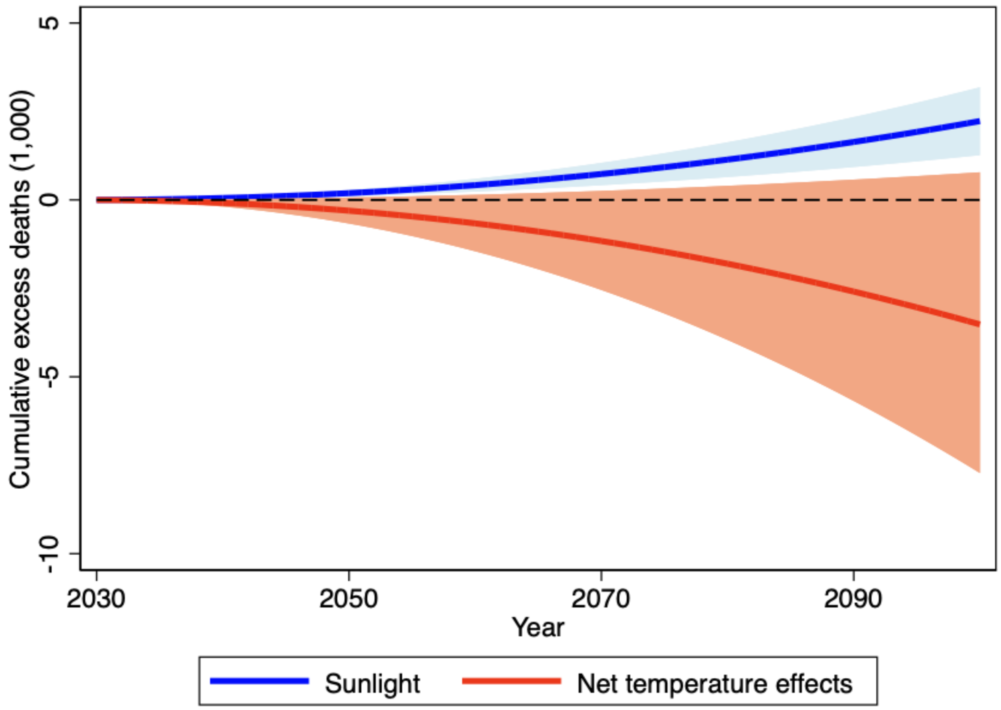
Notes: This figure plots the cumulative effect of sunlight in given and previous months, as given by $\beta_0 + \beta_{-1}$ and its 95% confidence interval based on Equation (3).

Figure 5: Effects of Sunlight on Depressive Language Searches from Google Trends



Notes: This figure plots the estimated cumulative effects of sunlight in given and previous months on the percentage change in Google Trends search interests for the set of depressive language terms as specified in the main text with various time effects as specified by the labels. The intercepts are adjusted to allow all curves to show no change in Google Trends values at the mean sunlight level. The thick blue line indicates the estimate from the observations at the state-year-month level, and the blue shaded area represents its 95% confidence interval. The other three lines are estimated from observations at the DMA-year-month level. All regressions additionally include the mean temperature and precipitation in a given and previous months. The underlying coefficients are presented in Table A.9.

Figure 6: Projected impacts of solar radiation management on suicides, 2030–2100



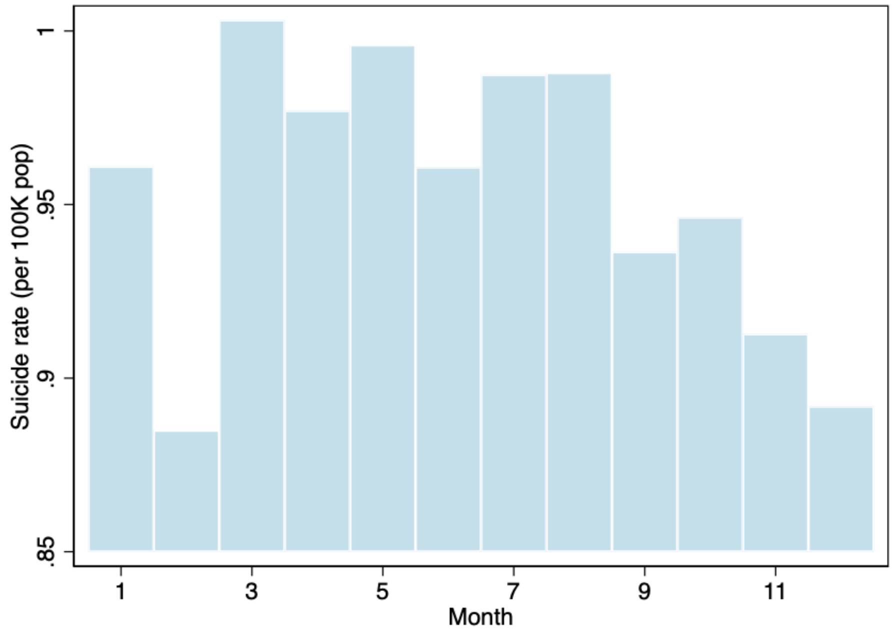
Notes: This figure plots the projected impacts of solar radiation management on suicides to keep the global temperature rise below 1.5 °C between 2030 and 2100. The blue line indicates the cumulative excess suicide deaths due to the negative radiative forcing, and the shaded area represents the 95% CI. The red line indicates the net increase in suicide deaths after accounting for averted suicides due to temperature fall, and the shaded area represents the 95% CI.

The Light of Life: The Effects of Sunlight on Suicide

Shinsuke Tanaka Tetsuya Matsubayashi

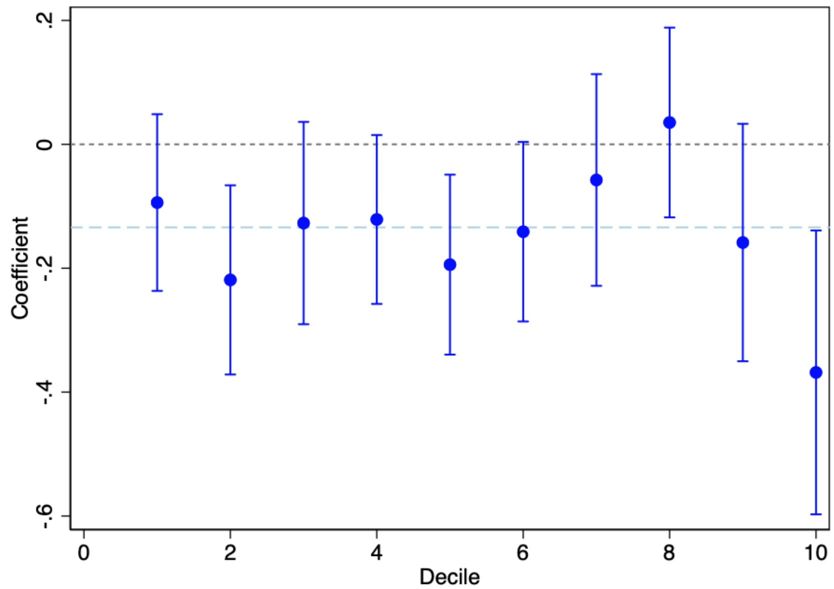
Online Appendix

Figure A.1: Seasonality Trends in the Suicide Rate



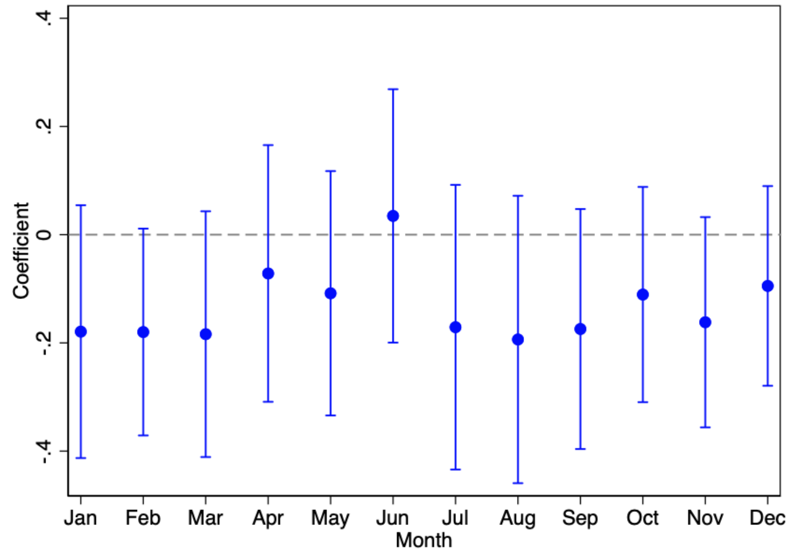
Notes: This figure shows the monthly average suicide rates based on the data for the analysis.

Figure A.2: The Effects of Sunlight on the Suicide Rate by Decile



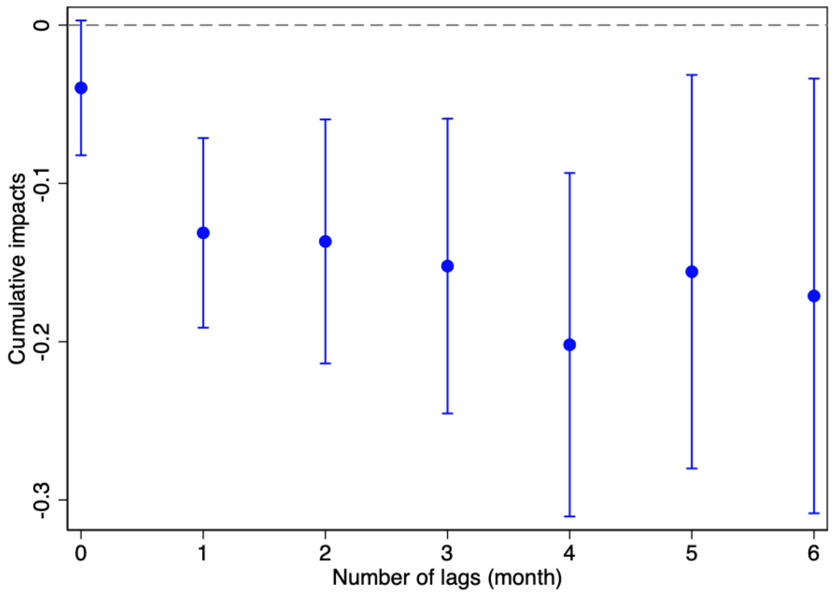
Notes: This figure plots the cumulative effect of sunlight in the current and previous months, as given by $\beta_0 + \beta_{-1}$ and its 95% confidence interval in each decile bin of the average amount of sunlight at the county level. The regression additionally controls for the average temperature, precipitation interacted, the county-by-month and state-by-year fixed effects. The regression is weighted by county population. The standard errors are clustered at the county level. The blue dashed line indicates the estimated effect from the main analysis for the reference purpose.

Figure A.3: The Effects of Sunlight on the Suicide Rate by Month



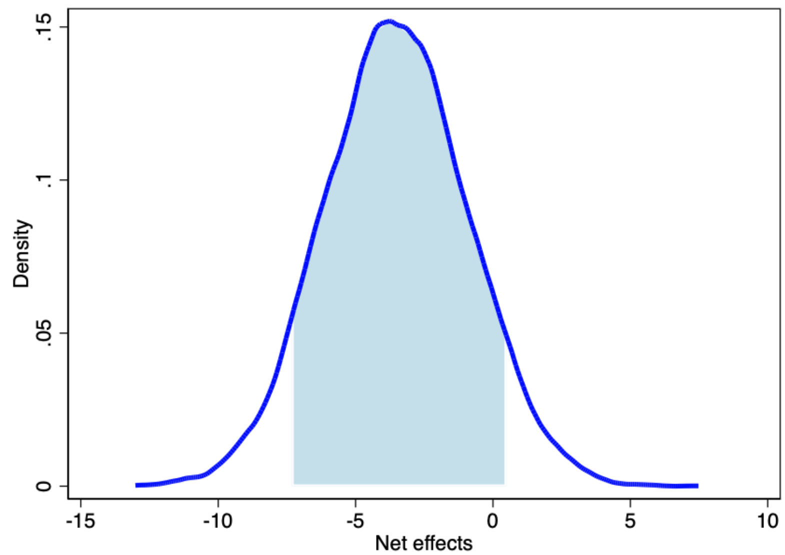
Notes: This figure plots the cumulative effect of sunlight in given and previous months, as given by $\beta_0 + \beta_{-1}$ and its 95% confidence interval in each month. The regression additionally controls for the average temperature and precipitation in given and previous months as well as the county-by-month and state-by-year fixed effects. The regression is weighted by county population. The standard errors are clustered at the county level.

Figure A.4: Robustness to Extensive Temporal Displacements



Notes: This figure plots the cumulative impacts on suicide rate of the log of sunlight exposure in the current and previous months. Each value reports $\sum_{l=k}^{0} \beta_l$ and associated 95% CI from a separate regression for each$l \in [0, 6]$, as we iteratively add an additional month in the past. All regressions additionally control for the monthly average temperature and precipitation with the same set of lags, the log of sunlight, temperature, and precipitation in the following month, and county-by-month and state-by-year fixed effects.

Figure A.5: Projected cumulative net impacts of solar radiation management on suicides in 2030–2100



Notes: This figure plots the cumulative net impacts of excess suicides due to reduced sunlight and averted suicides due to lower temperature to meet the goal of keeping the global temperature rise below 1.5 ℃ in 2030–2100. The values are based on the simulation of 10,000 replications based on the parameters described in the main text. The shaded area represents the 95% of the distribution.

Table A.1: Summary Statistics

variable	N	Mean	Std
Suicide rate (per 100K pop)	444,861	0.955	0.967
Sunlight (KJ/m^2/day)	444,861	16,422.91	6,449.22
Population	444,861	143,376	384,245
Temperature (°C)	444,861	13.822	9.120
Precipitation (mm)	444,861	0.073	0.059
Suicide rate, male nonviolent	444,861	0.210	0.578
Suicide rate, male violent	444,861	1.171	1.581
Suicide rate, female nonviolent	444,861	0.159	0.458
Suicide rate, female violent	444,861	0.215	0.633
Real income (USD)	439,202	31347.5	10047.4
Gun ownership	444,861	0.309	0.120

Notes: This table reports the summary statistics of the main variables. Each column reports the variable name, the number of observations, the mean value weighted by population (except for population, where the mean is the arithmetic average), and the standard deviation, respectively. The sample is restricted to what is used in the main analysis. The level of observations is at the county-by-month level.

Table A.2: The Effects of Sunlight on Suicide Rates

	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(\text{Sunlight})_0$	-0.049**	-0.052**	-0.045*	-0.060***	-0.043*	
	(0.022)	(0.022)	(0.025)	(0.022)	(0.023)	
$\ln(\text{Sunlight})_{-1}$	-0.085***	-0.083***	-0.086***	-0.093***	-0.077***	
	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	
$\ln(\text{Sunlight})_{-2}$	-0.003	0.001	-0.002	-0.008	0.003	
	(0.022)	(0.021)	(0.023)	(0.021)	(0.022)	
$\ln(\text{Sunlight})_1$	0.010	0.006	0.002	-0.004	0.017	
	(0.024)	(0.023)	(0.025)	(0.023)	(0.024)	
Temperature_0	0.008***	0.009***	0.009***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature_{-1}	-0.002**	-0.001	-0.001	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature_{-2}	0.000	0.001	0.001	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature_1	0.001	0.002*	0.002	0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Precipitation_0	-0.043	-0.012	-0.001	-0.032	-0.024	-0.043
	(0.032)	(0.034)	(0.036)	(0.032)	(0.033)	(0.033)
$\text{Precipitation}_{-1}$	-0.014	0.032	0.044	0.011	0.003	-0.013
	(0.036)	(0.038)	(0.041)	(0.037)	(0.036)	(0.036)
$\text{Precipitation}_{-2}$	-0.013	0.042	0.046	0.016	0.003	-0.011
	(0.034)	(0.037)	(0.040)	(0.032)	(0.034)	(0.034)
Precipitation_1	0.019	0.044	0.065*	0.029	0.040	0.020
	(0.032)	(0.031)	(0.033)	(0.032)	(0.033)	(0.032)
Sunlight						-0.020
						(0.013)
Sunlight^2						0.001
						(0.001)
Sunlight^3						-0.000
						(0.000)
Sunlight_{-1}						-0.011
						(0.013)
$\text{Sunlight}_{-1}{}^2$						-0.000
						(0.001)
$\text{Sunlight}_{-1}{}^3$						0.000
						(0.000)
Sunlight_{-2}						0.002
						(0.013)
$\text{Sunlight}_{-2}{}^2$						0.000
						(0.001)
$\text{Sunlight}_{-2}{}^3$						-0.000
						(0.000)
Sunlight_1						0.010
						(0.013)
$\text{Sunlight}_1{}^2$						-0.001
						(0.001)
$\text{Sunlight}_1{}^3$						0.000
						(0.000)
Constant	2.088***	2.025***	2.032***	17.855	1.828***	1.080***
	(0.461)	(0.408)	(0.454)	(36.095)	(0.477)	(0.158)
adj. R^2	0.11	0.11	0.11	0.11	0.16	0.11
$\beta_0 + \beta_{-1}$	-0.134	-0.136	-0.131	-0.152	-0.120	-0.141
$\text{se}(\beta_0 + \beta_{-1})$	0.031	0.030	0.034	0.030	0.031	0.047
$p(\beta_0 + \beta_{-1})$	0.000	0.000	0.000	0.000	0.000	0.003
Fixed effects	county × month + state × year	county ×month + year	county × month + year ×month	county × month + year + state trend	county × month + county × year	cubic polynomial

Notes: The dependent variable is the suicide rate per 10,000 population. The mean of the dependent variable is 0.955, and the mean of sunlight is 16422.91 KJ/m^2. The level of observations is at the county-month. The sample size is 444,861 across 3,107 counties. At the bottom of the table, we report the linear combination of $\beta_0 + \beta_{-1}$, which represents the cumulative effects of sunlight in a given and previous month as well as the associated standard errors and the p-values. The corresponding value in Column (5) has the same interpretation, which is the changes in the suicide rate by a 100% increase in sunlight from its mean value. All regressions are weighted by county population. The standard errors clustered at the county level are reported in the parentheses.
***$p < 0.01$, **$p < 0.5$, *$p < 0.1$

Table A.3: Robustness to Alternative Outcomes

	(1)	(2)	(3)	(4)
	ln(rate+1)	ln(count+1)	IHS	Count
$\ln(\text{Sunlight})_0$	-0.049**	-0.015	-0.038**	-0.052**
	(0.022)	(0.011)	(0.015)	(0.024)
$\ln(\text{Sunlight})_{-1}$	-0.085***	-0.019*	-0.055***	-0.089***
	(0.024)	(0.011)	(0.016)	(0.025)
$\ln(\text{Sunlight})_{-2}$	-0.003	-0.015	-0.005	-0.007
	(0.022)	(0.011)	(0.015)	(0.023)
$\ln(\text{Sunlight})_1$	0.010	0.020*	0.004	0.009
	(0.024)	(0.011)	(0.016)	(0.026)
Temperature_0	0.008***	0.003***	0.005***	0.008***
	(0.001)	(0.000)	(0.001)	(0.001)
Temperature_{-1}	-0.002**	-0.000	-0.001**	-0.002**
	(0.001)	(0.000)	(0.001)	(0.001)
Temperature_{-2}	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)
Temperature_1	0.001	0.000	0.001	0.001
	(0.001)	(0.000)	(0.001)	(0.001)
Precipitation_0	-0.043	-0.004	-0.028	-0.041
	(0.032)	(0.015)	(0.021)	(0.034)
$\text{Precipitation}_{-1}$	-0.014	0.001	-0.006	-0.013
	(0.036)	(0.015)	(0.025)	(0.038)
$\text{Precipitation}_{-2}$	-0.013	-0.008	-0.009	-0.014
	(0.034)	(0.016)	(0.022)	(0.035)
Precipitation_1	0.019	0.014	0.017	0.024
	(0.032)	(0.015)	(0.022)	(0.033)
ln(population)		0.430***		
		(0.034)		
Constant	2.088***	-3.828***	1.595***	-10.232***
	(0.461)	(0.387)	(0.309)	(0.484)
adj. R^2	0.11	0.73	0.19	
$\beta_0 + \beta_{-1}$	-0.134	-0.034	-0.093	-0.141
$\text{se}(\beta_0 + \beta_{-1})$	0.031	0.015	0.020	0.032
$p(\beta_0 + \beta_{-1})$	0.000	0.022	0.000	0.000

Notes: This table reports the estimates from various alternative specifications. In particular, Column (1) uses the log of the suicide rate per 10,000 population plus one as the dependent variable, Column (2) uses the log of the suicide count plus one as the dependent variable, Column (3) uses the inverse hyperbolic sine (IHS) of the suicide rate as the dependent variable, and Column (4) applies the Poisson model. The sample size is 444,861 in Columns (1)–(3) and 364,778 in Column (4), as Poisson pseudo-maximum likelihood regressions with multi-way fixed effects additionally detects and drops separated observations. All regressions control for county-month and state-year fixed effects. Regressions are weighted by population in Columns (1) and (3), while Column (2) additionally controls for the log of population, and Column (4) is estimated by the Poisson regression that includes the population as an exposure variable. The interpretations of the bottom parameters are the same as Table A.2.
***$p < 0.01$, **$p < 0.5$, *$p < 0.1$

Table A.4: Robustness to Alternative Levels of Clustering the Standard Errors

	(1)	(2)	(3)	(4)
$\beta_0 + \beta_{-1}$	-0.134***	-0.134***	-0.134***	-0.134***
se($\beta_0 + \beta_{-1}$)	(0.031)	(0.031)	(0.041)	(0.028)
$p(\beta_0 + \beta_{-1})$	[0.000]	[0.000]	[0.003]	[0.000]
Clustering	county	county + state-year	county + year	state

Notes: This table tests the robustness of the effects of sunlight on the suicide rates based on the same model as in Table A.2 Column (1) but at different levels of clustering the standard errors. In particular, the standard errors are clustered at the county level in Column (1) as the reference from the main analysis, the county + state-by-year level in Column (2), the county + year level in Column (3), and the state level in Column (4). The interpretations of the parameters are the same as Table S2. $N = 444,861$.
***$p < 0.01$, **$p < 0.5$, *$p < 0.1$

Table A.5: Robustness to Inclusion of Air Pollution

	(1) Baseline	(2) Add $PM_{2.5}$	(3) Add lagged $PM_{2.5}$
$\beta_0 + \beta_{-1}$	-0.197**	-0.196**	-0.189**
$\text{se}(\beta_0 + \beta_{-1})$	(0.084)	(0.084)	(0.086)
$p(\beta_0 + \beta_{-1})$	[0.020]	[0.020]	[0.028]

Notes: This table presents the results with controlling for the monthly average PM2.5 concentrations levels. The sample period is 2000–2004. The interpretations of the parameters are the same as Table A.2. Column (1) replicates the main analysis in Table A.2 Column (1). Column (2) adds the $PM_{2.5}$ concentrations in a given month, and Column (3) adds the lags in $PM_{2.5}$ as sunlight, i.e., the values in a given and past two months as well as the following month. N = 27,009.
$^{***}p < 0.01$, $^{**}p < 0.5$, $^{*}p < 0.1$

Table A.6: Estimated Effects of a set of Environmental Factors

	(1)	(2)	(3)	(4)	(5)
$\ln(\text{Sunlight})_0$	-0.009	-0.035*	-0.023	-0.049**	
	(0.019)	(0.020)	(0.022)	(0.022)	
$\ln(\text{Sunlight})_{-1}$	-0.063***	-0.080***	-0.074***	-0.085***	
	(0.020)	(0.021)	(0.024)	(0.024)	
$\ln(\text{Sunlight})_{-2}$	0.002	0.002	-0.005	-0.003	
	(0.020)	(0.020)	(0.022)	(0.022)	
$\ln(\text{Sunlight})_1$	-0.005	0.002	-0.000	0.010	
	(0.022)	(0.022)	(0.023)	(0.024)	
Temperature_0		0.008***		0.008***	0.007***
		(0.001)		(0.001)	(0.001)
Temperature_{-1}		-0.002**		-0.002**	-0.002***
		(0.001)		(0.001)	(0.001)
Temperature_{-2}		0.000		0.000	0.000
		(0.001)		(0.001)	(0.001)
Temperature_1		0.001		0.001	0.001
		(0.001)		(0.001)	(0.001)
Precipitation_0			-0.044	-0.043	-0.006
			(0.032)	(0.032)	(0.029)
$\text{Precipitation}_{-1}$			-0.029	-0.014	0.041
			(0.036)	(0.036)	(0.032)
$\text{Precipitation}_{-2}$			-0.017	-0.013	-0.017
			(0.033)	(0.034)	(0.030)
Precipitation_1			0.011	0.019	0.013
			(0.032)	(0.032)	(0.030)
Constant	1.677***	1.926***	1.939***	2.088***	0.875***
	(0.405)	(0.411)	(0.459)	(0.461)	(0.029)
$\beta_0 + \beta_{-1}$	-0.072	-0.115	-0.097	-0.134	
$\text{se}(\beta_0 + \beta_{-1})$	0.028	0.028	0.030	0.031	
$p(\beta_0 + \beta_{-1})$	0.009	0.000	0.001	0.000	

Notes: Columns (1)–(4) present the effects of sunlight on suicides with various sets of other controls, whereas Column (5) presents the effects of temperature and precipitation on suicides without controlling for sunlight. The interpretations of the bottom parameters are the same as Table A.2.
$^{***}p < 0.01$, $^{**}p < 0.5$, $^{*}p < 0.1$

Table A.7: Estimated Effects of Sunlight on Temperature

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted			Unweighted		
ln(Sunlight)			2.633***			1.479***
			(0.177)			(0.079)
Precipitation		-2.319***	-0.543***		-2.182***	-1.173***
		(0.236)	(0.193)		(0.060)	(0.072)
R^2	.9727	.9728	.9731	.9708	.9709	.9710
ΔTemp (°C)			-1.328			-.732
ΔTemp (SD)			-0.144			-0.074

Notes: This table presents the estimated effects of sunlight and precipitation as well as the county-by-month and state-by-year fixed effects on temperature. Columns (1) and (4) include only the fixed effects. Columns (1)–(3) are weighted by population as in the main analysis, whereas Columns (4)–(6) are not weighted. The last two rows indicate the effect of a 1-standard deviation (SD) decrease in sunlight on temperature in °C and SD, respectively. ***$p < 0.01$, **$p < 0.5$, *$p < 0.1$

Table A.8: Estimated Effects of Sunlight on Suicides based on Time-Series Analysis

	(1)	(2)	(3)	(4)
ln(Sunlight)$_0$	0.050***	0.041**	0.044***	0.044***
	(0.016)	(0.016)	(0.016)	(0.016)
ln(Sunlight)$_{-1}$	-0.016	-0.019	-0.019	-0.019
	(0.016)	(0.016)	(0.016)	(0.016)
$\beta_0 + \beta_{-1}$	0.034	0.022	0.025	0.026
se($\beta_0 + \beta_{-1}$)	0.013	0.013	0.014	0.013
$p(\beta_0 + \beta_{-1})$	0.012	0.104	0.071	0.057
Fixed effects	County	County + year	County + state-by-year	County-by-year

Notes: This table shows the estimated effects of sunlight on suicides based on the time-series analysis that mimics the literature. In particular, we run the same model as in Table A.2 Column (1) but with different fixed effects as specified in each column. The interpretations of the bottom parameters are the same as Table A.2. N = 444,864.
***$p < 0.01$, **$p < 0.5$, *$p < 0.1$

Table A.9: Effects of Sunlight on Depressive Language Searches from Google Trends

	(1)	(2)	(3)	(4)
Panel A: All keywords				
Effect	-8.464***	-10.896***	-5.860**	-5.549**
	(1.038)	(2.608)	(2.817)	(2.306)
p	[0.000]	[0.000]	[0.039]	[0.017]
N	4655	8796	8774	8774
Panel B: depression, depressed, depress				
Effect	-8.881***	-12.557***	-8.697	-7.746
	(2.426)	(4.805)	(6.388)	(6.158)
p	[0.001]	[0.010]	[0.175]	[0.210]
N	4655	8785	8763	8763
Panel C: suicide, suicidal				
Effect	-4.584***	-7.545	-5.507	-5.287
	(1.193)	(4.632)	(5.278)	(5.006)
p	[0.000]	[0.105]	[0.298]	[0.292]
N	4655	8697	8675	8675
Region type	State	DMA	DMA	DMA
Fixed effects	State	DMA	DMA	DMA
	+ yr	+ yr	+ state × yr	+ state × mo
	+ mo	+ mo	+ state × mo	+ state trend

Notes: Each panel reports the effect of a one-log point increase in sunlight in a given and previous months on the Google Trends index in the first row, the standard errors clustered at the region level in the second row, the p-value at the third row, the number of observations in the fourth row, the mean value of the dependent variable in the fifth row, and the mean value of sunlight (KJ/m2) in the last row. The dependent variable is scaled from 0 to 100 with respect to the highest point in each region (see Methods for data processing). Column (1) uses observations at the state-year-month level, and Columns (2)–(4) use observations at the DMA-year-month level.
***$p < 0.01$, **$p < 0.5$, *$p < 0.1$

Table A.10: Marginal Impacts of Weather vs. Climate

	(1)	(2)	(3)	(4)	(5)
Climate (β)	-0.078***	-0.070***	-0.081***	-0.078***	-0.076***
	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Weather (δ)	-0.124***	-0.129***	-0.130***	-0.146***	-0.115***
	(0.030)	(0.033)	(0.029)	(0.029)	(0.030)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Fixed effects	County + month + state $\times$ year	County + month $\times$ year	County + month + year	County + month + year + state-trend	County + month + county $\times$ year

Notes: This table reports the estimated effects from Equation (5) in Methods. "Climate (β)" reports the β's and "Weather (δ)" reports the δ's from Equation (5). The standard errors, clustered at the county level, are reported in the parentheses, and the p-values are reported in the square brackets. The sample size is 451,371.
***$p < 0.01$, **$p < 0.5$, *$p < 0.1$

Table A.11: Changes in sunlight required to achieve the equivalent impacts of other interventions

Intervention	%change in suicide rate			Equivalent % change in sunlight			Equivalent SD change in sunlight		
	Estimate	Lower bound	Upper bound	Estimate	Upper bound	Lower bound	Estimate	Upper bound	Lower bound
10-$\mu g/m^2$ change in PM_{10}, meta-analysis	2	0	3	-13.28	0.00	-19.25	-0.34	0.00	-0.49
1°C increase in monthly average temperature, US	0.42	0.21	0.63	-2.95	-1.49	-4.39	-0.08	-0.04	-0.11
State firearm regulations, US	-5.6	-7.4	-3.9	49.05	69.45	32.04	1.25	1.77	0.82
National suicide prevention program, OECD countries	-6.62	-11.31	-1.93	60.31	123.92	14.77	1.54	3.16	0.38
Celebrity suicide, JPN	4.6	2.4	6.7	-27.95	-15.72	-37.97	-0.71	-0.40	-0.97
1% increase in suicide, EU	0.49	-0.04	1.02	-3.43	0.29	-7.01	-0.09	0.01	-0.18
COVID-19, JPN	16	11	21	-68.03	-54.34	-77.61	-1.73	-1.38	-1.98

Notes: This figure describes the amount of changes in sunlight in both percentage and standard deviation (SD) that is required to achieve the equivalent impacts of other interventions estimated in previous studies. "Intervention" describes the type of intervention, "Equivalent % change in suicide rate" describes the percentage change in suicide rate by the intervention, "Equivalent % change in sunlight" indicates the percentage change in sunlight that is required to achieve the same magnitude of impact as the intervention, and "Equivalent SD change in sunlight" describes the change in the standard deviation of sunlight that is required to achieve the same magnitude of the impact as the intervention. Each number under "Estimate" represents the mean impact, and those under "Lower bound" and "Upper bound" represent the 95% CI.

Table A.12: Projected impacts of solar radiation management geoengineering

Temperature limit	Sunlight	Temperature	Net
Panel A: 0%			
1.5 °C	2.23 (1.26, 3.18)	-5.75 (-10.69, -1.23)	-3.52 (-7.72, 0.781)
2 °C	1.46 (0.83, 2.08)	-3.77 (-7.00, -0.81)	-2.31 (-5.06, 0.509)
Panel B: 1%			
1.5 °C	1.78 (1.01, 2.55)	-4.61 (-8.56, -0.99)	-2.82 (-6.19, 0.623)
2 °C	1.02 (0.58, 1.45)	-2.63 (-4.89, -0.56)	-1.61 (-3.53, 0.354)
Panel C: 3%			
1.5 °C	1.22 (0.70, 1.75)	-3.17 (-5.89, 0.68)	-1.94 (-4.26, 0.426)
2 °C	0.47 (0.27, 0.67)	-1.22 (-2.26, -0.26)	-0.746 (-1.63, 0.163)
Panel D: 5%			
1.5 °C	0.91 (0.52, 1.30)	-2.35 (-4.37, -0.50)	-1.44 (-3.16, 0.316)
2 °C	0.17 (0.10, 0.24)	-0.44 (-0.81, -0.09)	-0.267 (-0.585, 0.058)

Notes: This table summarizes the cumulative additional suicides due to the negative radiative forcing (in the second column) and averted suicides due to temperature fall (in the third row) to meet the goal of keeping global temperature rise below 1.5 °C in the first row and 2 °C in second row of each panel. The last column represents the net effect of sunlight and temperature effects estimated from the simulation (see Methods). The numbers in the parentheses represent the 95% CI. All numbers are in thousands of deaths in 2100. Each panel title refers to annual emissions reduction rate between 2031 and 2100.