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Estimating the role of air quality improvements in the decline of suicide rates in China

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Emerging evidence suggests that air pollution may play a role in shaping suicide risk by altering brain function. However, this link is difficult to quantify and has yet to be investigated in China, where 16% of global suicides occur. Here we apply a statistical model that leverages random increases in particulate pollution ($PM_{2.5}$) due to meteorological conditions to comprehensive data on suicide rates across Chinese counties. We find that a 1 s.d. (σ) increase in $PM_{2.5}$ raises weekly suicide rates by ~25%. This effect occurs without delay, consistent with neurobiological evidence that $PM_{2.5}$ influences emotional regulation and impulsive–aggressive behaviour. Effects are sex and age specific; women over 65 exhibit significantly higher vulnerability. We estimate that $PM_{2.5}$ reductions under China's Air Pollution Action Plan prevented 13,000–79,000 (95% confidence interval) suicides over 2013–2017, accounting for ~10% of this period's observed suicide rate decline. Our findings uncover a causal link between particulate pollution and suicide, adding urgency to calls for pollution control policies across the globe.

Over 700,000 lives are lost each year to suicide, reflecting an extensive societal mental health burden[1]. While rates of self-harm remain high, an encouraging decline in reported suicide rates has recently emerged. The global average suicide rate fell by ~16% between 2000 and 2019, with declines 1.7 times larger in developing countries than in the Organisation for Economic Co-operation and Development (OECD) (Fig. 1a). Mental health and self-harm are influenced by a complex interaction of social, cultural, economic and environmental factors[2], implying that there are many possible drivers of these declines that are difficult to empirically untangle. Establishing robust explanations for suicide patterns over space and time is particularly challenging in low- and middle-income countries, where 80% of global suicides occur[1], but where data and research tend to be scarce[3].

Here we investigate whether improvements in air quality may contribute to reductions in suicide rates. We study China, home to 16% of today's global suicides, where pollution has fallen dramatically in recent years and suicides are simultaneously declining (Fig. 1b,c). While these shared trends are striking, many other risk factors have also shifted over this time period, making the influence of air quality unclear. In particular, robust economic growth and increasing urbanization have been linked to recent suicide risk reduction in China[4–7], as the rural poor have historically accounted for the majority of suicide deaths[8]. Cultural transformations, including the elderly no longer living with their children, may have elevated suicide risk for some groups[8,9], while reductions in the lethality of pesticides, the predominant method of suicide in rural China, have lowered suicide rates for other subpopulations[10]. Changes in physical health[11,12] and educational attainment[7,11,12] may have further influenced evolving suicide trends in the country. Whether and to what extent cleaner air has additionally played a role in suicide risk reduction in China is unknown.

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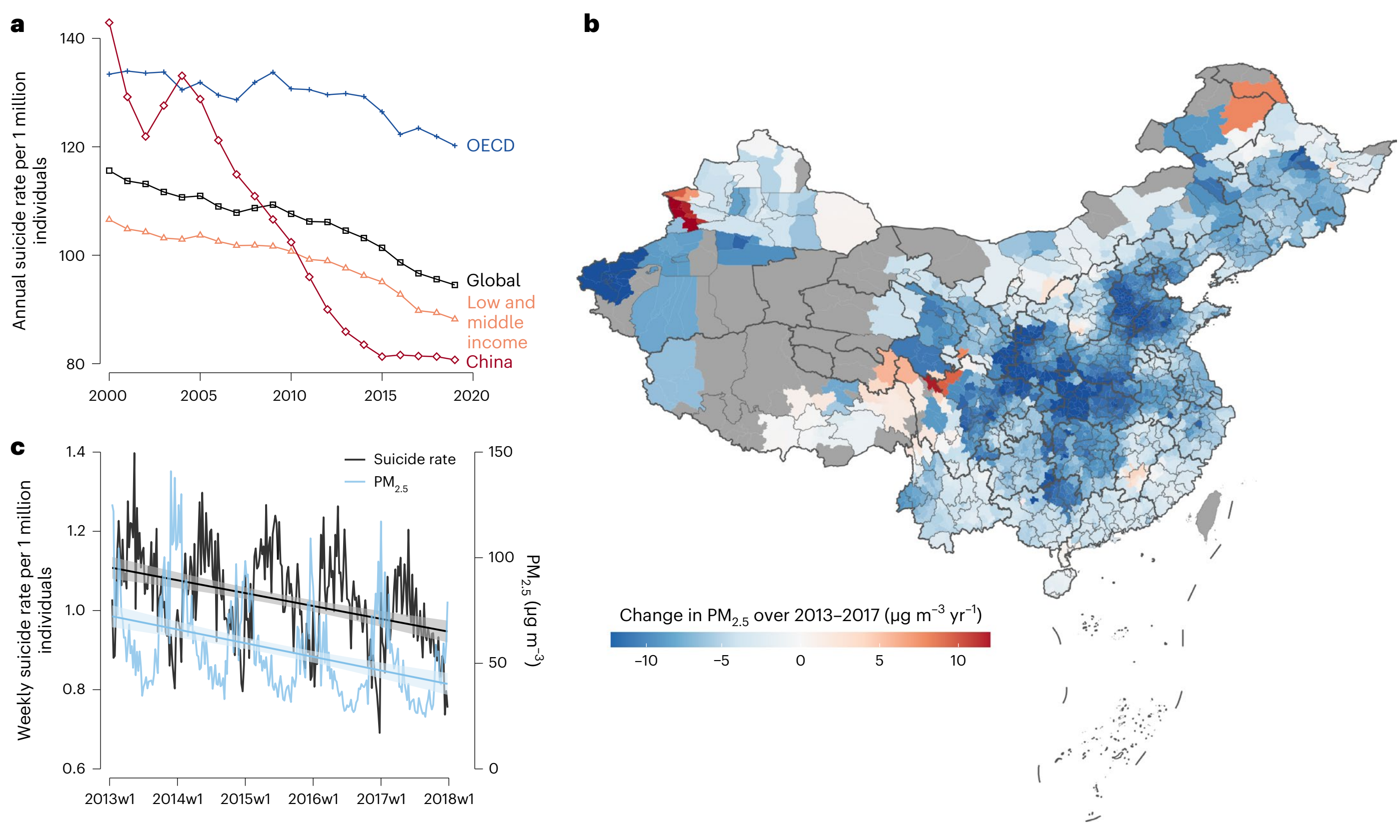

Fig. 1 | Air pollution and suicide rates in China have declined substantially in recent years. a, Time series of annual average suicide rates globally ($n = 183$ countries), for the OECD ($n = 26$ countries), for low- and middle-income countries ($n = 129$ countries) and for China ($n = 1$ country). Unweighted averages are shown using annual country-level data from ref. 1. **b**, County-specific trends in $PM_{2.5}$ over the period 2013 to 2017 are mapped across 2,785 counties, measured in μg m^{-3} yr^{-1}. Prefectures are outlined in light grey and provinces in dark grey. Solid grey regions indicate insufficient air pollution monitor data. **c**, Time series of average weekly suicide rates and $PM_{2.5}$ across Chinese counties ('w1' indicates the first week of each year). Suicide averages are population weighted across 597 nationally representative counties, and $PM_{2.5}$ averages are population weighted across the 2,785 counties shown in **b**. Linear trend estimates are shown for each variable, with 95% confidence intervals shaded. Basemap in **b** for 2015 from the Chinese Resource and Environmental Science Data Registration and Publishing System (https://www.resdc.cn/?aspxerrorpath=/DOI,2023.DOI:10.12078/2023010101).

Our work builds on a growing body of epidemiological and neurobiological research uncovering links between air pollution and suicide[13–18]. Hypothesized channels connecting these two phenomena include: direct neurological effects of particulate matter on brain function, particularly through modulating the release of serotonin[14,19,20]; effects of air pollution on physical health (such as cardiovascular and respiratory diseases)[21,22] that lead to later declines in mental health[23]; and effects of air pollution on economic output and productivity[24,25], which can lead to economically motivated suicide[26]. A robust empirical literature has consistently uncovered positive associations between a range of air pollutants and suicide risk in locations as diverse as Utah, Mexico City and urban South Korea[27–29]. However, many outstanding questions remain. Existing studies limit their geographic coverage to a few cities[30], a single county[27] or a small country[31], and no country-wide analysis for China exists. Findings diverge across study contexts for reasons that remain unclear, and mechanisms for observed suicide–pollution relationships are uncertain[13,14,28]. In addition, time-varying confounding variables make causal interpretation in these studies difficult[15]. Variation in air pollution over space and time is driven by, and thus correlated with, a wide array of social and economic activities, such as industrial production and transportation patterns. It is therefore difficult to isolate the effects of air pollution on suicide from many other confounding factors that covary with both phenomena. While previous research leverages short-run temporal variations in air quality to address these issues, time-varying confounders remain a challenge[13].

To address temporal confounding, we use a statistical model that exploits random variation in a particular combination of climatological conditions that trap air pollution near Earth's surface. We apply this model to spatio-temporal pollution and suicide data across Chinese counties to estimate the causal effect of air pollution on suicides. We investigate which subpopulations are at highest risk of suicide under elevated air pollution and characterize the temporal dynamics of the pollution–suicide relationship. Finally, we use these empirical results to estimate the suicide reduction effects of air quality improvements realized under China's Air Pollution Prevention and Control Action Plan (APPC-AP).

To implement this approach, we match 139,196 observations of weekly county-level suicide reports from 2013 to 2017 to a set of ~1,400 air pollution monitors across China, constructing a longitudinal dataset for 597 representative counties. Over the sample period, air pollution and suicide rates exhibit strong seasonality and aggregate downward trends (Fig. 1c). To isolate the effects of pollution from the roles of other changing socioeconomic or demographic factors, we use an instrumental variables strategy within a panel regression framework (Supplementary Note 1.2.2). Specifically, we model weekly suicide rates per 1 million individuals as a function of $PM_{2.5}$, the concentration of particulate matter that is 2.5 μm or less in width (measured in micrograms per cubic metre of air, or μg m^{-3}), and a set of county- and week-specific weather conditions, including flexible functional forms of temperature, rainfall, sunshine duration, barometric pressure and wind speed. A set of semiparametric spatial controls (called 'fixed effects' in econometrics)

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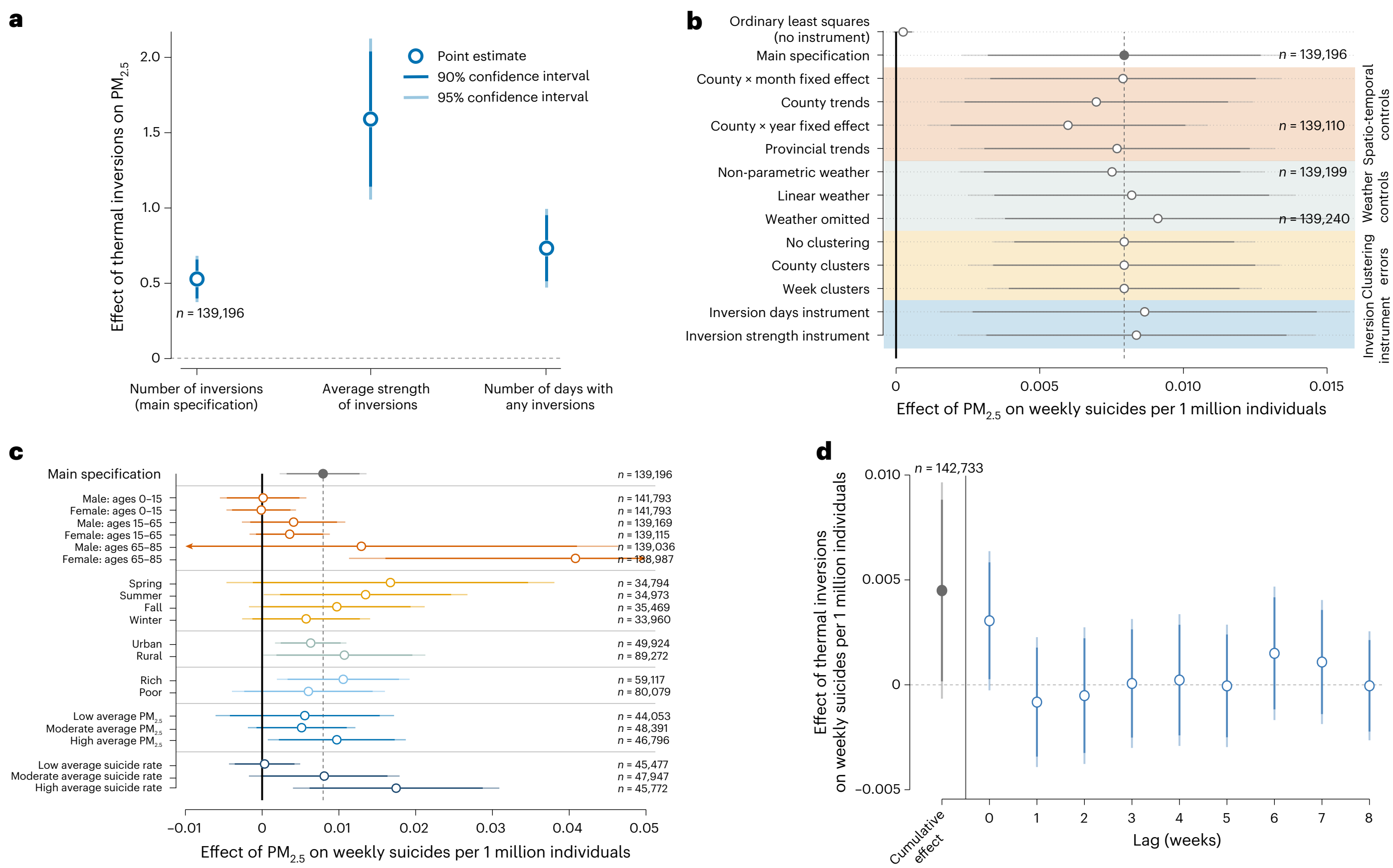

Fig. 2 | Estimated effects of air pollution on suicide rates in China. a, Estimated relationship between $PM_{2.5}$ and thermal inversions using three definitions of thermal inversion. **b**, Estimated effect of a 1 μg m^{-3} increase in $PM_{2.5}$ on the suicide rate per 1 million individuals. The top row shows a correlational relationship between suicide rates and $PM_{2.5}$, estimated using a two-way fixed-effects model following Supplementary Equation 1. The main specification in the second row uses thermal inversions to the instrument for $PM_{2.5}$ via equations (1) and (2). Other estimates below show the robustness of the instrumental variable approach to the alternative: semiparametric spatio-temporal controls (rows 3–6), weather controls (rows 7–9), clustering of standard errors (rows 10–12) and definitions of thermal inversions (rows 13 and 14). **c**, Heterogeneity in the effect of $PM_{2.5}$ on the suicide rate. The point estimate and associated confidence intervals for the main specification are shown in grey. All other estimates use subsamples of the data, splitting by age and sex (orange), season of the year (yellow), county-level urban and rural designation (green), wealthiest 15 provinces and all others (light blue), terciles of sample average $PM_{2.5}$ (blue) and terciles of average suicide rate (navy). **d**, Dynamic effect of thermal inversions on the suicide rate (Supplementary Equation 4). The cumulative effect represents the total effect of inversions on suicide rates over 8 weeks; individual lagged effects indicate the effect of contemporaneous (lag zero) thermal inversions and those up to 8 weeks previously (see Supplementary Note 1.2.3 for details). In **a**–**d**, central estimates shown with circles are regression point estimates, dark-coloured lines indicate 90% confidence intervals and light-coloured lines indicate 95% confidence intervals. All regressions are estimated using a sample of n = 139,196 county-by-week observations, unless otherwise noted.

are included, which account for all time-invariant differences across counties, such as income, industrial composition and local mental health resources, without needing to measure each variable explicitly. Similarly, a set of temporal fixed effects control for time-varying factors that affect all counties, such as long-run trends and short-run shocks arising from economic recessions, improvements in mental health services, and seasonality (Methods).

As in time series analyses or case-crossover designs[32], these controls address many confounding factors. However, short-run variation in air pollution within a location is often driven by human activity, such as manufacturing production shocks or changes in local transportation patterns, which may influence suicide rates for reasons unrelated to air pollution, even after accounting for a rich set of controls. Therefore, we isolate changes in air pollution driven by random variation in a climatological event called a thermal inversion, in which the standard decline in temperature with altitude is reversed, generally owing to rapid nocturnal cooling of Earth's surface[33]. Inversion events occur due to a complex combination of weather conditions interacting with local topography (Supplementary Note 1.1). Importantly, inversions themselves pose no health risk, but when they occur in regions with vehicle and/or industrial emissions, pollutants are trapped between a layer of colder air near the surface and hotter air at higher atmospheric levels, resulting in declines in air quality on the ground[34]. Inversions have been widely documented as an important determinant of pollution, which we confirm with our data. The unpredictability of these events creates a natural experiment in which air pollution increases when conditions arise that cause an inversion. This randomness allows us to isolate variation in pollution that is uncorrelated with other socioeconomic drivers of suicide, following previous studies using inversions to investigate air pollution effects on physical health[34], migration[35] and productivity[24].

The effect of air pollution on suicide rates in China

We find that thermal inversions are strong predictors of $PM_{2.5}$ across Chinese counties. On average, one additional inversion per week raises weekly county-level $PM_{2.5}$ by 0.51 μg m^{-3} (±0.08, range indicates ±1 s.e.), or about 1% of the sample mean (Extended Data Tables 1 and 2). The Kleibergen–Paap F-statistic of this first stage regression is 41.84

(Extended Data Table 3), and results are robust to alternative characterizations of thermal inversions (Fig. 2a and Extended Data Table 4).

Using thermal inversions as an instrumental variable for $PM_{2.5}$, we estimate that a 1 s.d. (σ) increase in $PM_{2.5}$ causes an increase in weekly suicide rates of 0.24 (±0.09) per 1 million individuals, amounting to a ~25% increase above the average weekly suicide rate. This coefficient is highly statistically significant, with a two-sided t-test statistic of $t(257) = 2.75$ and $P = 0.006$, and is robust to the weak identification tests of refs. 36,37 (Extended Data Table 3). By contrast, using linear regression with no instrumental variable (often called a 'two-way fixed effects' regression), an approach similar to the case-crossover design used with patient-level data in epidemiology[32] (Supplementary Note 1.2.1), leads to a small and statistically insignificant ($t(257) = 1.29$, $P = 0.20$) estimate of the suicide–$PM_{2.5}$ relationship (Fig. 2b). This finding is consistent with previous literature showing that two-way fixed-effects models can suffer from measurement error and/or omitted variable bias, confounding relationships between $PM_{2.5}$ and health[38], as well as between $PM_{2.5}$ and economic productivity[24]. It underscores the importance of using random variation in thermal inversions to isolate changes in pollution that are uncorrelated with other risk factors.

Our estimate of the suicide–$PM_{2.5}$ relationship is robust to alternative specifications, including the selection of semiparametric controls (Fig. 2b, rows 3–6), the structure or omission of weather controls (Fig. 2b, rows 7–9), assumptions regarding the model error structure (Fig. 2b, rows 10–12) and alternative definitions of the instrumental variable (Fig. 2b, rows 13 and 14). Additional robustness results and sensitivity analyses are shown in Extended Data Tables 4–7. Supplementary Tables 1 and 2 show that results are similar using a nonlinear Poisson estimator following ref. 39 and using alternative air pollutants, such as PM_{10} and SO_2. Supplementary Table 3 shows that this empirical strategy recovers expected positive effects of $PM_{2.5}$ on respiratory and cardiovascular mortality, consistent with a large previous literature[40].

Heterogeneous effects

To make progress uncovering mechanisms connecting air quality to suicide, we investigate heterogeneity in the suicide–$PM_{2.5}$ relationship. Higher sensitivity in certain groups (for example, lower-income individuals) may indicate that certain mechanisms (for example, economic productivity effects) are driving the full sample aggregate effects. To implement these tests, we divide our data into subsets based on demographic information, the season in which the suicide took place, and the spatial characteristics of each county, and re-estimate our main regression model for each subset (Supplementary Note 1.2.3). These tests sometimes shrink the sample size and, in many cases, increase outcome variance, leading to lower statistical precision. We note that while our county-level suicide data are representative at provincial and national scales for demographic subpopulations, as well as for urban and rural breakdowns, other subpopulation results should not be interpreted as representative of regions outside the 597 counties included in our sample (Methods).

These analyses reveal that suicide rates in people aged 65–85 are far more sensitive to $PM_{2.5}$ than in other age groups (standard errors are large for these groups, as the standard deviation in suicide rates is 5 and 7 times larger than those of the full sample for 65–85-year-old women and men, respectively). In particular, older women are far more susceptible than other groups (Fig. 2c): the suicide rate for women aged 65–85 increases by 0.04 per 1 million individuals for each 1 μg m^3 (±0.01, $P = 0.007$), or 63% per σ. Across alternative specifications, female adults show statistically significant suicide rate responses to $PM_{2.5}$, while effects for males are inconsistent and uncertain (Extended Data Table 3 and Supplementary Table 2).

This difference across ages and sexes may be due to the higher physical vulnerability of older women to particulate matter. Previous work has shown that inhaled particles are deposited more readily in the lungs of women and girls[41], that women and girls suffer more physical ailments in the presence of elevated air pollution[42] and that the physical health effects of pollution are highest for the elderly[38]. However, this finding could also be consistent with the direct neurological effects of particulates, which tend to be larger for women. For example, older women appear most vulnerable to the effect of pollution on dementia [43,44], a key risk factor for suicide in older adults[45], and female brain volumes are highly sensitive to particulate matter[46]. This finding may also reflect particular characteristics of suicidology in China, where female suicide attempts and deaths are both high relative to global averages, particularly in rural areas[8,47]. Previous literature suggests that the low social and educational status of women in rural areas and other forms of gender discrimination, including unequal land titling practices, may contribute to high rates of depression and suicide in rural Chinese women[8]. It is therefore possible that our estimates of elevated vulnerability of older women to $PM_{2.5}$ are attributable to high background rates of suicidal ideation in this group.

We find no strong evidence of differential $PM_{2.5}$ effects on suicide across counties of different incomes or population densities. Similarly, $PM_{2.5}$ effects on suicide are statistically indistinguishable across seasons, although point estimates are largest in the spring, when suicide rates themselves peak (Extended Data Fig. 1). Effects are also largest for counties with higher average suicide rates (Fig. 2c). These findings are consistent with some existing studies identifying stronger correlations between air pollution and suicide in the 'shoulder seasons' of spring and fall[16,27], and for populations with high baseline suicide rates[48], although results are mixed in this literature[29,31]. These estimates are also consistent with possible 'suicide contagion' effects, whereby a suicide within a given community raises the risk of suicide for other members of the community. Interestingly, while the effects of short-run increases in $PM_{2.5}$ on suicide appear smallest during winter, when average $PM_{2.5}$ levels are highest, effects are largest in locations where baseline $PM_{2.5}$ levels are high. Both results are statistically imprecise, but suggest that mechanisms operating seasonally, such as time spent outdoors, may differ from those influencing suicide risks of pollution across space, such as access to mental health services.

Temporal dynamics

Different mechanisms linking suicide and $PM_{2.5}$ are likely to unfold over different time scales. Previous neurobiological and epidemiological literature has focused primarily on acute effects in which suicide risk is elevated within 7 days owing to near-immediate impacts on respiratory, cardiovascular and/or neurological functioning[13,14,19]. For example, fine particulate matter can change brain chemistry, altering aggression and emotional control within 24 h[49,50]. Similarly, impacts of air pollutants on the brain-derived neurotropic factor have been shown to rapidly affect the ability of individuals to cope with crises[19]. Experimental studies show that human neuronal cell death increases within 72 h of exposure to $PM_{2.5}$ (ref. 51). In contrast, chronic brain inflammation and neurodegeneration probably impact suicidal ideation and depression, but manifest over longer time frames[19,50,52]. Similarly, economic or physical health mechanisms are likely to operate with longer-run dynamics, as the links between economic losses and suicide, and between physical health and mental health, have been uncovered at time frames of months to years[26,53]. To assess these dynamics in our setting, we estimate the relationship between suicide rates and thermal inversions over an 8 week period. This approach—called the 'reduced form'—allows us to estimate dynamic effects while avoiding the small sample biases that can arise with many weak instruments[54] (Supplementary Note 1.2.3). While this model enables us to investigate short- to medium-run dynamics, it does not allow us to assess the effects of chronic exposure to $PM_{2.5}$ over months to years.

We find that suicide rates respond very quickly to climate conditions that increase $PM_{2.5}$: weekly suicide rates rise with contemporaneous thermal inversions, which raise $PM_{2.5}$, but there is no discernible effect of inversions on suicides even 1 week into the future (Fig. 2d).

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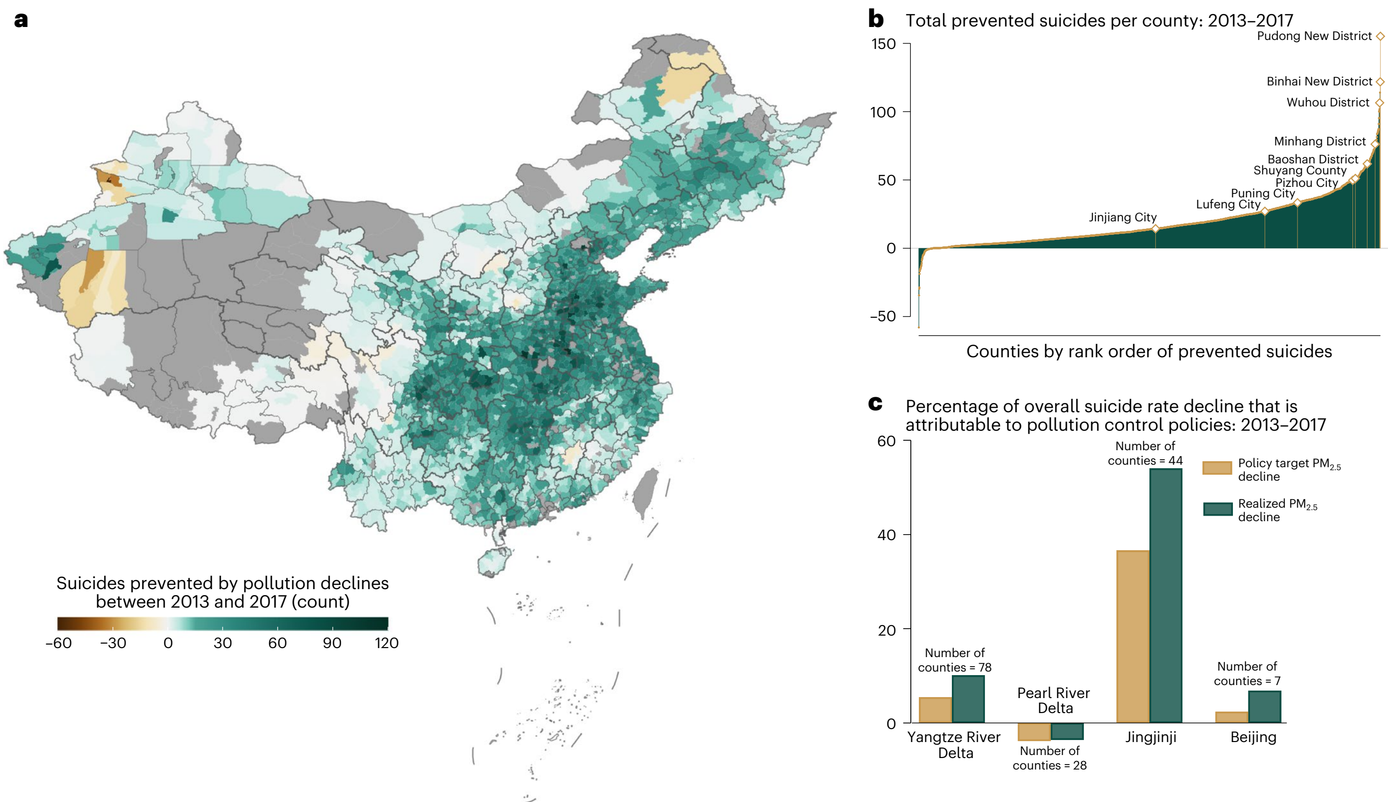

Fig. 3 | Prevented suicides attributable to recent pollution declines. **a**, Estimates of suicides prevented by observed declines in $PM_{2.5}$ between 2013 and 2017 for 2,500 counties. Prefectures are outlined in light grey and provinces in dark grey. Solid grey regions indicate areas with no available population and/or $PM_{2.5}$ data. **b**, Rank order plot of suicides caused or prevented by changes in $PM_{2.5}$ between 2013 and 2017 for the 2,500 counties. The ten most populous counties are indicated with a diamond symbol. **c**, Proportion of 2013–2017 suicide trends in four key regions that are attributable to the APPC-AP, as identified by ref. 56. Tan bars indicate declines attributable to targets set by the APPC-AP, while green bars indicate declines attributable to realized $PM_{2.5}$ levels. In the Pearl River Delta, suicide rates increased from 2013 to 2017, but declines in $PM_{2.5}$ slowed the rate of increase, leading to negative values shown. Basemap in **a** for 2015 from the Chinese Resource and Environmental Science Data Registration and Publishing System (https://www.resdc.cn/?aspxerrorpath=/DOI,2023.DOI:10.12078/2023010101).

Importantly, there is also no compensating negative effect on suicides in future weeks, as one would expect if changes in air pollution simply changed the timing of suicides without influencing the total quantity. Instead, all lagged effects are small in magnitude and statistically indistinguishable from zero using a two-sided *t*-test (Extended Data Table 8). This positive cumulative effect indicates that these are 'additional' suicides—deaths that would otherwise never have occurred had air quality not deteriorated. Our findings of rapid and additional suicides are consistent with the hypothesis that particulate matter has a direct physiological effect on the brain that can increase the propensity to attempt and/or complete suicide[19]. Moreover, they align with previous reports of high rates of impulsivity in female Chinese suicide victims, in which suicides are pursued in response to acute crises within hours to days after exposure to a shock[8]. Related, relatively low levels of depression have been recorded in Chinese suicide victims, suggesting an important role for short-run shocks[47]. These results also reinforce a growing body of epidemiological evidence identifying correlations between air pollution and suicide that manifest within 1 week[13,14].

Estimated impacts of recent pollution prevention policies

We use the above regression results, along with nationwide pollution and population data, to compute county- and year-specific estimates of the change in suicide deaths attributable to changes in $PM_{2.5}$ since 2013, the year China's APPC-AP became effective. There are many plausible causes of suicide rate declines over this period, including safer use of pesticides, economic growth and urbanization[5,6,10]; these calculations isolate the role of $PM_{2.5}$ from other drivers, but do not attempt to identify all factors contributing to observed declines. They should therefore be interpreted as presenting a partial, and necessarily incomplete, picture of the drivers of suicide risk trends in China over this period.

We estimate that $PM_{2.5}$ improvements across China in 2013–2017 prevented 45,970 (±16,712) suicides. Prevented suicide death totals are estimated to be highest in the central and eastern regions, where $PM_{2.5}$ declines are substantial and counties are populous (Fig. 3a). We estimate that $PM_{2.5}$ improvements in Pudong New District, a district of Shanghai, prevented 155 suicides (±56) in just 5 years, while in Binhai, a district of Tianjin, and Wuhou, a district of Chengdu, 122 (±44) and 106 (±39) suicides, respectively, were prevented (Fig. 3b). Just 5% of counties for which both $PM_{2.5}$ and population data are available experienced increased suicide deaths due to air quality deterioration (Fig. 3b). Figure 3a shows that these counties are located primarily in central and central–western China, where $PM_{2.5}$ is rising owing to environmental changes in dust storms and dust transport, as opposed to direct anthropogenic emissions[55].

Observed declines in $PM_{2.5}$ have largely been driven by increasingly stringent air quality and environmental regulations imposed by the central government of China and implemented by regional and local authorities. In particular, the APPC-AP lowered $PM_{2.5}$ in populated and highly polluted regions by targeting industries, non-point sources and vehicle emissions and accelerating clean energy development[56]. In fact, in most regions, declines in $PM_{2.5}$ surpassed the targets set by the APPC-AP. Figure 3c uses estimates of the effectiveness of these policies in four key regions from ref. 56 to compute the suicides prevented in each region due to the APPC-AP. These results show that 54% of the observed decline in suicide rate in Jingjinji can be attributed to the APPC-AP, with an estimated 24 suicides prevented in 2013–2017. By contrast, in Beijing and the Yangtze River Delta, only 7% and 10%, respectively, of the observed decline in suicide rate can be attributed to pollution control, with an estimated 4 (Beijing) and 45 (Yangtze River Delta) suicide deaths prevented, indicating that other factors are largely responsible for falling suicide risks in these regions. In the Pearl River Delta, suicide rates increased in 2013–2017, but we estimate that air pollution control policies slowed the rate of increase by 4%, preventing 6 suicides.

These calculations assume that county-level populations do not respond to $PM_{2.5}$ trends. However, recent studies find evidence that gradual (5 year) increases in $PM_{2.5}$ can induce outmigration in China[35], implying that the estimates shown in Fig. 3 may be overestimated. However, such mobility responses have only been shown in the working age population, while our suicide risk responses to air pollution are driven by the 65–85 age group (Fig. 2c). This demographic group has low overall mobility in China[57], making it unlikely that these estimates are substantially influenced by migration.

Discussion

China has experienced consistent declines in suicide in recent history, with potential explanations ranging from increasing incomes[4] to cultural shifts[8] and improvements in the safe use of pesticides[10], among other factors. While a growing literature raises the possibility that reductions in air pollution may also have contributed, the impact of air quality in this decline has not yet been assessed. We combine weekly, county-level data on suicide rates across China with a statistical model that isolates random fluctuations in air pollution to show that ~10% of China's recent downward trend in suicide rates is attributable to improvements in $PM_{2.5}$. While many other socioeconomic and demographic shifts have been crucial in shaping suicide rates in China in recent years, our findings uncover air pollution as a significant contributing factor.

This study has important limitations that highlight key areas for future work. First, our empirical research design does not enable us to directly identify the mechanisms linking suicide to $PM_{2.5}$. Our results are consistent with a neurobiological channel in which particulate matter rapidly influences brain chemistry, but future research is needed to follow the full causal chain connecting air quality to suicide. For example, the impact of air pollution on neurotransmitters like serotonin may influence suicidal ideation through effects on sleep quality[58]. However, reduced lung function under prolonged exposure to particulate matter may also lead to hypoxia, altering serotonin synthesis and leading to mood disturbances unrelated to sleep[19]. Future research leveraging individual-level data may be able to tie specific neurobiological mechanisms more concretely to observed suicide patterns. Similarly, datasets over extended time periods may uncover mechanisms operating on longer time scales; while we show that suicide rates respond nearly immediately to elevated concentrations of particulate matter with no compensating effect in future weeks, our sample from just 5 years is insufficient to identify possible impacts of chronic pollution exposure.

Second, data limitations may lead to some mismeasurement throughout our analysis. Incomplete pollution and population data imply that our calculations of prevented suicide deaths are not fully comprehensive and tend to omit systematically less populous and less wealthy regions of China. Early literature suggests that such rural regions exhibit substantially higher suicide risk than their urban counterparts[47]. Improvements in air quality monitoring and systematic demographic surveys could improve coverage. Relatedly, we interpolate air pollution readings across space to construct county-level pollution exposure variables. Such measurements undoubtedly exhibit measurement error. While bias from such measurement error is mitigated by our instrumental variables design[54], advances in pollution monitoring would further diminish any remaining impacts of measurement error on downstream analysis.

Finally, $PM_{2.5}$ is highly correlated with other air pollutants, such as PM_{10} and nitrogen dioxide, and thermal inversions change the concentrations of these other pollutants when they change $PM_{2.5}$. Therefore, like much of the air pollution literature (for example, ref. 34), our estimates should be interpreted as the effects of a complex combination of correlated air pollutants, rather than the effects of $PM_{2.5}$ alone. Indeed, we show in Supplementary Table 1 evidence of statistically significant positive effects of PM_{10}, ozone, nitrogen dioxide, sulfur dioxide, and an air quality index on suicide risk across China, in addition to the $PM_{2.5}$ results emphasized throughout the paper.

While there remain many open questions regarding the connections between air quality, mental health and suicide, this analysis adds urgency to calls for pollution control policies across the globe. In just 5 years, we estimate that remarkable air quality improvements realized through targeted pollution interventions in China prevented nearly 46,000 suicide deaths, indicating that large mental health gains may be possible for localities actively working to clear the skies.

Methods

Data

We obtained $PM_{2.5}$ records from monitoring stations maintained by the China National Environmental Monitoring Center (CNEMC), which is affiliated with the Ministry of Ecology and Environment of China. CNEMC began publishing hourly air pollution data in 2013, including the air quality index, $PM_{2.5}$, PM_{10}, ozone (O_3), sulfur dioxide (SO_2), nitrogen dioxide (NO_2) and carbon monoxide (CO). Approximately 1,400 monitoring stations reported data by the end of our sample in 2017, but this number grew over time, starting at just 465 in 2013. There were also missing station-hour observations for individual monitors; ~3% of station-hours are missing in the unbalanced panel of monitor observations. We averaged hourly data to the station-day level and used inverse-distance weighting with a radius of 200 km to convert data from station to the county level. We averaged across days to generate county-level weekly values. Any missing station-hour observations in the raw data were omitted in this spatial and temporal aggregation. Our main analysis relied on $PM_{2.5}$, but we conducted this same calculation and show empirical results for all available pollutants in Supplementary Table 1. Weather data were analogously obtained and processed from ~800 weather stations maintained by the China Meteorological Data Service Center. Weather variables include temperature, precipitation, relative humidity, wind speed and sunshine duration.

We obtained thermal inversion data from the product M2I6NPANA version 5.12.4 from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) released by the US National Aeronautics and Space Administration. The data were reported on a $0.5 \times 0.625°$ (~50×60 km) grid with air temperature metrics at 42 vertical layers ranging from 110 m to 36,000 m above the surface, for each 6 h period. To aggregate thermal inversion data from grid to county, we first bilinearly interpolated within the original grid to obtain 10×12 km resolution, which better accommodates small counties. We then used an area-weighted average across all grids to aggregate to county level. To define thermal inversions, we followed ref. 24 and calculated the temperature difference between the second layer (320 m) and the first layer (110 m) within each 6 h period. If the difference is positive, there exists a thermal inversion. We then aggregated the number of thermal inversions from the 6 h period to the week using three different measures: (1) the total number of inversions per week, (2) the positive difference in temperature between the 320 m layer and the 110 m layer (when there is no inversion, the 320 m layer is cooler than the 110 m layer, and this strength measure is given a value of zero) and (3) the count of days in a week in which there is at least one inversion.

We acquired suicide data from the Chinese Center for Disease Control and Prevention (CCDC), which reports suicide rate data by sex and age cohorts for 597 counties under the Disease Surveillance Point (DSP) system at a weekly level from 2013 to 2017. In these counties, every death that occurred in a hospital or home is recorded, including deaths of registered and non-registered Chinese residents; residents of Hong Kong, Macao and Taiwan; and foreign nationals. All deaths that occur within all levels and types of medical and health institutions are required to be reported. For these deaths, causes of death are determined by medical and health personnel with valid medical practitioner qualifications and are recorded on the death certificate. For deaths that occur at home or in other places, a village or community doctor reports the death to the township health centre (also called a community health service centre). The CCDC doctor at the township health centre then infers the cause of death based on the medical history, symptoms and/or medical diagnosis of the deceased provided by family members or other informed individuals, and fills out the death certificate, including the cause(s) of death. For death cases that require a judicial or public security intervention, the public security and/or judicial departments determine the nature of the death and issue a death certificate, with CCDC doctors at township health centres filling out the death certificate.

Since 2008 (and therefore including our entire sample period), this national death monitoring system has been fully digitized through the Death Registration Reporting Information System of the CCDC. After a death certificate is issued by medical personnel, reporters have up to 7 days to upload death information to the digitized system, and death counts are released to researchers as weekly aggregates. The CCDC performs data quality control on the data reported by each province, including verification and correction for identified problems. This DSP system covers more than 324 million people, or 24.3% of the total population in China, and is representative at both provincial and national levels. Extended Data Fig. 1b maps all DSP counties.

While the digitized DSP system mitigates many concerns of mismeasurement, two potential challenges remain. First, suicides may still be under-reported, particularly if they take place at home in regions where cultural norms discourage accurate reporting of mental health symptoms or diagnoses by family members. Second, individuals may be exposed to pollution in one county, but may die and be reported as a suicide victim in another county. This would introduce measurement error into our measure of air pollution exposure, as our analysis assigns pollution exposure based on the county of death. If this error is classical, attenuation bias is mitigated by the use of two-stage least squares (2SLS) regression[54]. However, if this error is nonrandom, which would occur if, for example, travel behaviours are affected by pollution, it is possible that biases are introduced that cannot be addressed by the 2SLS approach. However, our estimates indicate that the suicide–pollution relationship is very short lived; therefore, individuals would need to be travelling across county borders in response to short-run pollution shocks for such measurement error bias to arise. Moreover, our estimates are driven by the 65–85 year age group, who generally exhibit low mobility in China[57]. We therefore view it as unlikely that this possibility of misassignment of pollution exposure introduces substantial bias into our results.

Population data necessary to compute suicide rates from suicide counts are provided by the CCDC. For population data in other counties, which are used to estimate counterfactual suicide rates for all counties where pollution data are available as shown in Fig. 3, we use county–year-level population data from the China County Statistical Yearbook.

We merge pollution, weather and suicide data together to form a dataset of n = 139,196 county-by-week observations. This sample was used in all statistical analyses shown in Figs. 1c and 2a–d, except as noted in figure legends. Figure 1b maps $PM_{2.5}$ trends for the 2,785 counties with sufficient monitor coverage to compute inverse-distance weighted $PM_{2.5}$ exposure estimates. These trends are computed using a total of n = 4,657,217 county-by-day observations. Figure 3a,b shows estimates of total suicides prevented (or caused) owing to recent pollution trends. These statistics were computed using a sample of n = 708,050 county-by-week observations of $PM_{2.5}$ for 2,500 counties for which $PM_{2.5}$ data could successfully be merged with population totals from the Chinese County Statistical Yearbook.

Average global suicide trends shown in Fig. 1a rely on a country-by-year suicide rate dataset from the World Health Organization (WHO), with a total sample size of n = 3,660 observations covering 2000–2019. The WHO data are available publicly at https://www.who.int/data/data-collection-tools/who-mortality-database. We note that in Fig. 1a, these data indicate a nonlinear trend for Chinese suicide rates over the 2013–2017 study period, while we observe a linear trend in the CCDC county-by-week data used throughout the analysis and shown in Fig. 1c. The WHO data involve inconsistencies in data collection over space and time, as well as substantial model-based approximations documented at https://cdn.who.int/media/docs/default-source/gho-documents/global-health-estimates/ghe2019_cod_methods.pdf?sfvrsn=37bcfacc_5&ua=1. These data are helpful for painting an overall picture of suicide trends across the globe, but we see the linear trend estimated directly from the CCDC data as a far more reliable statistic.

Empirical model

Our empirical methods are summarized here, but additional details are provided in Supplementary Note 1.

Statistical analyses relating suicide rates to air pollution are complicated by the fact that air pollution concentrations are correlated with many unobservable anthropogenic factors. These unobserved variables may lead to spurious correlations between air pollution and suicide risk, or may attenuate regression coefficients toward zero and lead to false rejection of a null hypothesis.

To overcome this challenge, we used an instrumental variables approach. This method leverages a variable called an 'instrument', which has no direct effect on the outcome of interest (here, suicide rates), but influences the regressor of interest (here, $PM_{2.5}$). Under certain conditions, this instrument can be used in a 2SLS regression to isolate variation in the regressor that is uncorrelated with any other determinants of the outcome, providing an unbiased estimate of the coefficient of interest[54]. We specifically used thermal inversion activity as an instrument for $PM_{2.5}$ when estimating the suicide–pollution relationship. The atmospheric conditions that lead to thermal inversions have no direct effect on suicide rates, once a set of semiparametric and weather controls are accounted for that remove the influence of geography, seasonality, and correlated ground conditions[34]. However, these events do cause substantial variation in air pollution (as shown in Fig. 2a), making their presence and intensity valid instruments for air pollution.

Our implementation of instrumental variables consists of estimating the following two equations using 2SLS:

$$\mathrm{PM}_{2.5iwt} = \psi \mathrm{TI}_{iwt} + \rho \mathbf{X}_{iwt} + \alpha_i + \gamma_{wt} + \epsilon_{iwt} \tag{1}$$

$$y_{iwt} = \beta \widehat{\mathrm{PM}_{2.5iwt}} + \delta \mathbf{X}_{iwt} + \alpha_i + \gamma_{wt} + \mu_{iwt}, \tag{2}$$

where i indicates county, w indicates week of year and t indicates year. y_{iwt} is the weekly number of suicides per 1 million population. TI_{iwt} indicates the number of thermal inversions occurring in county i, week w and year t. Equation (1) estimates the relationship between $PM_{2.5}$ and thermal inversions, while equation (2) uses predicted values from equation (1) in place of observed $PM_{2.5}$ to estimate the relationship between suicide rates and $PM_{2.5}$. The coefficient β in equation (2) represents the estimated change in suicide rate associated with a 1 μg m^{-3} increase in $PM_{2.5}$ and is identified using variation in $PM_{2.5}$ driven only by variations in thermal inversions. The terms ε_{iwt} and μ_{iwt} indicate model error terms. In both equations, standard errors are clustered at the county and week levels, allowing for correlation in model errors across all weeks within a county and across all counties in a given week. In all estimations of equations (1) and (2), suicide rates are winsorized at the 2% level.

The controls in equations (1) and (2) are critical to ensuring a causal interpretation of the effect of β. The vector $\mathbf{X}_{iwt}$ includes county-level, time-varying controls for weekly average temperature, precipitation, sunshine duration, wind speed, relative humidity, barometric pressure and the square of each of these variables, addressing known correlations between weather conditions and air pollution[59]. α_i indicates a set of dummy variables for each county; these spatial 'fixed effects' account for all time-invariant characteristics of counties, such as availability of mental health services, average suicide rates, religious composition of the population and other such factors. Because thermal inversion activity can also differ substantially across space, these spatial fixed effects ensure that the variation we use to identify changes in pollution does not include comparisons across locations.

Finally, γ_{wt} indicates a set of week-of-sample 'fixed effects', which are a set of dummy variables for each week in the 2013–2017 sample. These variables control for all country-wide temporal trends and shocks, such as seasonal patterns of suicide, long-run socioeconomic trends, changes in the lethality of pesticide poisoning and trends in mental health services. Many of these variables have been identified as drivers of suicide trends in China. For example, a rich previous literature shows that Chinese suicide rates are associated with changing socioeconomic conditions[4–7], physical health[11,12], educational status[7,11,12], urbanization[4] and changing lethality of specific suicide methods, such as pesticides[10]. If thermal inversions similarly exhibit seasonal and/or longer-run trending behaviour, effects of air pollution could be conflated with effects driven by other temporally varying factors. The temporal fixed-effects γ_{wt} ensure that the variation in pollution that we exploit is isolated from these other important time-trending risk factors.

With this set of controls, the variation in thermal inversions that we use as an instrument for air pollution is 'net' of differences across counties, in weather at Earth's surface, seasonal and long-run time trends, and shared country-wide temporal shocks. Figure 2b shows the robustness of results to alternative specifications of equations (1) and (2), including controls for seasonality and longer-run time trends that vary in sign and magnitude across heterogeneous Chinese counties.

In Fig. 2b, we show that the use of instrumental variables is critically important for accurately recovering the causal effect of $PM_{2.5}$ on suicide in China. The top row of this figure shows the coefficient from an ordinary least squares regression detailed in Supplementary Note 1 (Supplementary Equation 1). This regression includes the fixed effects and weather controls in equations (1) and (2), but does not isolate variation in $PM_{2.5}$ driven only by thermal inversions—such a regression is often referred to as a 'two-way fixed effects' model. In this model, short-run changes in other socioeconomic and/or behavioural conditions that influence air pollution, such as traffic patterns or shocks to manufacturing production, are not controlled for. These factors introduce bias into our estimation of the effects of $PM_{2.5}$ on suicide rates, as they can influence suicide risk for reasons unrelated to air pollution.

Estimating temporal dynamics

To investigate the temporal structure of the effect of $PM_{2.5}$ on suicide rates, we estimate a distributed lag version of the 'reduced form' regression, which directly relates suicide rates to thermal inversions. If thermal inversions influence only suicide rates through changes in $PM_{2.5}$, the dynamics recovered in this model represent the dynamics of the suicide–$PM_{2.5}$ relationship. We take this approach instead of using 2SLS with many lags, as each lagged $PM_{2.5}$ variable would require its own instrument. While lagged values of thermal inversions are possible candidate instruments for such a regression, this approach suffers from the 'many weak instruments' problem, in which coefficients are biased in smaller samples when many instrumental variables are used simultaneously[60]. Our method is detailed in Supplementary Note 1.2.2.

Estimating heterogeneous effects

We quantify heterogeneity in the suicide–$PM_{2.5}$ relationship by estimating equations (1) and (2) using various subsets of the full sample. Specifically, we split the sample by spatial characteristics of a county (for example, urban versus rural), by time (for example, spring versus summer) or by demographic group (for example, young men versus older women) before running the 2SLS regression. We note that while the county-level suicide data we use from the DSP system are representative at provincial and national scales for some subpopulations studied using this approach, other subpopulation results should not be interpreted as representative of regions outside the 597 counties directly included in our sample. In particular, the DSP system is designed to be representative demographically (that is, for all age and sex subpopulations shown) and for urban and rural counties[61]. However, all other subpopulation analyses shown are not necessarily representative of the full Chinese population.

Estimating the effects of recent pollution prevention policies

To estimate the total number of suicides prevented in each county owing to $PM_{2.5}$ trends in 2013–2017, we first estimate county-specific linear trends in $PM_{2.5}$. We then compute the total number of suicides prevented in county i using estimates of the magnitude of this trend multiplied by the estimated regression coefficient $\hat{\beta}$ from equations (1) and (2). These results are shown in Fig. 3a,b. In Fig. 3c, we use two values of $PM_{2.5}$ declines in each of four key regions from ref. 56 to compute suicides prevented due to the specific air pollution control policies implemented in these locations under the APPC-AP. In one set of values, we used region-specific target $PM_{2.5}$ declines, and in the second, we used 'observed' $PM_{2.5}$ declines (as measured using satellite-based $PM_{2.5}$), both from ref. 56. We divide predicted changes in the suicide rate due to target and observed $PM_{2.5}$ declines by each region's overall suicide rate change, reporting the 'proportion' of the overall change in suicide rates that is attributable to the APPC-AP. Details are provided in Supplementary Note 1.3.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Station-level air pollution data are publicly available through the CNEMC (http://www.cnemc.cn/en/). Cleaned and processed air pollution data used in this analysis are hosted publicly on Zenodo (https://doi.org/10.5281/zenodo.10433249). Weather data are provided under restricted access from the China Meteorological Data Service Center; researchers can apply for access to these data at https://data.cma.cn/data/cdcdetail/dataCode/A.0012.0001.S011.html. Suicide data are confidential and were obtained with permission directly from the CCDC. The basemaps used in Figs. 1b and 3a and Extended Data Fig. 1b are from https://www.resdc.cn/?aspxerrorpath=/DOI,2023.DOI:10.12078/2023010101; researchers can apply for access at the same link.

Code availability

All code necessary to replicate the analysis is provided in a public GitHub repository available at https://github.com/tcarleton/suicide-pm (ref. 62).

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Author contributions

P.Z. and T.C. conceptualized the study. P.Z., L.L. and M.Z. obtained and processed the data. P.Z. and T.C. conducted data analysis. T.C. designed and made display items. T.C. wrote the paper and P.Z. edited the paper.

Competing interests

The authors declare no competing interests.

Additional information

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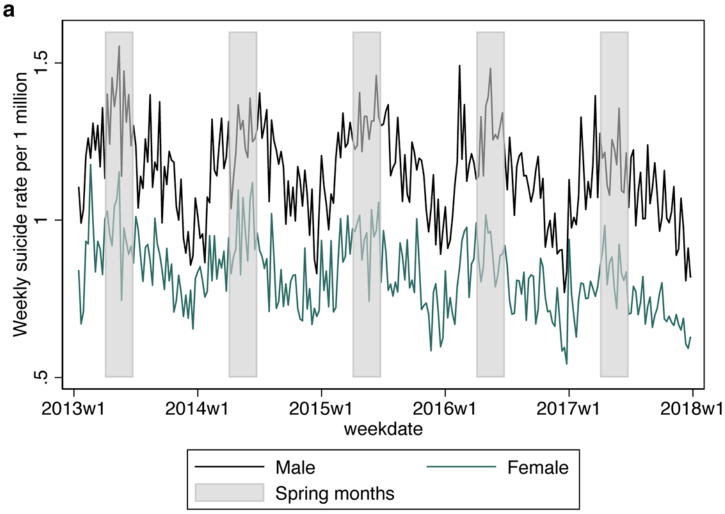
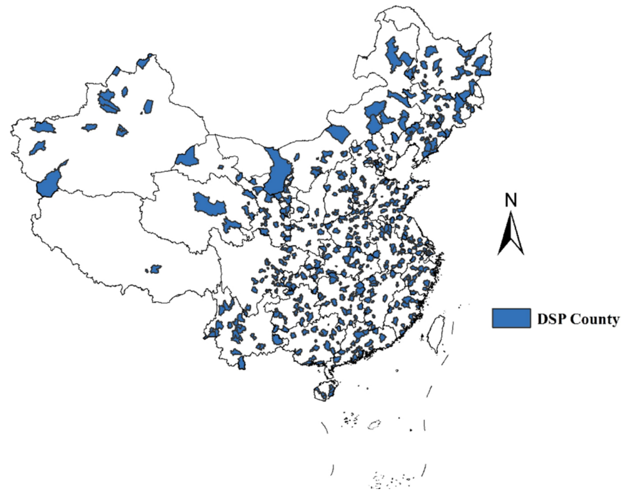
a



b



Extended Data Fig. 1 | Suicide data from the Chinese Center for Disease Control and Prevention Disease Surveillance Point (DSP) system. **a**, Population-weighted average weekly suicide rate per 1 million population for males (black) and females (green) across weeks of the sample ('w1' indicates the first week of the year). Spring months (April, May, and June) are shaded in grey each year. **b**, Map of the 597 nationally representative counties for which suicide data are available through the DSP system. Basemap in **b** for 2015 from the Chinese Resource and Environmental Science Data Registration and Publishing System (https://www.resdc.cn/?aspxerrorpath=/DOI,2023.DOI:10.12078/2023010101).

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Extended Data Table 1 | Summary statistics

	Mean	SD	Min	Max
Total weekly suicide rate (per 1 mil.)	0.96	1.58	0.00	7.68
Female weekly suicide rate (per 1 mil.)	0.69	1.67	0.00	9.29
Male weekly suicide rate (per 1 mil.)	1.01	2.07	0.00	10.90
PM2.5	54.25	34.78	0.00	1,166.72
Weekly number of inversions	4.64	4.56	0.00	28.00
Daily average temperature (C)	14.79	10.49	-34.09	34.21
Daily precipitation (mm)	2.86	4.49	0.00	118.78
Daily average sunshine duration (h)	5.43	2.66	0.00	13.58
Daily average wind speed (m/s)	2.12	0.72	0.31	10.59
Daily average relative humidity (%)	69.03	14.87	6.62	99.46
Daily average barometric pressure (hpa)	962.35	69.96	578.65	1,033.48

Table shows sample summary statistics for all variables used in the main empirical specification. All suicide rate variables have been winsorized at the 2% level. See Methods for details on data sources.

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Extended Data Table 2 | Impact of thermal inversions on $PM_{2.5}$

	(1)	(2)	(3)
No. of inversions	0.513***		
	(0.079)		
	0.000		
Inversion strength (°)		1.509***	
		(0.274)	
		0.000	
No. days with inversion			0.754***
			(0.130)
			0.000
Observations	139,196	139,196	139,196
R-squared	0.673	0.672	0.672
County FE	X	X	X
Week-of-sample FE	X	X	X

Table displays regression results for the effects of thermal inversions on $PM_{2.5}$, measured in units of $\mu g/m^3$. Each column uses a different variable to measure exposure to thermal inversions, but all columns define a thermal inversion as conditions where the second atmospheric layer (measured at 320 meters above Earth's surface) has a temperature that exceeds that at the first atmospheric layer (measured at 110 meters). Column (1) uses the number of weekly thermal inversions, where inversions are measured every 6 hours such that the maximum weekly number of inversions is 168. Column (2) uses the weekly average strength of thermal inversions, which is measured as the average difference in degrees Celsius between temperature at the two atmospheric layers. Column (3) uses the count of days in the week for which at least one thermal inversion occurred. In all columns, standard errors in parentheses are clustered by county and week and *p*-values from two-sided t-tests are listed under standard errors. No adjustments were made for multiple hypotheses tests. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Extended Data Table 3 | Comparison of two-way fixed effects to instrumental variables

	Full pop.		Female		Male	
	2SLS	TWFE	2SLS	TWFE	2SLS	TWFE
PM2.5	0.0079***	0.0001	0.0064**	0.0003	0.0048	0.0000
	(0.0029)	(0.0002)	(0.0030)	(0.0002)	(0.0033)	(0.0003)
	0.0064	0.4635	0.0311	0.1850	0.1441	0.9582
Observations	139,196	139,196	139,105	139,105	139,187	139,187
County FE	X	X	X	X	X	X
Week-of-sample FE	X	X	X	X	X	X
KP F-stat	41.84		41.99		43.04	
p-value	1.61e-08		1.55e-08		1.12e-08	
AR Chi2 p-value	0.00249		0.0214		0.134	
SW S-stat	0.00244		0.0197		0.124	

Table displays estimated effects of $PM_{2.5}$ on suicide rates under the instrumental variables strategy employed in this analysis (2SLS) and for a panel data fixed effects regression approach, estimated using ordinary least squares (TWFE). Columns (1), (3), and (5) use instrumental variables and show the effect of a 1 $\mu g/m^3$ increase in weekly average $PM_{2.5}$ on suicide rates per 1 million population for the entire population, for women only, and for men only, respectively. The number of weekly thermal inversions is used to instrument for weekly $PM_{2.5}$, as described in the main text and in Supplementary Note 1.2.2. Columns (2), (4), and (6) show analogous results for the two-way fixed effects regression approach, which uses a set of spatio-temporal controls but does not isolate plausibly random variation $PM_{2.5}$. KP F-stat values and *p*-values refer to the Kleibergen-Paap underidentification LM statistic, while AR Chi2 *p*-values and SW S-stat values refer to the Anderson and Rubin[36] and Stock and Wright[37] weak identification-robust tests for the statistical significance of the 2SLS estimate, respectively. In all columns, standard errors in parentheses are clustered by county and week and *p*-values from two-sided t-tests are listed under standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Extended Data Table 4 | Robustness of main specification to definition of instrumental variable

	(1)	(2)	(3)
PM2.5	0.0079***	0.0084***	0.0087**
	(0.0029)	(0.0032)	(0.0036)
	0.0064	0.0090	0.0182
Observations	139,196	139,196	139,196
IV	TINumD1	TIStrD1	TIIndD1
County FE	X	X	X
Week-of-sample FE	X	X	X
KP F-stat	41.84	30.27	33.57
p-value	1.61e-08	9.75e-07	1.24e-07
AR Chi2 p-value	0.00249	0.00224	0.00980
SW S-stat	0.00244	0.00252	0.00692

Table displays estimated effects of a 1 $\mu g/m^3$ increase in $PM_{2.5}$ on total population suicide rates per 1 million under the instrumental variables strategy outlined in Supplementary Note 1.2.2. Each column uses a different variable to measure exposure to thermal inversions. As in Table ED2, Column (1) uses the number of weekly thermal inversions, where inversions are measured every 6 hours such that the maximum weekly number of inversions is 168. Column (2) uses the weekly average strength of thermal inversions, which is measured as the average difference in degrees between temperature at the two atmospheric layers. Column (3) uses the count of days in the week for which at least one thermal inversion occurred. KP F-stat values and *p*-values refer to the Kleibergen-Paap underidentification LM statistic, while AR Chi2 *p*-values and SW S-stat values refer to the Anderson and Rubin[36] and Stock and Wright[37] weak identification-robust tests for the statistical significance of the 2SLS estimate, respectively. In all columns, quadratic weather controls are included, standard errors in parentheses are clustered by county and week, and *p*-values from two-sided t-tests are listed under standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Extended Data Table 5 | Robustness of main specification to spatio-temporal controls

	(1)	(2)	(3)	(4)	(5)
PM2.5	0.0079***	0.0060**	0.0079***	0.0077***	0.0070**
	(0.0029)	(0.0025)	(0.0028)	(0.0028)	(0.0028)
	0.0064	0.0167	0.0053	0.0066	0.0130
Observations	139,196	139,110	139,196	139,196	139,196
County FE	X	–	–	X	X
County-year FE	–	X	–	–	–
County-month FE	–	–	X	–	–
Week-of-sample FE	X	X	X	X	X
Prov. time trend	–	–	–	X	–
County time trend	-	–	–	–	X
KP F-stat	41.84	60.06	58.99	48.04	45.04
p-value	1.61e-08	1.40e-10	9.06e-11	2.58e-09	6.21e-09
AR Chi2 p-value	0.00249	0.0102	0.00427	0.00248	0.00720
SW S-stat	0.00244	0.00854	0.00429	0.00242	0.00654

Table displays estimated effects of a 1 $\mu g/m^3$ increase in $PM_{2.5}$ on total population suicide rates per 1 million under the instrumental variables strategy outlined in Supplementary Note 1.2.2. Each column shows results using an alternative set of spatio-temporal controls, or "fixed effects". Column (1) is our main specification, which includes county and week-of-sample fixed effects, which account for all time-invariant differences across counties as well as all nation-wide temporal shocks and seasonal patterns. Column (2) uses county-by-year in place of county fixed effects, which adds controls for county-specific annual shocks. Column (3) replaces county-by-year with county-by-month fixed effects, accounting for county-specific seasonality. Column (4) includes province-specific quadratic time trends in addition to the controls in the main specification, accounting for any province differences in suicide and/or $PM_{2.5}$ trends. Column (5) similarly adds county-specific quadratic time trends, allowing for trending behavior that may vary at the county level. KP F-stat values and *p*-values refer to the Kleibergen-Paap underidentification LM statistic, while AR Chi2 *p*-values and SW S-stat values refer to the Anderson and Rubin[36] and Stock and Wright[37] weak identification-robust tests for the statistical significance of the 2SLS estimate, respectively. In all columns, the number of weekly thermal inversions is used to instrument for weekly $PM_{2.5}$, weather controls are included in quadratic form, standard errors in parentheses are clustered by county and week, and *p*-values from two-sided t-tests are listed under standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Extended Data Table 6 | Robustness of main specification to weather controls

	(1)	(2)	(3)	(4)
PM2.5	0.0091***	0.0082***	0.0079***	0.0075***
	(0.0032)	(0.0029)	(0.0029)	(0.0027)
	0.0052	0.0052	0.0064	0.0060
Observations	139,240	139,196	139,196	139,199
County FE	X	X	X	X
Week-of-sample FE	X	X	X	X
Weather	None	Linear	Quadratic	Binned
KP F-stat	33.15	41.27	41.84	54.43
p-value	2.29e-07	1.32e-08	1.61e-08	3.60e-10
AR Chi2 p-value	0.00104	0.00163	0.00249	0.00291
SW S-stat	0.00168	0.00208	0.00244	0.00409

Table displays estimated effects of a 1 $\mu g/m^3$ increase in $PM_{2.5}$ on total population suicide rates per 1 million under the instrumental variables strategy outlined in Supplementary Note 1.2.2. Each column shows results using an alternative set of weather controls. Column (1) includes no weather controls. Column (2) includes a linear function of weekly average temperature, total precipitation, average sunshine duration, average wind speed, average relative humidity, and average barometric pressure. Column (3) includes a quadratic function of all weather variables in column (1). Column (4) is the most flexible approach and includes a binned specification for all weather variables. Specifically, this specification includes a set of 10 dummy variables for each weather variable indicating when its value falls into each decile of the sample distribution. KP F-stat values and *p*-values refer to the Kleibergen-Paap underidentification LM statistic, while AR Chi2 *p*-values and SW S-stat values refer to the Anderson and Rubin[36] and Stock and Wright[37] weak identification-robust tests for the statistical significance of the 2SLS estimate, respectively. In all columns, the number of weekly thermal inversions is used to instrument for weekly $PM_{2.5}$, standard errors in parentheses are clustered by county and week, and *p*-values from two-sided t-tests are listed under standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Extended Data Table 7 | Robustness of main specification to clustering of standard errors

	(1)	(2)	(3)	(4)
PM2.5	0.0079***	0.0079***	0.0079***	0.0079***
	(0.0023)	(0.0024)	(0.0028)	(0.0029)
	0.0006	0.0013	0.0043	0.0064
Observations	139,196	139,196	139,196	139,196
County FE	X	X	X	X
Week-of-sample FE	X	X	X	X
Clustering	None	Week	County	County and week
KP F-stat	961.7	57.88	125.7	41.84
p-value	0	0	0	1.61e-08
AR Chi2 p-value	0.000577	0.000393	0.00283	0.00249
SW S-stat	0.000577	0.000375	0.00291	0.00244

Table displays estimated effects of a 1 μg/m^3 increase in $PM_{2.5}$ on total population suicide rates per 1 million under the instrumental variables strategy outlined in Supplementary Note 1.2.2. Each column shows results relying on alternative assumptions about the structure of regression error terms. Column (1) assumes that errors are independently and identically distributed. Column (2) clusters standard errors by week, allowing for correlation in error terms across all county observations within the same week. Column (3) clusters standard errors at the county level, allowing for correlation in error terms across all weekly observations within a given county. Finally, column (4) uses two-way clustering, clustering standard errors at both the county and week level, allowing for both spatial and temporal correlation of regression model errors. KP F-stat values and *p*-values refer to the Kleibergen-Paap underidentification LM statistic, while AR Chi2 *p*-values and SW S-stat values refer to the Anderson and Rubin[36] and Stock and Wright[37] weak identification-robust tests for the statistical significance of the 2SLS estimate, respectively. In all columns, the number of weekly thermal inversions is used to instrument for weekly $PM_{2.5}$ and weather controls are included in quadratic form. Standard errors are listed in parentheses and *p*-values from two-sided t-tests are listed under standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Extended Data Table 8 | Lagged effects of thermal inversions on suicide rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inversions, lag 0	0.0036**	0.0035**	0.0035**	0.0032**	0.0031**	0.0031*	0.0031*	0.0031*
	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0017)
	0.0129	0.0165	0.0189	0.0346	0.0435	0.0537	0.0514	0.0724
Inversions, lag 1	-0.0003	-0.0006	-0.0008	-0.0007	-0.0009	-0.0008	-0.0009	-0.0008
	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0016)
	0.8126	0.6745	0.6006	0.6158	0.5342	0.5930	0.5562	0.6023
Inversions, lag 2		0.0004	-0.0002	-0.0002	-0.0002	-0.0005	-0.0006	-0.0005
		(0.0014)	(0.0015)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0017)
		0.8036	0.9023	0.8817	0.8752	0.7551	0.7228	0.7569
Inversions, lag 3			0.0010	0.0006	0.0003	0.0002	0.0000	0.0001
			(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0016)
			0.4876	0.6774	0.8391	0.8988	0.9913	0.9674
Inversions, lag 4				0.0009	0.0008	0.0003	0.0001	0.0002
				(0.0015)	(0.0014)	(0.0015)	(0.0016)	(0.0016)
				0.5233	0.5804	0.8236	0.9335	0.8876
Inversions, lag 5					0.0006	0.0000	-0.0000	-0.0001
					(0.0014)	(0.0014)	(0.0014)	(0.0015)
					0.6796	0.9830	0.9927	0.9729
Inversions, lag 6						0.0019	0.0015	0.0015
						(0.0015)	(0.0016)	(0.0016)
						0.2184	0.3680	0.3561
Inversions, lag 7							0.0013	0.0011
							(0.0014)	(0.0015)
							0.3624	0.4722
Inversions, lag 8								-0.0000
								(0.0013)
								0.9717
Observations	147,438	146,730	146,042	145,368	144,699	144,042	143,388	142,733
Cum. effect	.0033	.0033	.0035	.0038	.0036	.0042	.0045	.0045
Cum. effect SE	.0015	.0017	.0018	.002	.0022	.0024	.0025	.0026
Cum. effect t-stat	2.1386	1.8962	1.9188	1.8994	1.6611	1.7668	1.7888	1.708

Table shows results for a distributed lag model estimating the effect of lagged counts of weekly thermal inversions on total weekly suicides per 1 million population. The effect of "Inversions, lag 0" is the contemporaneous effect of thermal inversions on weekly suicide rates, while all other rows indicate the effect of inversions with weekly lags ranging from 1 to 8 weeks. Cumulative effects are shown at the bottom of the table and indicate the total effect of thermal inversions on suicide rates over the total number of lags included in each column's specification. Column (1) includes just 1 weekly lag, while column (8) includes 8 weeks of lags. In all columns, weather controls are included in quadratic form, standard errors in parentheses are clustered by county and week, and *p*-values from two-sided t-tests are listed under standard errors. No adjustments were made for multiple hypotheses tests. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used to collect data.
Data analysis	All code necessary to replicate the analysis is provided in a public GitHub repository available at https://github.com/tcarleton/suicide-pm.

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Station-level air pollution data are publicly available through the China National Environmental Monitoring Center (CNEMC) (http://www.cnemc.cn/en/). Cleaned and processed air pollution data used in this analysis are hosted publicly on Zenodo (DOI: 10.5281/zenodo.10433249). Weather data are provided under restricted access from the China Meteorological Data Service Center; researchers can apply for access to these data at https://data.cma.cn/data/cdcdetail/dataCode/A.0012.0001.S011.html. Suicide data are confidential and were obtained with permission directly from the Chinese Center for Disease Control and Prevention

(CCDC). All basemaps (used in Figures 1, 3, and Extended Data Figure ED1b) are from the year 2015 and are provided by the Chinese Resource and Environmental Science Data Registration and Publishing System. They were accessed at http://www.resdc.cn/DOI,2023.DOI:10.12078/2023010101 and researchers can apply for access at the same link.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	There are no direct human research participants in our study. However, we are conducting research on human populations and therefore reporting on sex and gender is relevant. We use the term "sex" throughout our manuscript to refer to female- or male-specific suicides and/or populations. While we assume that "female" and "male" categories refer to sex as opposed to gender in our dataset, there is some uncertainty regarding this distinction as individuals in local hospitals and local CDC branches are responsible for recording deaths and there may be differences in approach with respect to these definitions.
Reporting on race, ethnicity, or other socially relevant groupings	n/a
Population characteristics	n/a
Recruitment	n/a
Ethics oversight	n/a

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

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Behavioural & social sciences study design

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Study description	We conduct a statistical analysis of the relationship between population-level suicide rates and exposure to air pollution (particulate matter of size 2.5 micrograms per meter cubed, or smaller) in China. We use these empirical estimates to quantify the role of policy-driven air quality improvements in lowering Chinese suicide rates over the period 2013-2017.
Research sample	Our main sample consists of 597 counties that fall under the Chinese Disease Surveillance Point (DSP) system and are observed weekly from 2013 to 2017. Every death that occurred either in a hospital or at a home in each of these counties is recorded in these data, and trained staff in local hospitals or local Center for Disease Control and Prevention (CCDC) branches determine the cause(s) of death. The DSP system covers more than 324 million people, or 24.3% of the total population of China, and is representative at both provincial and national levels. This sample of counties was chosen because it represents the most comprehensive data available on suicide in China. The years 2013-2017 were chosen because these were the maximum years of data the CCDC agreed to release in the data use agreement established at project initiation.
Sampling strategy	We used all available data provided by the CCDC DSP system at the time of project initiation. The DSP counties were chosen by the CCDC using a stratified random sampling approach where strata were determined by degree of urbanization, population size, and the crude mortality rate. The total number of sampling points per province was determined based on population size, and provincial and national representativeness was ensured using the 2010 census. Additional information on DSP sampling after 2013 can be found in Liu et al. (2016) available at https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4709796/.
Data collection	Suicide data were collected by CCDC staff via the fully digitized Death Registration Reporting Information System and distributed to the authors directly. Air pollution data were collected at the station-by-hour level by the China National Environmental Monitoring Center and accessed by the authors via the online portal at http://www.cnemc.cn/en/. Weather data were collected at the station-by-hour level by the China Meteorological Data Service Center and distributed to the authors via a restricted access user agreement.
Timing	Data are weekly county-level observations, beginning on January 20, 2013 and ending on December 24, 2017.
Data exclusions	We exclude counties for which air pollution monitor data or weather station data are unavailable.
Non-participation	No participants were directly involved in the study. Data from the CCDC are intended to be comprehensive for selected counties.
Randomization	An instrumental variables design was used to assign observations to quasi-experimental groups. Thermal inversions were used as an instrument for air pollution, isolating variation in air quality driven by inversion events. Weather conditions on Earth's surface were

controlled for, as well as dummy variables for county and week-of-sample to control for average differences across space and across weeks of the sample.

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