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Supplementary information

Exposure to unconventional oil and gas development and all-cause mortality in Medicare beneficiaries

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Supplementary Information for

Exposure to Unconventional Oil and Gas Development and All-cause Mortality in Medicare Beneficiaries

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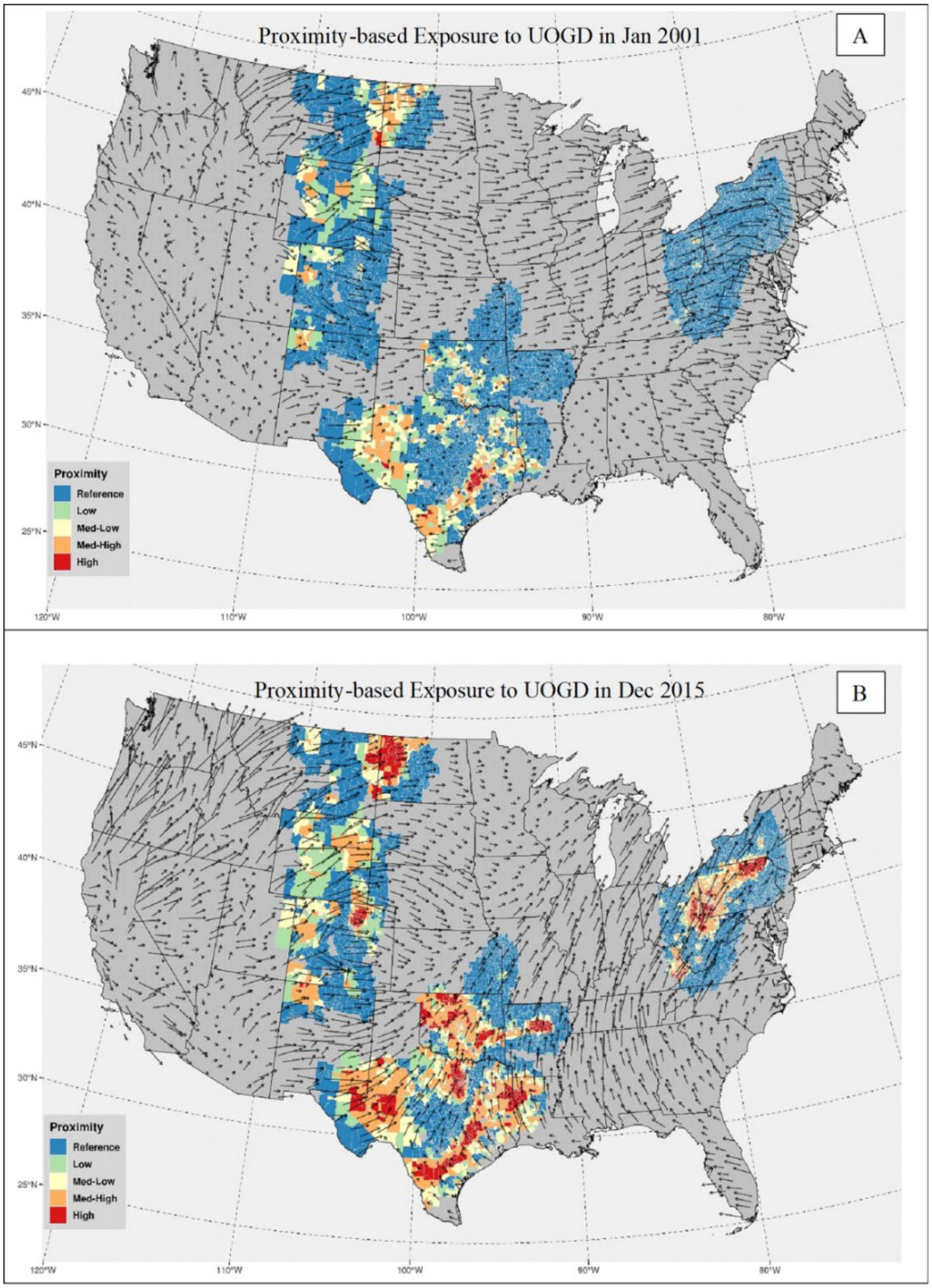
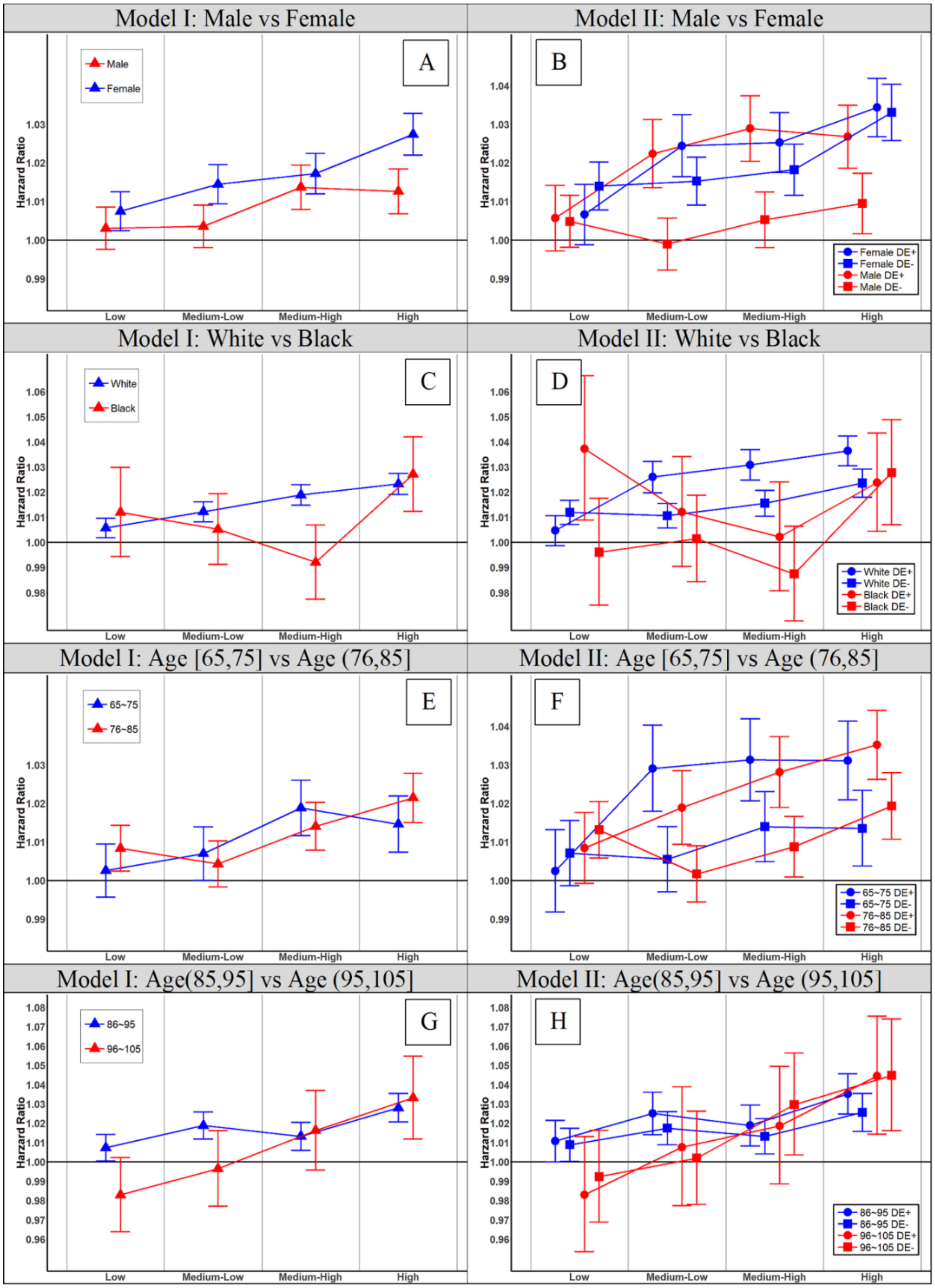
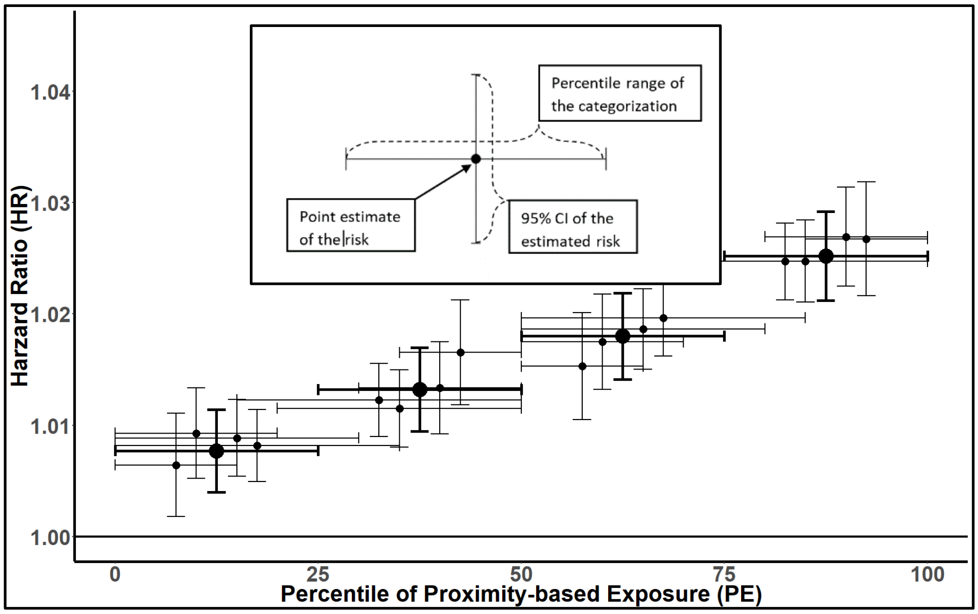
Supplementary Figures



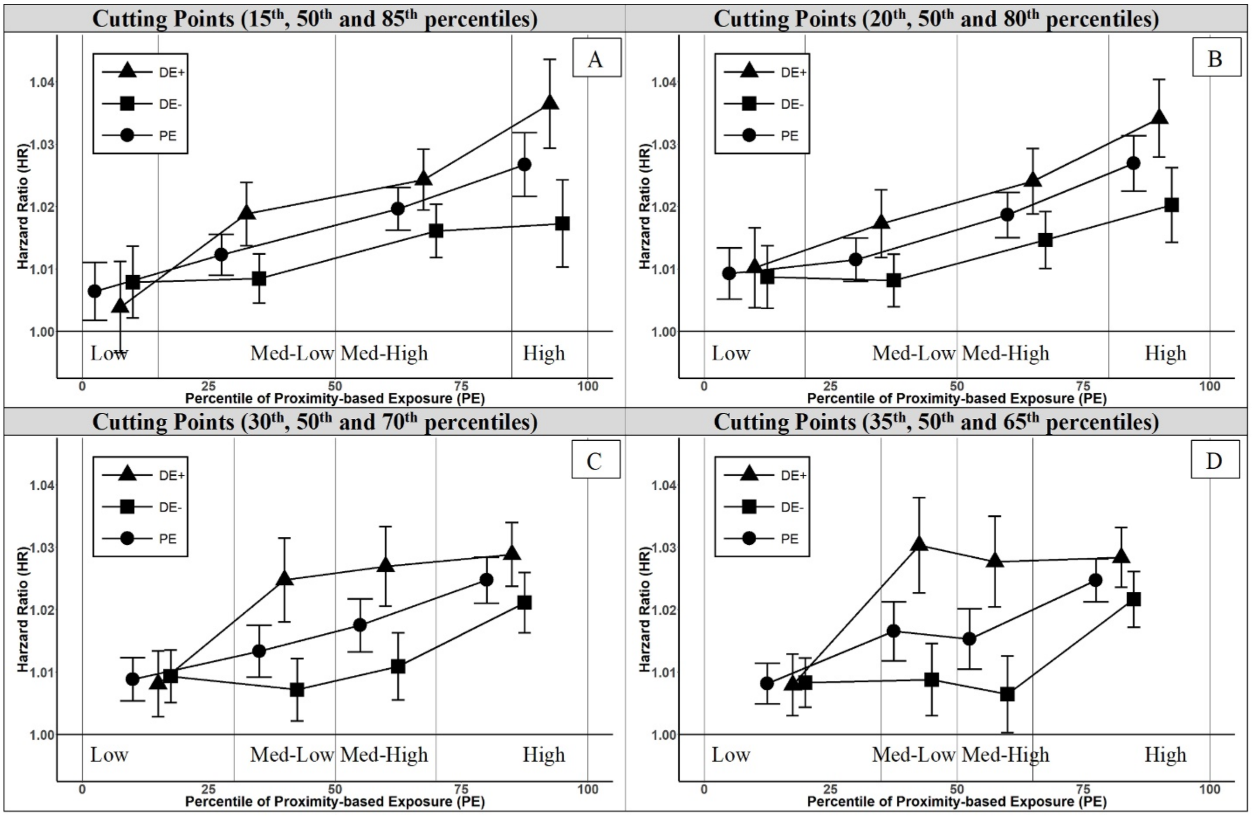
Supplementary Figure 1. Comparison of proximity-basee exposure to UOGD at the beginning (Panel A) and the end (Panel B) of our study period. The color in two panels indicates ZIP Code-level exposure. Wind vectors are created based on the annual average wind velocity and direction.



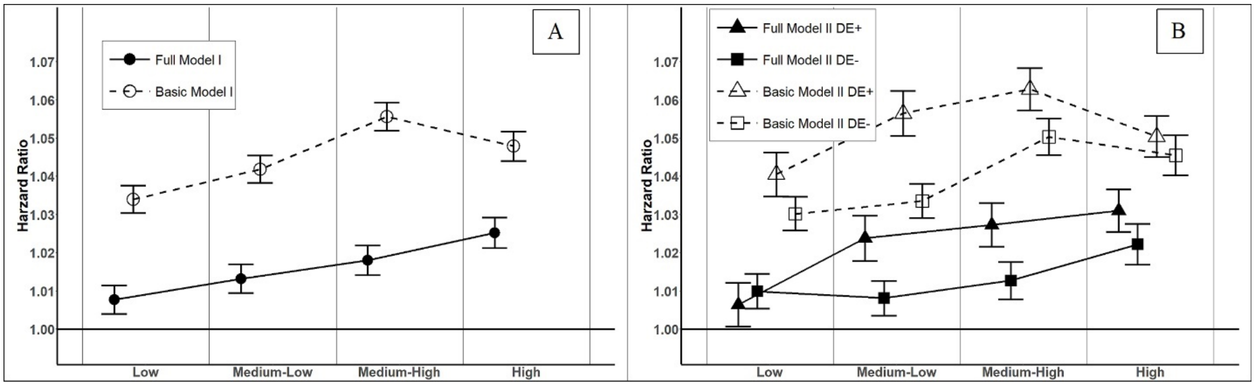
Supplementary Figure 2. Results of the subgroup analyses using both Cox proportional hazards models. The centerpoints represent the point estimations and the bars represent the 95% confidence intervals.



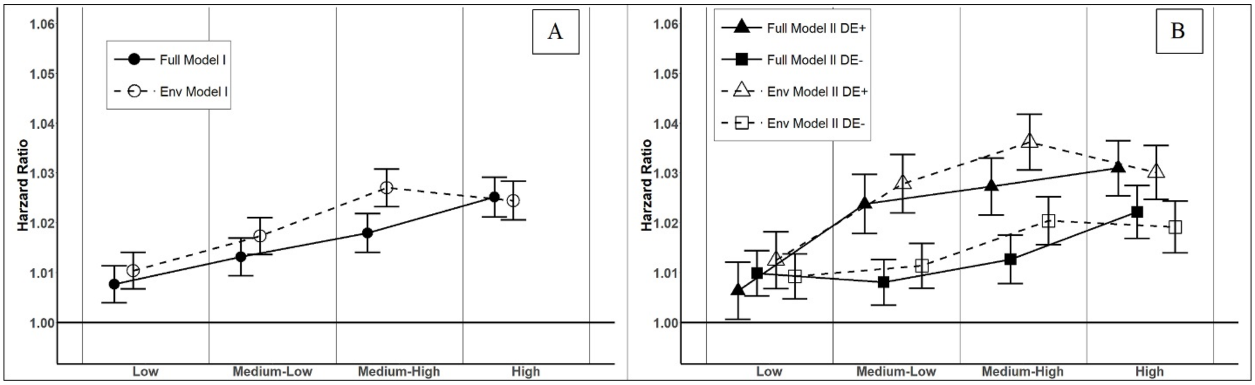
Supplementary Figure 3. The estimated risk of mortality associated with each category of PE to UOGD according to the sensitivity analysis of Model I. Bold black crosses indicate results using the original Model I. The centerpoints represent the point estimations and the bars represent the 95% confidence intervals.



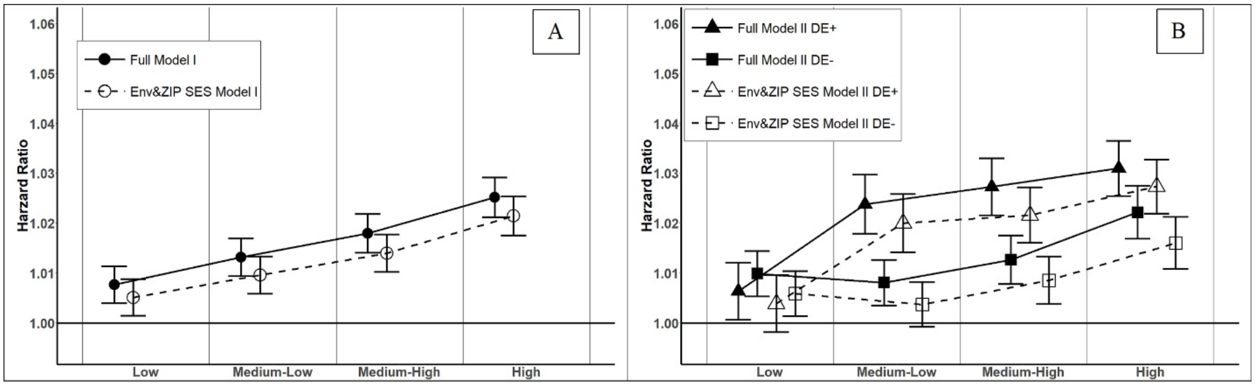
Supplementary Figure 4. The estimated risk of mortality associated with each category of PE to UOGD according to the sensitivity analysis. Bold black crosses indicate the results of the original Model I. The centerpoints represent the point estimations and the bars represent the 95% confidence intervals.



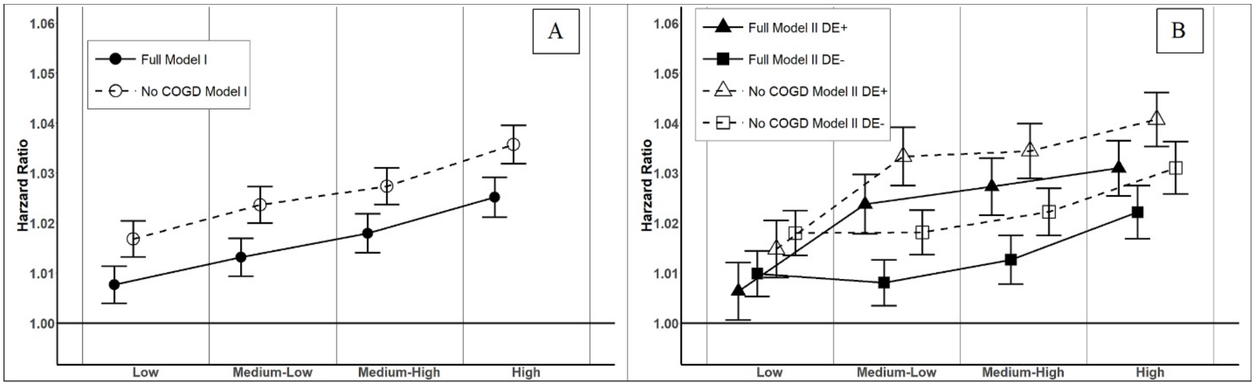
Supplementary Figure 5. A comparison between the full models and the basic models in which only individual-level factors are adjusted. Panel A shows the comparison of a full Model I and a correpsonding basic Model I that does not adjust for ZIP code-level environmental factors, ZIP code-level socioeconomic factors, or county-level behavioral risk factors. Panel B shows the comparison of a full Model II and a basic Model II that does not adjust for ZIP code-level environmental factors, ZIP code-level socioeconomic factors, or county-level behavioral risk factors. The centerpoints represent the point estimations and the bars represent the 95% confidence intervals.



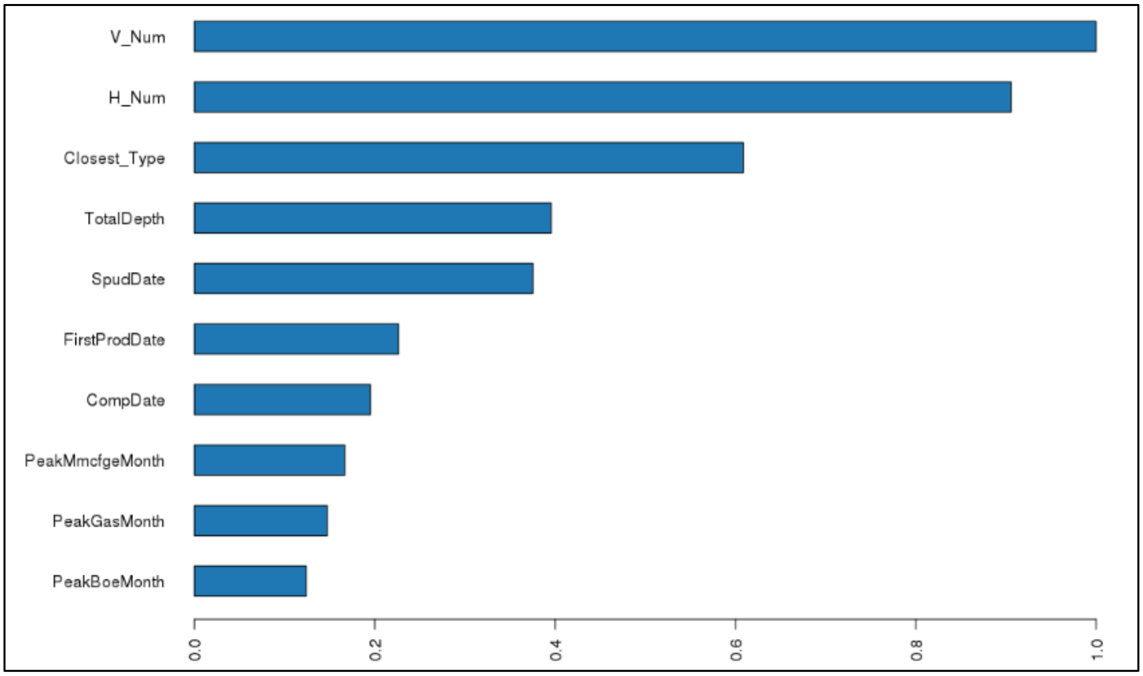
Supplementary Figure 6. A comparison between full models and the moderately simplified models that are adjusted for only individual-level factors and ZIP code-level environmental factors. Panel A shows the comparison of a full Model I and a correpsonding moderately simplified Model I without adjusting for ZIP code-level socioeconomic factors or county-level behavioral risk factors; Panel B shows the comparison of a full Model II and a corresponding lightly modified Model II without adjusting for ZIP code-level socioeconomic factors or county-level behavioral risk factors. The centerpoints represent the point estimations and the bars represent the 95% confidence interval.



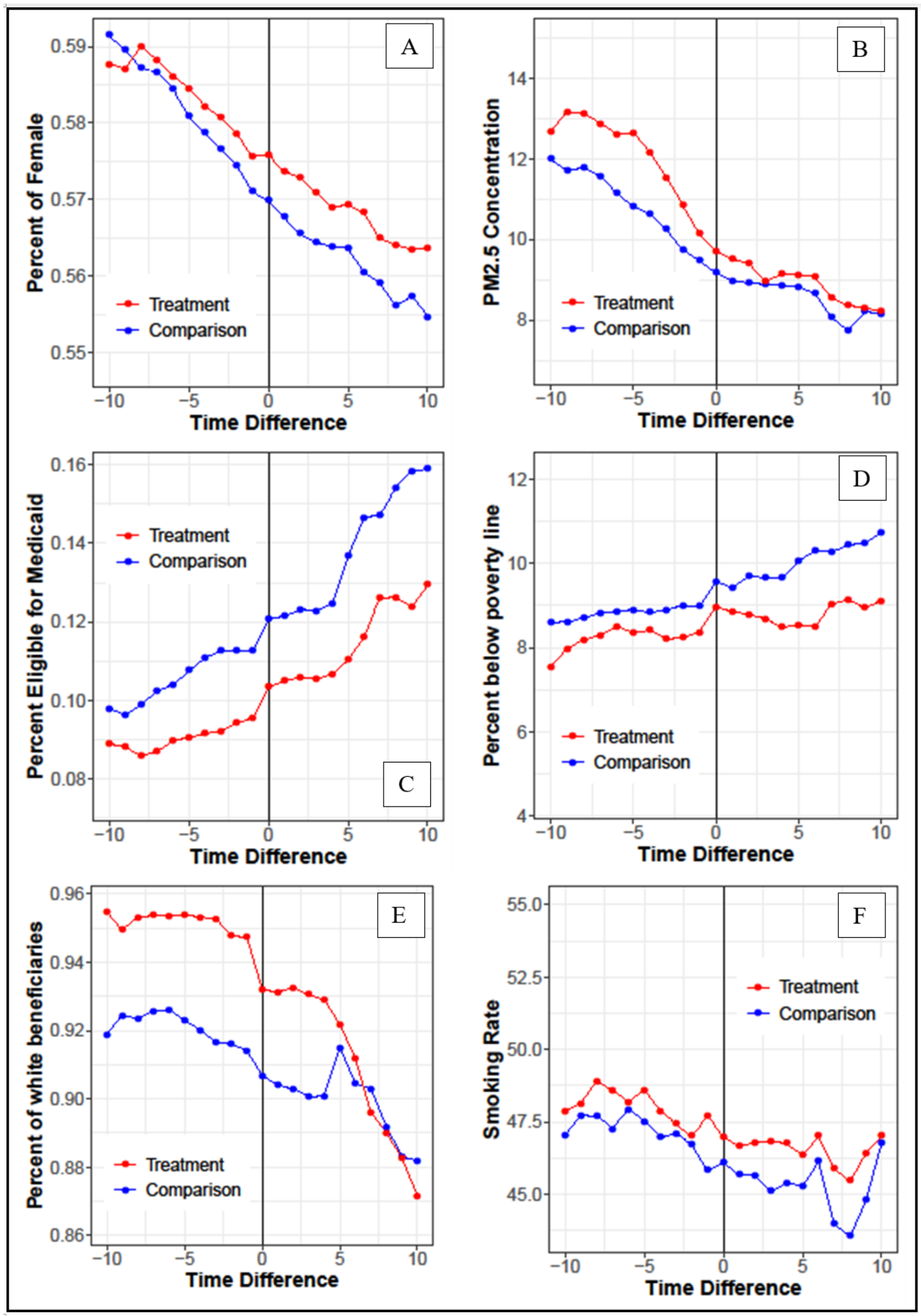
Supplementary Figure 7. A comparison between full models and the slightly simplified models adjusted only for individual-level factors, ZIP code-level environmental factors, and socioeconomic factors. Panel A shows the comparison of a full Model I and a correpsonding slightly modified Model I without adjusting for county-level behavioral risk factors; Panel B shows the comparison of a full Model II and a corresponding slightly modified Model II without adjusting for county-level behavioral risk factors. The centerpoints represent the point estimations and the bars represent the 95% confidence intervals.



Supplementary Figure 8. A comparison between full models and the modified models in which PE to COGD is omitted. Panel A shows the comparison of a full Model I and a corresponding modified Model I without adjusting for COGD; Panel B shows the comparison of a full Model II and a corresponding modified Model II without adjusting for COGD. The centerpoints represent the point estimations and the bars represent the 95% confidence intervals.



Supplementary Figure 9. Relative importance of covariates in the random forest model. Listed covariates from top to bottom: number of conventional wells within 10 km; number of unconventional wells within 10 km; drilling type of the closest well with known drilling type; total drilling depth; spudding date; date of the first production record; completion date; date of peak million cubic feet of gas equivalent production; date of peak natural gas production; and date of peak barrel of oil equivalent production.



Supplementary Figure 10. Pre- and post-drilling trends in covariates: Gender (Panel A), $PM_{2.5}$ (Panel B), Dual eligibility for Medicaid (Panel C), Poverty (Panel D), Race (Panel E), and Smoking rate (Panel F).

Supplementary Tables

Years	PE to UOGD	PE to COGD	Person-Years	Deaths	Mortality
Northern Region					
[2001,2003]	0.021	2.920	1,761,323	87,398	4.96%
[2004,2007]	0.032	3.370	2,524,946	115,638	4.58%
[2008,2011]	0.071	3.400	2,849,780	122,281	4.29%
[2012,2015]	0.403	3.700	3,256,531	132,032	4.05%
Eastern Region					
[2001,2003]	0.001	7.340	14,662,750	791,712	5.40%
[2004,2007]	0.002	8.100	19,642,761	1,015,742	5.17%
[2008,2011]	0.065	8.920	20,397,279	1,004,922	4.93%
[2012,2015]	0.417	9.080	21,635,110	1,032,606	4.77%
Southern Region					
[2001,2003]	0.235	4.620	8,739,250	474,872	5.43%
[2004,2007]	0.656	5.040	12,341,594	627,732	5.09%
[2008,2011]	3.100	5.450	13,540,645	644,641	4.76%
[2012,2015]	4.890	5.350	14,863,090	682,075	4.59%

Supplementary Table 1. The spatiotemporal variability of PE to UOGD and PE to COGD from 2001 to 2015.

PE level	DE level	Hazard Ratio	95% CI	P-value	DE+ vs DE- Diff	95%CI	P-value
Low	--	1.008	(1.004,1.011)	<0.001	--	--	--
Med-Low	--	1.013	(1.009,1.017)	<0.001	--	--	--
Med-High	--	1.018	(1.014,1.022)	<0.001	--	--	--
High	--	1.025	(1.021,1.029)	<0.001	--	--	--
Low	DE-	1.010	(1.005,1.014)	<0.001	--	--	--
Low	DE+	1.006	(1.001,1.012)	0.0142	-0.004	(-0.009, 0.002)	0.884
Med-Low	DE-	1.008	(1.004,1.013)	<0.001	--	--	--
Med-Low	DE+	1.024	(1.018,1.030)	<0.001	0.016	(0.010,0.022)	<0.001
Med-High	DE-	1.013	(1.008,1.018)	<0.001	--	--	--
Med-High	DE+	1.027	(1.022,1.033)	<0.001	0.015	(0.009,0.020)	<0.001
High	DE-	1.022	(1.017,1.028)	<0.001	--	--	--
High	DE+	1.031	(1.025,1.037)	<0.001	0.009	(0.003,0.014)	<0.001

Supplementary Table 2. The results of full Model I and Model II (the data source of Figure 4 in the main text). Cox proportional hazard models were used in both analyses. In Model II, two-sided t-tests were used to detect the wind-dependent differences in mortality influences.

Sub-region	PE level	DE level	HR	95% CI	P-value	DE+ vs DE- Diff	95%CI	P-value
North	Low	--	1.016	(1.003,1.030)	0.008	-0.024	(-0.052,0.005)	0.103
North	Low	DE-	1.017	(0.983,1.053)	0.161	--	--	--
North	Low	DE+	0.994	(0.970,1.018)	0.300	--	--	--
North	Med-Low	--	1.037	(1.021,1.054)	<0.001	0.034	(0.010,0.057)	0.006
North	Med-Low	DE-	1.022	(1.004,1.040)	0.007	--	--	--
North	Med-Low	DE+	1.056	(1.022,1.091)	0.001	--	--	--
North	Med-High	--	1.038	(1.018,1.060)	<0.001	0.042	(0.015,0.070)	0.003
North	Med-High	DE-	1.010	(0.984,1.037)	0.219	--	--	--
North	Med-High	DE+	1.052	(1.022,1.084)	<0.001	--	--	--
North	High	--	1.052	(1.024,1.080)	<0.001	0.033	(-0.004,0.069)	0.082
North	High	DE-	1.023	(0.989,1.058)	0.093	--	--	--
North	High	DE+	1.055	(1.014,1.099)	0.004	--	--	--
East	Low	--	0.999	(0.992,1.005)	0.341	-0.013	(-0.027,0.001)	0.063
East	Low	DE-	1.004	(0.990,1.017)	0.195	--	--	--
East	Low	DE+	0.991	(0.977,1.005)	0.030	--	--	--
East	Med-Low	--	1.010	(1.003,1.017)	0.002	0.010	(0.001,0.020)	0.032
East	Med-Low	DE-	1.006	(0.997,1.015)	0.113	--	--	--
East	Med-Low	DE+	1.016	(1.006,1.026)	0.001	--	--	--
East	Med-High	--	1.019	(1.012,1.026)	<0.001	0.018	(0.009,0.027)	<0.001
East	Med-High	DE-	1.013	(1.005,1.021)	0.001	--	--	--
East	Med-High	DE+	1.031	(1.020,1.041)	<0.001	--	--	--
East	High	--	1.029	(1.020,1.038)	<0.001	0.012	(0.000,0.024)	0.046
East	High	DE-	1.024	(1.011,1.037)	<0.001	--	--	--
East	High	DE+	1.036	(1.025,1.048)	<0.001	--	--	--
South	Low	--	1.001	(0.995,1.007)	0.347	0.011	(0.002,0.019)	0.015
South	Low	DE-	0.997	(0.990,1.005)	0.231	--	--	--
South	Low	DE+	1.008	(0.998,1.017)	0.058	--	--	--
South	Med-Low	--	1.009	(1.005,1.014)	<0.001	0.003	(-0.003,0.009)	0.346
South	Med-Low	DE-	1.008	(1.003,1.013)	0.001	--	--	--
South	Med-Low	DE+	1.011	(1.004,1.018)	0.001	--	--	--
South	Med-High	--	1.003	(0.998,1.008)	0.104	0.000	(-0.006,0.006)	0.935
South	Med-High	DE-	1.003	(0.997,1.009)	0.165	--	--	--
South	Med-High	DE+	1.003	(0.997,1.009)	0.161	--	--	--
South	High	--	1.010	(1.003,1.015)	<0.001	0.023	(0.015,0.031)	<0.001
South	High	DE-	0.998	(0.990,1.005)	0.266	--	--	--
South	High	DE+	1.021	(1.013,1.029)	<0.001	--	--	--

Supplementary Table 3. The results of subregional analyses. Both Cox proportional hazards models were used. In subregional Model II, two-sided t-tests were used to detect the wind-dependent differences in mortality influences.

PE level	DE level	Hazard Ratio	95% CI	P-value	DE+ vs DE- Diff	95%CI	P-value
Low	--	1.004	(0.994,1.015)	0.213			
Med-Low	--	1.010	(0.996,1.023)	0.080			
Med-High	--	1.015	(1.005,1.025)	0.002			
High	--	1.023	(1.013,1.034)	0.000			
Low	DE-	1.005	(1.001,1.010)	0.010			
Low	DE+	1.003	(0.997,1.008)	0.186	-0.003	(-0.008,0.003)	0.831
Med-Low	DE-	1.004	(0.999,1.008)	0.058			
Med-Low	DE+	1.020	(1.015,1.026)	0.000	0.017	(0.011,0.023)	0.000
Med-High	DE-	1.009	(1.004,1.014)	0.000			
Med-High	DE+	1.022	(1.017,1.028)	0.000	0.013	(0.008,0.019)	0.000
High	DE-	1.020	(1.015,1.025)	0.000			
High	DE+	1.027	(1.022,1.032)	0.000	0.007	(0.002,0.012)	0.006

Supplementary Table 4. The results of modified Model I and Model II after omitting $PM_{2.5}$. Cox proportional hazard models were used in both analyses. In Model II, two-sided t-tests were used to detect the wind-dependent differences in mortality risk.

PE level	DE level	Hazard Ratio	95% CI	P-value	E-value for point estimation	E-value for CI
Low	--	1.008	(1.004,1.011)	1.1e-^{2}	1.1	1.07
Med-Low	--	1.013	(1.009,1.017)	5.8e-^{4}	1.13	1.1
Med-High	--	1.018	(1.014,1.022)	3.4e^{-6}	1.15	1.13
High	--	1.025	(1.021,1.029)	2.1e^{-10}	1.19	1.17

Supplementary Table 5. The evidence-value of the associations estimated by Model I.

	Pre-Drilling Treatment Group		Pre-Drilling Comparison Group		
	Mean	Standard Deviation	Mean	Standard Deviation	P-Value
Sample size	2,532,350		2,471,333		
Mortality rate	5.18%	0.222	5.17%	0.221	0.307
% Female	58.30%	0.493	58.20%	0.493	0.012
% Dual Eligibility	9.10%	0.287	10.50%	0.307	$<1e^{-10}$
Age (years)	75.3	7.430	75.4	7.580	$<1e^{-10}$
Calendar year	2005.28	3.280	2005.77	2.940	$<1e^{-10}$
$PM_{2.5}$ (μg/m^3)	12	3.08	10.9	3.27	$<1e^{-10}$
Highest monthly temperature (°C)	17	2.81	18.7	4.48	$<1e^{-10}$
Poverty (%)	8.23	5.68	8.78	5.33	$<1e^{-10}$
Population Density (K person per km^2)	0.9	1.18	0.78	1.57	$<1e^{-10}$
BMI	26.8	1.08	26.9	1.15	$<1e^{-10}$
Smoking rate	48	5.35	47.3	6.93	$<1e^{-10}$

Supplementary Table 6. Pre-drilling balance test between the treatment and comparison groups for mortality rate and other covariates.

Supplementary Notes

Supplementary Note 1. Details of the study area

Our study area (shown in Figure 2) included all counties around or within major UOGD production regions. A total of 9244 ZIP codes within these counties were included. The target formations (shales) underground in these regions include the Bakken formation, primarily underneath western North Dakota; Niobrara formation, primarily underneath eastern Colorado and northern Utah; Marcellus and Utica formations underneath Pennsylvania, West Virginia, eastern Ohio, and southern New York; Woodford formation underneath Oklahoma; Fayetteville formation underneath central Arkansas; Permian formation underneath southeastern New Mexico and western Texas; Barnett formation underneath central and northern Texas; Eagle Ford formation underneath southern Texas; and Haynesville formation underneath eastern Texas and western Louisiana. The boundaries of these formations are determined by the U.S. Energy Information Administration (EIA). Counties around the Bakken shale and Niobrara shale were clustered as the northern subregion. Counties around the Marcellus shale and Utica shale were clustered as the eastern subregion. All other counties were grouped as the southern subregion.

Supplementary Note 2. Spatiotemporal patterns of UOGD & COGD exposure and mortality

During our study period, UOGD expanded rapidly across major shale regions (Supplementary Figure 1). We calculated the average PE levels for both UOGD and COGD in each subregion during our study period (Supplementary Table 1). Due to the rapid expansion of UOGD, the mean of PE to UOGD increased, especially after 2007 in the southern subregion and after 2011 in the northern and eastern subregions. The expansion of COGD during the same period was not as rapid, and COGD exposure even declined slightly in southern subregion.

At the beginning of our study period (Supplementary Figure 1A), UOGD was not widely adopted for economic reasons. Only two small areas, one above Eagle Ford shale and one above Bakken shale, were assigned to the high PE level. Approximately 40,000 residents lived in these regions. At the end of our study period (Supplementary Figure 1B), more than 18 million U.S residents were living within high PE level regions across the contiguous U.S.

Supplementary Note 3. Subgroup analysis

We performed subgroup analyses by restricting person-years to a specific subgroup of the study population and refitting both Model I and Model II. As shown in Supplementary Figure 2A, relative risks associated with PE levels in female beneficiaries were uniformly higher than those of male beneficiaries. As shown in Supplementary Figure 2B, the relative risks associated with the DE^+ subgroups are higher than those associated with the corresponding DE^- subgroups, exluding at the low PE level, regardless of the gender of the beneficiaries. However, the downwind-upwind difference was more pronounced in male beneficiaries compared to female beneficiaries. This difference could be explained by gender-based differences in behavior. As shown in Supplementary Figure 2C and Figure 2D, the estimated risks associated with each PE level in African American subgroups have wider CIs than those for white beneficiaries, due to a smaller sample size. For this reason, most of the exposure levels are not significantly associated with elevated risk, thus making it difficult to investigate ethnicity-based differences in the association. As shown in Supplementary Figure 2E and 2G, there were no remarkable differences in the PE-associated risks of mortality among the four age groups. However, the downwind vs upwind difference in the associated risk was more pronounced in the two younger age subgroups (65 to 75 years of age and 76 to 85 years of age), compared to the two older age subgroups (86 to 95 years of age and 96 to 105 years of age). These age-dependent differences in the associated risk could be explained by differences in behavior. For example, younger medicare beneficiaries may be more active and thus spend more time outdoors compared to their senior counterparts.

Supplementary Note 4. Robustness to cut point selection

In the original analysis, we categorized above-zero continuous PE to UOGD by quartiles to define four PE levels: low (0, 25^{th} percentile], medium-low (25^{th} ,50^{th} percentile], medium-high (50^{th}, 75^{th} percentile], and high (75^{th} ,100^{th} percentile]. The estimated relative risks associated with each PE level are shown in Supplementary Figure 3 as bold black crosses. We designed another four sets of percentile-based cut points: Set 1 (15^{th}, 50^{th} and 85^{th} percentiles), Set 2 (20^{th}, 50^{th} and 80^{th} percentiles), Set 3 (30^{th}, 50^{th}, and 70^{th} percentiles), and Set 4 (35^{th}, 50^{th} and 65^{th} percentiles). We re-categorized the PE based on these four cut points and re-fitted both models to test the robustness of the associations to the cut point selection.

The relative risks of mortality estimated using the model with the four cutpoints were comparable because they use the same reference group of no exposure. We plotted them together in Supplementary Figure 3. Each estimated risk is visualized by a black cross, with the horizontal line representing the range determined by the cut point, the vertical line representing the 95% CI of the estimated risk, and the center point located at the mid-point of the percentile range. As shown in Supplementary Figure 3, the estimated mortality risk was in general linearly associated with the mid-point of the PE range, indicating that the results of Model I are robust to our cut point selection.

After re-categorizing populations based on the four sets of cut points, we further dichotomized the four PE levels into downwind (DE^+) and upwind (DE^-) subgroups using the same method as the original analysis. According to the results of the re-fitting of Model II (Supplementary Figure 4), the downwind-upwind difference in the estimated mortality risk was pronounced at the medium-low and medium-high PE levels. When the high PE level started higher than the 75^{th} percentile (>80^{th} percentile in Set 2 and >85^{th} percentile in Set 1), the downwind-upwind difference was pronounced. When the high PE level started lower than the 75th percentile (>65th percentile in Set 3 and >60th percentile in Set 2), this difference was not as remarkable.

Supplementary Note 5. Robustness to the exclusion/inclusion of covariates

We analyzed the data with a basic version of Model I and Model II that do not account for any ZIP code- or county-level covariates. With basic Model I (Supplementary Figure 5A), every PE level was significantly associated with an elevated risk of mortality; however, the estimated risk did not monotonically increase along with the PE level. In addition, the estimated risks were remarkably higher than those predicted by full Model I. The downwind-upwind difference in the relative risk estimated by basic Model II was pronounced for three PE levels, however (Supplementary Figure 5B).

Using moderately simplified versions of Model I and Model II that were only adjusted for individual-level covariates and ZIP code-level environmental factors (Supplementary Figure 6A), the association between PE to UOGD and all-cause mortality was still not monotonic. Yet the estimated relative risks were of the same magnitude as those from full Model I. According to the moderately simplified Model II (Supplementary Figure 6B), the downwind-upwind difference in the estimated risks was remarkable at all PE levels, and not influenced by omitting ZIP code-level covariates and county-level behavioral risk factors.

We also tested a slightly simplified Model I and Model II adjusted for individual factors, ZIP code-level environmental factors, and ZIP code-level socioeconomic factors while omitting county-level behavioral risk factors. As shown in Supplementary Figure 7A, the slightly simplified Model I estimated lower relative risks for each level of PE; however, omitting county-level behavioral risk factors did not change the trend of the association. As shown in Supplementary Figure 7B, the downwind-upwind difference in the estimated risk was robust to omitting county-level behavioral risk factors.

We then focused on the influence of omitting COGD exposure terms, which was highlighted in HEI's review as a key limitation in some previously published studies. We fitted a single-pollutant Model I that only contains PE to UOGD without adjusting for PE for COGD. As shown in Supplementary Figure 8A, excluding COGD exposure from Model I leads to a higher predicted risk associated with each UOGD PE level. This indicates the importance of including COGD exposure in health effect studies concerning UOGD. Models unadjusted for COGD may overestimate the health effects of UOGD. Despite predicting greater risk, the results of the single-pollutant Model I still show a clear trend that greater PE to UOGD is associated with a greater risk of all-cause mortality Supplementary Figure 8A. According to the results of the single-pollutant Model II (Supplementary Figure 8B), the downwind-upwind difference was robust to the omission of COGD.

Supplementary Note 6. Data source of exposure assessment

State energy agencies were the major data source for the Enverus™ database used in this study. Wells in the Enverus™ database are classified into horizontal wells, vertical wells, and directional wells. However, the definition of directional wells varies among states. For example, directionally drilled wells and horizontally drilled wells are both grouped as a single class in Colorado as directional well, while are classified separately in New Mexico. As a result, there is a visually remarkable difference in the percentage of horizontal wells, which are considered unconventional wells in our study, across state lines even though they share the same target geological formation and apply a similar drilling method. Consequently, we could not assume that all directionally drilled wells are UOGD. In addition, the raw dataset from Enverus™ does not provide drilling type information for more than 75% of the wells, which were mostly drilled before 2000. It is also inaccurate to assume that all wells without drilling type information were conventional because reporting the drilling type is not required by some state agencies. To solve these problems, we needed to predict the binary drilling type based on the drilling types of neighboring wells and other secondary information.

We trained a random forest model to perform this binary prediction. Random forest is a regression tree-based algorithm that is good at capturing non-linear relationships between the primary variable and secondary variables, and is thus suitable for solving this binary classification problem. Secondary variables incorporated in the model included: 1) the drilling type of the nearest well with known drilling type information; 2) the distance to the nearest conventional/unconventional well; 3) the percentage of conventional and unconventional wells of the nearest 10 wells with known drilling type; 4) the oil and gas (O&G) reservoir where the well is positioned; 5) the spudding/completion time; 6) the drilling depth; 7) the natural gas/liquid production in the first 6 months; and 8) the production declining rate of gas/liquid. After running a grid search for optimal performance, the parameters of the model were set as the following: number of trees is 100, maximum depth is 15, minimum size of node is 5. The accuracy of this model was 99.83% for conventional O&G wells and 93.1% for unconventional O&G wells. The performance difference was potentially caused by re-fracturing of some conventional O&G wells. As shown in Supplementary Figure 9, the three most important covariates were the number of conventional wells within 10 km, the number of unconventional wells within 10 km, and the drilling type of the closest well with known drilling type. We used the random forest algorithm implemented in h2o to fit and evaluate our model.

We excluded wells without any temporal information about spudding, completion, production, and abandonment. We then calculated the annual region-specific average length of construction period and estimated the construction-related dates for wells with only production records.

Supplementary Note 7. Details about Analysis set I

In Model I, we used the following formula:

$$\lambda\left(t \middle| \boldsymbol{Z}(t)\right) = \lambda_0 exp\left(\boldsymbol{\beta} \times \boldsymbol{Z}(t)\right)$$

$\boldsymbol{Z}(t) =$	$\boldsymbol{PE}(t) +$	Exposure term of Model I
	$\text{strata}\left(Gender, Race, Medicaid, Year, Age(t)\right) +$	Individual-level factors
	$PM_{2.5}(t) + \%Develop(t) + \%Veg(t) + COGD(t) +$	ZIP code-level environmental factors
	$\%Highschool(t) + \%Poverty(t) + Density(t) +$ $Housevalue(t) + Income(t) + \%Ownership(t) +$	ZIP code-level socioeconomic factors
	$\%Smoking(t) + BMI(t)$	County-level behavioral risk factors

where $\boldsymbol{Z}(t)$ is a mix of time-varying covariates including the exposure term, individual-level demographic factors, ZIP code-level environmental factors, ZIP code-level socioeconomic factors, and county-level behavioral risk factors. The hazard at time t (denoted as $\lambda(\mathrm{t})$) depends on the value of covariates at that time (denoted as $\boldsymbol{Z}(t)$). The regression coefficient of $\boldsymbol{Z}(\cdot)$, denoted as $\boldsymbol{\beta}$, is constant over time. The stratification term $strata\left(Gender, Race, Medicaid, Year, Age(t)\right)$ allows the baseline function, denoted as λ_0, to vary across subgroups. The exposure term of Model I is only PE (denoted as $\boldsymbol{PE}(t)$).

We added an interaction term between downwind-based exposure to UOGD (DE) and proximity-based exposure to UOGD (PE) to the Model I formula. In this way, we modified $\boldsymbol{Z}^*(t)$ as

$\boldsymbol{Z}^*(t) =$	$\boldsymbol{DE}(t) \times \boldsymbol{PE}(t)$	Exposure term of Model II
	$\text{strata}\left(Gender, Race, Medicaid, Year, Age(t)\right) +$	Individual-level factors
	$PM_{2.5}(t) + \%Develop(t) + \%Veg(t) + COGD(t) +$	ZIP code-level environmental factors
	$\%Highschool(t) + \%Poverty(t) + Density(t) +$ $Housevalue(t) + Income(t) + \%Ownership(t) +$	ZIP code-level socioeconomic factors
	$\%Smoking(t) + BMI(t)$	County-level behavioral risk factors

Supplementary Note 8. Details about Analysis Set II

We first conducted a DiD analysis to estimate the proximity-related mortality risk to support the findings of Model I (Analysis Set I). We used residential proximity to active UOGD wells (PE) jointly with the drilling dates of the nearby UOGD to define a time-varying exposure. More specifically, an "*intervention*" occurs when UOGD drilling happens within 15 km from the bound of the ZIP code for the first time. A "*treatment*" community is a ZIP code with high and medium-high PE by the end of 2015. A "*comparison*" community is a ZIP code with low and medium-low PE by the end of 2015. Pre-intervention health records (dead and alive) are used as a "*control*" group for both treatment and comparison groups.

Please note that the intervention occurred to each treatment and comparison community at different times because the drilling time varies across ZIP codes. Both treatment and comparison groups experienced zero PE exposure during pre-intervention period. The post-intervention PE in the treatment group was higher (high, medium-high) than that of comparison group (low, medium-low).

We implemented a fixed effect linear regression model using the following formula:

$$Y_{i,t} = \theta_i + \gamma_t + \beta_1 Post_{i,t} + \beta_2 Trt_i + \beta_3 (Post_{i,t} \times Trt_i) + X_{i,t}\delta + \epsilon_{i,t}$$

where $Y_{i,t}$ is a binary outcome variable indicating whether subject i is dead or alive in the calendar year t, $Y_{i,t} = 0$ indicates the subject i is alive in calendar year t, $Y_{i,t} = 1$ indicates the subject i is dead at the end of calendar year t, θ_i is the individual fixed effect, γ_t is the time fixed effect, $Post_{i,t}$ is a binary variable denoting whether $Y_{i,t}$ happened after drilling ($Post_{i,t} = 1$) or before drilling ($Post_{i,t}$=0), Trt_i is a binary variable indicating whether the beneficiary lives in a treatment community ($Trt_i = 1$) or comparison community ($Trt_i = 0$), and β_3 is the coefficient of the two-way interaction term between treatment and pre- or post-intervention. The estimation of β_3 identifies the pre-post difference in the risk of death for the treated communities minus the pre-post difference in the risk of death for the comparison communities. $X_{i,t}$ is a vector of the time-variant individual and ZIP code-level covariates including age, dual eligibility for Medicaid, $PM_{2.5}$ concentration, annual highest monthly average temperature, poverty rate, smoking rate, and body mass index (BMI). A cluster-robust sandwich estimator was used to account for the serial autocorrelation between repeated within-person measurements.

The point estimate of β_3 is 0.19% (95% CI: 0.12%-0.27%, p-value < 1×10^{-16}), suggesting the interaction term is statistically significantly greater than zero. Specifically, the pre-post change in the likelihood of death for the treated communities is 0.19% higher than the pre-post change in the likelihood of death for the comparison communities. This means that, during the post-drilling period, living in a community with high/medium-high PE leads to a significant increase in the likelihood of death compared living in a community with medium/medium-low PE. The results of the DiD are consistent with the results reported with Model I.

We then fitted a Difference-in-Difference-in-Differences (DDD, also referred to as triple difference) model to estimate the wind-dependent difference in mortality risks associated with UOGD activities. The definitions of "treatment" and "intervention" are identical to the ones used for the DiD analysis (Analysis Set II). Moreover, an ***"upwind" (DE$^+$)*** community is a ZIP code with more than 50% PE contributed by upwind wells and a ***"downwind" (DE$^-$)*** community is a ZIP code with more than 50% PE contributed by downwind wells.

We used a similar linear regression model with additional interaction terms for the wind direction using the following formula:

$$Y_{i,t} = \theta_i + \gamma_t + \beta_1 Post_{i,t} + \beta_2 Trt_{i,t} + \beta_3 Up_{i,t} + \beta_4 (Post_{i,t} \times Trt_{i,t}) + \beta_5 (Post_{i,t} \times Up_{i,t}) + \beta_6 (Trt_{i,t} \times Up_{i,t}) + \beta_7 (Trt_{i,t} \times Up_{i,t} \times Post_{i,t}) + X_{i,t}\delta + \epsilon_{i,t}$$

where $Up_{i,t}$ is a binary variable denoting whether a subject lives in a community downwind or upwind of UOGD activities in calendar year *t*. The coefficient of the three-way interaction term (β_7) is used as our DDD estimator of interest. A cluster-robust sandwich estimator was used to account for the serial autocorrelation between repeated within-person measurements.

The point estimate of β_7 was 0.68% (95% CI: 0.53%-0.83%, p-value$<1\times10^{-16}$), indicating a statistically significant three-way interaction. Specifically, this means that the DiD estimation of risk in communities mostly downwind of UOGD activities is greater than the DiD estimation of risk in communities mostly upwind of UOGD activities. The results of the DDD are consistent with the results reported using Model II.

Supplementary Note 9. Testing the assumption of parallel pre-drilling mortality trends of DiD analysis

We conducted an event-study regression to assess the plausibility of parallel trends assumption in mortality rates between the treatment and the control communities before the intervention (i.e., before drilling). The results are shown in Figure 6. Specifically, we fitted an event-study regression, which accounts for the lags and leads of a drilling (intervention) event with the following formula:

$$\begin{aligned} Y_{i,t} = \theta_i + \gamma_t &+ \beta_{-4}(Trt_i \times Post_{i,t-4}) + \beta_{-3}(Trt_i \times Post_{i,t-3}) + \beta_{-2}(Trt_i \times Post_{i,t-2}) \\ &+ \beta_{-1}(Trt_i \times Post_{i,t-1}) + \beta_1(Trt_i \times Post_{i,t+1}) + \beta_2(Trt_i \times Post_{i,t+2}) \\ &+ \beta_{3(}Trt_i \times Post_{i,t+3}) + \beta_4(Trt_i \times Post_{i,t+4}) + X_{i,t}\delta + \epsilon_{i,t} \end{aligned}$$

where $Y_{i,t}$ is the mortality record of subject *i* at year *t* (0 means alive and 1 means dead); θ_i is the individual fixed effect; $\gamma_t$is the time fixed effect; $Trt_i \times Post_{i,t+k}$ is a two-way interaction indicating whether subject *i* has been in a treatment community for *k* years after drilling at time *t*. Positive *k*s indicate lag effects of the treatment, negative *k*s indicate lead effects. $X_{i,t}$ is a vector of individual- and ZIP code-level time-varying covariates including age, eligibility for Medicaid, PM, temperature, poverty rate, education, smoking rate, and BMI.

As shown in Figure 6, the estimated coefficients for the lead terms ($\beta_{-4}, \beta_{-3}, \beta_{-2}, \beta_{-1}$) are not statistically significantly different from zero, suggesting the plausibility that the mortality trends are parallel between the treatment and control communities before the intervention. Meanwhile, the estimated coefficients of four lag terms ($\beta_4, \beta_3, \beta_2, \beta_1$) are significantly greater than zero, indicating that the mortality trends for the treatment communities compared to the comparison communities are statistically significantly different than zero during post-drilling period.