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Polluted Morality: Air Pollution Predicts Criminal Activity and Unethical Behavior

Jackson G. Lu[1], Julia J. Lee[2], Francesca Gino[3], and Adam D. Galinsky[1]
[1]Columbia Business School, Columbia University; [2]Stephen M. Ross School of Business, University of Michigan; and [3]Harvard Business School, Harvard University

Abstract
Air pollution is a serious problem that affects billions of people globally. Although the environmental and health costs of air pollution are well known, the present research investigates its *ethical* costs. We propose that air pollution can increase criminal and unethical behavior by increasing anxiety. Analyses of a 9-year panel of 9,360 U.S. cities found that air pollution predicted six major categories of crime; these analyses accounted for a comprehensive set of control variables (e.g., city and year fixed effects, population, law enforcement) and survived various robustness checks (e.g., balanced panel, nonparametric bootstrapped standard errors). Three subsequent experiments involving American and Indian participants established the causal effect of psychologically experiencing a polluted (vs. clean) environment on unethical behavior. Consistent with our theoretical perspective, results revealed that anxiety mediated this effect. Air pollution not only corrupts people's health, but also can contaminate their morality.

Keywords
pollution, environment, anxiety, crime, ethics, morality, unethical behavior, open materials, preregistered

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Air pollution is a serious problem that affects billions of people across the globe. According to the Environmental Protection Agency (EPA), about 142 million Americans still reside in counties with dangerously polluted air ("The Colour of Pollution," 2014). In India, air pollution is the primary cause of death, killing over 1.6 million people a year ("Air Pollution in India," 2015). Similarly, breathing Beijing's air is equivalent to smoking almost 40 cigarettes a day ("Mapping the Invisible Scourge," 2015). Although the environmental and health costs of air pollution are clear, limited research has examined its *ethical* costs.

We theorize that air pollution can increase criminal activity and unethical behavior by inducing anxiety. Following Brooks and Schweitzer (2011), we define anxiety as a state of distress or physiological arousal in reaction to the potential for undesirable outcomes. It is well established that air pollution increases anxiety (e.g., Power et al., 2015). For example, air pollution can heighten mortality salience, thereby elevating anxiety (Greenberg et al., 2003). As a result, air pollution has been linked to increases in depression (Szyszkowicz, 2007) and suicide attempts (A. C. Yang, Tsai, & Huang, 2011).

There is also evidence that anxiety can increase both violent unethical behavior (e.g., aggression; Corrigan & Watson, 2005) and nonviolent unethical behavior (e.g., cheating to earn money; Kouchaki & Desai, 2015). For example, anxiety due to negative societal changes (e.g., economic crisis) can lead individuals to be more hostile and aggressive (Barlett & Anderson, 2014). This is partly because transgressive behavior itself (e.g., damaging public property, cheating to get ahead) can function as an aberrant strategy for coping with anxiety (Lazarus & Folkman, 1984). Consistent with the reasoning that transgressing can lower anxiety, the level of the stress hormone cortisol tends to drop after individuals

Corresponding Author:
Jackson Lu, Columbia Business School, Columbia University, 3022 Broadway, New York, NY 10027
E-mail: jackson.guannan.lu@gmail.com

engage in unethical acts (Lee, Gino, Jin, Rice, & Josephs, 2015).

To test the hypothesis that air pollution can increase criminal activity and unethical behavior by increasing anxiety, we conducted a large-scale archival study and three controlled experiments. The archival study analyzed a 9-year panel of 9,360 U.S. cities to investigate the effects of air pollution on seven crime categories. The three experiments then sought to establish the causal effect of psychologically experiencing air pollution and the mediating role of anxiety. To ascertain the generalizability of our findings, we conducted these experiments in both less and more polluted countries (the United States and India).

Several economics researchers have recently explored the effect of air pollution on criminal activity in two cities (Chicago and Los Angeles; Herrnstadt, Heyes, Muehlegger, & Saberian, 2016). Exploiting daily changes in wind direction as a source of quasiexperimental variation in air pollution exposure, this study found that air pollution increased violent crime. The present research extended this study in several important ways. First, Herrnstadt and colleagues (2016) were "agnostic on the mechanism (or mechanisms) underpinning the results" (pp. 4–5). To fill this gap in knowledge, we drew on the psychology literature (e.g., Kouchaki & Desai, 2015; Lee et al., 2015) to propose and test anxiety as an underlying mechanism for the effect of air pollution on unethical behavior. Second, whereas Herrnstadt et al.'s (2016) research involved two U.S. cities, our large-scale panel study examined the effect of air pollution on crime across all U.S. cities for which air pollution and crime data were available ($N = 9{,}360$). Third, the present research not only investigated the effect of experiencing air pollution on criminal behavior but also used three different measures to investigate the effect of experiencing air pollution on unethical behavior in general. Importantly, the definition of unethical behavior—behavior that is "illegal or morally unacceptable to the larger community" (Jones, 1991, p. 367)—includes but is not limited to criminal behavior.

In this article, we report all the studies we have conducted on the relationship between air pollution and unethical behavior. In each study, we report all the measures collected.

Study 1: Air Pollution Predicts Criminal Activity

In Study 1, we collected and analyzed a 9-year panel of 9,360 U.S. cities to investigate the effects of air pollution on seven crime categories. We took careful steps to preclude plausible alternative explanations. First, all of our regression models included *city fixed effects* to control for any unobserved heterogeneity among cities (e.g., city area, legal system) and *year fixed effects* to control for any unobserved time-varying effects (e.g., trend, macroeconomic conditions). Second, we collected a comprehensive list of time-varying city-level control variables, including population, law enforcement, median age, gender, race, education, income, poverty, and unemployment. Third, we tested whether our findings were reliable across a variety of robustness checks, such as a balanced panel and nonparametric bootstrapped standard errors.

Data collection

Pollution data. We sourced city-level air pollution data from the EPA between 1999 and 2009 on six major pollutants: carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), total suspended particulate (TSP), particulate matter PM_{10}, and particulate matter $PM_{2.5}$. All pollutants decreased from 1999 to 2009 (Fig. 1). We standardized each of the six pollutants and then averaged the standardized scores to compute a composite measure of air pollution for each city.

Crime data. We collected city-level crime data from the Uniform Crime Reporting Program of the U.S. Federal Bureau of Investigation (FBI). Covering law enforcement agencies responsible for over 97% of the U.S. population (FBI, 2010), this reliable data set is widely used in criminology, economics, and psychology (e.g., Ranson, 2014). We limited the crime data to the 2001 through 2009 period because the FBI does not provide data on cities that have fewer than 10,000 citizens prior to the year 2001. The FBI tabulates offenses in seven major categories: murder and nonnegligent manslaughter, forcible rape, robbery, aggravated assault, burglary, larceny-theft, and motor vehicle theft. Along with air pollution, criminal activity also trended downward from 2001 to 2009 (Fig. 2). Matching the crime data with the air pollution data yielded a total of 9,360 cities.[1]

Control variables.

City population. Each year, the FBI reports each city's population along with its criminal activities. Unlike air pollution and crime, city population increased from 2001 to 2009 (Fig. 2), suggesting that changes in crime were not solely driven by changes in population. Since cities with greater population tend to have both heavier air pollution and more crime, we controlled for log population (unit = 100,000 people) as a potential confounding variable.

Law enforcement employees. Because a city's institutional regulation may influence both air pollution and crime levels, we also controlled for the number of full-time law enforcement employees per 1,000 citizens (provided by the FBI).

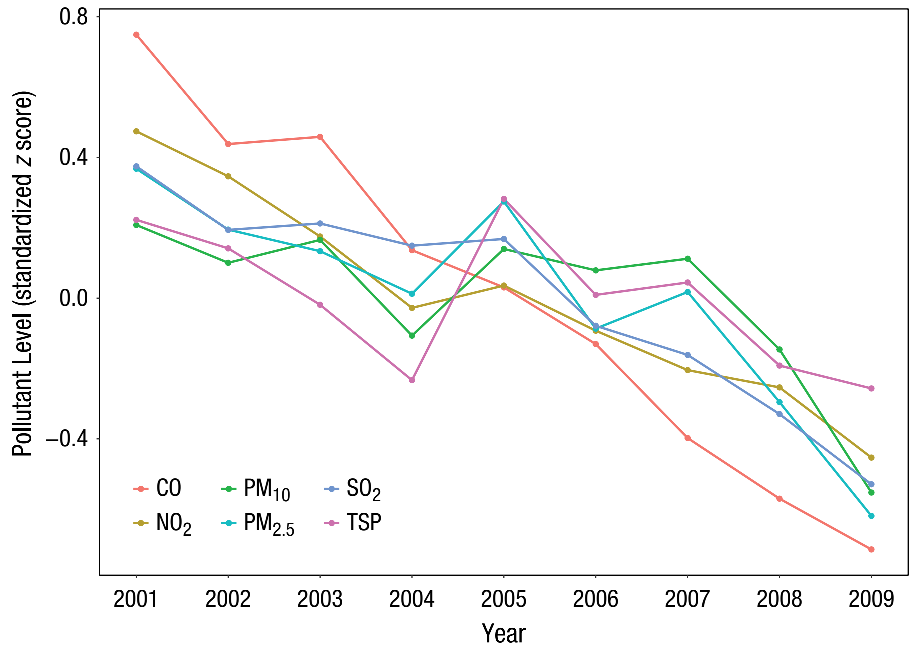

Fig. 1. Study 1: pollutant levels from 2001 to 2009. CO = carbon monoxide; NO_2 = nitrogen dioxide; PM_{10} = particulate matter with aerodynamic diameter ≤ 10 μm; $PM_{2.5}$ = particulate matter with aerodynamic diameter ≤ 2.5 μm; SO_2 = sulfur dioxide; TSP = total suspended particulate.

Economic variables. Because the economic environment of a given city may be related to both air pollution and crime levels, we controlled for (a) inflation-adjusted per capita income ($1,000), (b) poverty rate, (c) female unemployment rate, and (d) male unemployment rate. Moreover, since a city's degree of urbanization and industrialization may affect both air pollution and crime levels, we further controlled for the percentages of the population that worked in the primary sector (e.g., agriculture, forestry), the secondary sector (e.g., manufacturing, construction), and the tertiary sector (i.e., service). These data were sourced from the U.S. Census American Community Survey (www.usa.com).

Demographic variables. Finally, we controlled for the following city-level demographic variables: (a) median age, (b) percentage of male population, (c) population percentage of each race, and (d) percentage of population who completed at least some college. These data were also sourced from the U.S. Census American Community Survey.

Data analysis

Descriptive statistics and bivariate correlations are displayed in Table 1. The unit of analysis in our panel data set is the city-year. Following prior research on crime (e.g., Ranson, 2014), we estimated the effects of air pollution on criminal activities with fixed-effects Poisson regression models via maximum likelihood estimation (Hausman, Hall, & Griliches, 1984; Wooldridge, 1999). Although the results were similar when we used fixed-effects ordinary least squares (OLS) regression models, this Poisson regression approach is the more appropriate analytic strategy for three reasons. First, our dependent variables—crime incidents—are positively skewed count variables that take only nonnegative integer values. This violates the assumption of homoscedastic, normally distributed errors in the linear OLS approach. Second and relatedly, the Poisson approach is superior to a log-linear OLS approach because the former accommodates the fact that many observations recorded zero offense (e.g., 78% of the observations recorded zero incidence of murder; 41% recorded zero incidence of rape; Ranson, 2014). Third, even though the Uniform Crime Reporting Program data do not perfectly follow a Poisson distribution, Poisson regression models with maximum likelihood estimation yield unbiased coefficient estimates (Azoulay, Zivin, & Wang, 2010; Ranson, 2014; Wooldridge, 1999).

For each of the seven crime categories, we present two Poisson regression models: (a) the effect of air pollution while accounting for log population only and (b) the effect of air pollution while accounting for all the control variables. Critically, all models include both (a) city fixed effects to control for any unobserved heterogeneity among cities (e.g., city area, legal system) and (b) year fixed effects to control for any unobserved

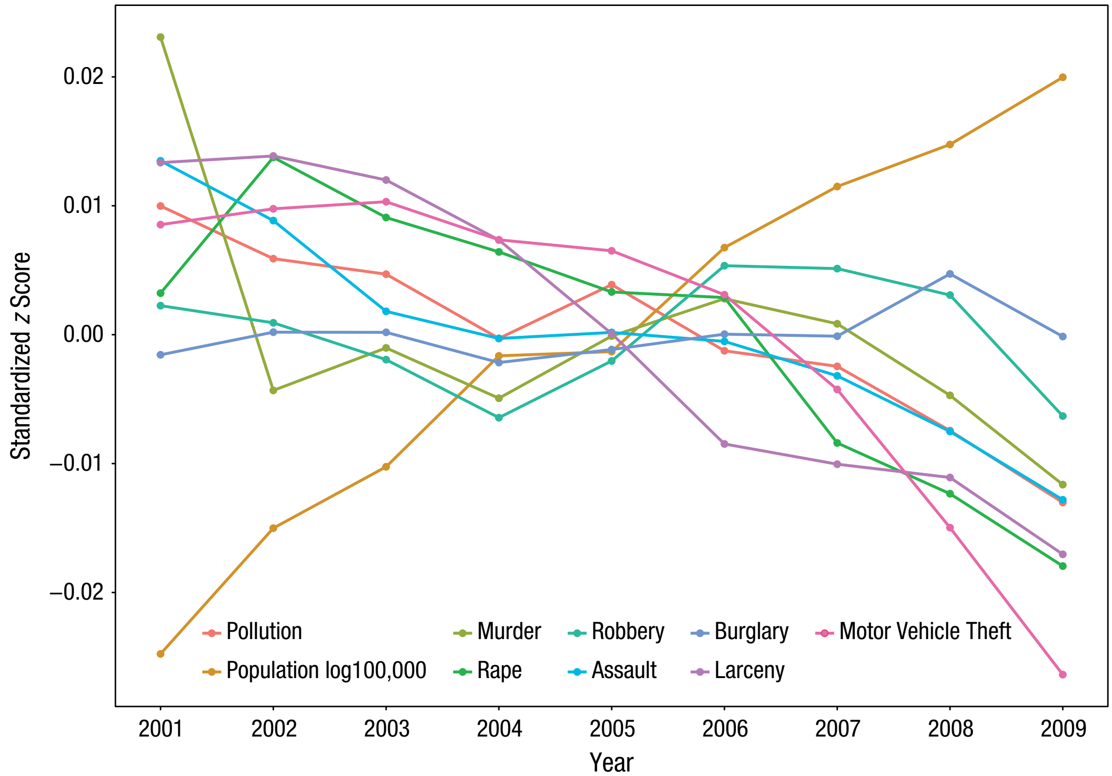

Fig. 2. Study 1: composite air pollution, seven major categories of crime, and population from 2001 to 2009 (all standardized z scores).

time-varying effects (e.g., trend, macroeconomic conditions). The inclusion of these fixed effects helped rule out alternative explanations (e.g., cities with less developed legal systems may have heavier air pollution and also more crime).

Results and robustness checks

In support of our hypothesis, air pollution positively predicted incidents of every crime category in all models (all $ps < .001$; Table 2). As an initial robustness check, we repeated each fixed-effects Poisson regression with robust standard errors (Stock & Watson, 2008); the effect of air pollution remained significant for every crime category (all $ps < .05$; Table 3) except for larceny. This nonsignificant result might be because larceny is the most underreported crime category, as victims of larceny often decide not to report to the police unless their loss is substantial (Hagan, 2010).

As an additional robustness check, we repeated the above fixed-effects Poisson regressions with a balanced panel (4,097 cities across all 9 years) in which there was no missing observation for any of the crime categories. All results remained substantively unchanged: Air pollution still positively predicted incidents of every crime category (all $ps < .05$) except for larceny (Table 4).

Although Poisson regression models with maximum likelihood estimation yield unbiased coefficient estimates (Azoulay et al., 2010; Ranson, 2014; Wooldridge, 1999), this robustness might not apply to estimated variance-covariance matrices (Ranson, 2014). Therefore, as a further robustness check, we also used nonparametric bootstrapping to generate the standard errors (Ranson, 2014), which yielded similar results (Table 5).

Discussion

Analyzing a large archival panel of 9,360 U.S. cities, Study 1 offered evidence that cities with heavier air pollution also tend to have more criminal activity. This effect was reliable when accounting for a host of control variables and across a variety of robustness checks.

Although Study 1 likely did not suffer from reverse causality (i.e., crime causing air pollution), it might have been prone to omitted-variable bias. Even though our regression models controlled for both city and year fixed effects and also controlled for many pertinent time-varying variables, the correlational nature of our panel data prevents the elimination of all potential alternative explanations. To examine the causal effect of air pollution on unethical behavior, we next conducted three experiments.

Table 1. Study 1: Descriptive Statistics and Correlations

			Correlations																												
Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
1. Air pollution (composite)	0.00	0.59	—																												
2. CO	0.46	0.18	.44	—																											
3. NO_2 (×100)	1.18	0.57	.71	.26	—																										
4. PM_{10}	22.02	5.97	.61	.12	.27	—																									
5. $PM_{2.5}$	11.59	2.75	.69	.10	.40	.38	—																								
6. SO_2 (×100)	0.32	0.19	.59	.06	.38	.07	.45	—																							
7. TSP	44.35	14.91	.49	−.01	.20	.32	.10	.10	—																						
8. Murder	1.62	20.11	.07	.03	.06	.04	.05	.02	.03	—																					
9. Rape	7.89	38.60	.06	.03	.06	.06	.04	−.02	.04	.70	—																				
10. Robbery	46.21	475.91	.07	.03	.07	.05	.06	.02	.03	.84	.87	—																			
11. Assault	79.28	623.18	.07	.04	.06	.06	.05	.01	.04	.83	.87	.96	—																		
12. Burglary	187.85	948.14	.07	.04	.06	.07	.05	−.02	.04	.72	.91	.86	.87	—																	
13. Larceny	625.79	3036.86	.07	.05	.06	.06	.04	−.02	.04	.74	.91	.90	.90	.95	—																
14. Motor vehicle theft	112.32	826.60	.10	.06	.09	.08	.06	−.00	.06	.75	.87	.86	.87	.91	.88	—															
15. Population (100,000)	0.23	1.29	.08	.04	.09	.06	.05	.00	.05	.76	.82	.93	.91	.80	.90	.78	—														
16. Law enforcement rate	3.31	11.56	.04	.03	.05	.02	.03	−.01	.02	.00	−.01	.00	.00	−.00	−.00	.00	−.01	—													
17. Median age	38.10	6.33	−.08	−.07	−.03	−.12	−.07	.07	−.06	−.05	−.12	−.06	−.07	−.11	−.10	−.09	−.08	.05	—												
18. % male	48.36	3.51	−.00	.03	.02	.05	−.09	−.09	.05	.00	.02	.01	.01	.02	.02	.02	.02	.02	−.15	—											
19. % Asian	1.94	4.38	.17	.09	.27	.10	.09	−.03	.06	.05	.10	.07	.07	.10	.11	.11	.13	−.00	−.04	.07	—										
20. % Black	9.72	16.78	−.02	.04	−.07	.01	.16	−.04	−.16	.10	.11	.10	.10	.13	.10	.10	.06	.02	−.16	−.10	−.05	—									
21. % Hispanic	9.53	15.74	.04	.06	.04	.20	−.09	−.24	.18	.05	.10	.07	.08	.11	.10	.11	.10	.03	−.31	.18	.12	−.07	—								
22. % Native American	1.04	3.61	−.09	.05	−.10	−.03	−.16	−.09	.02	−.01	−.00	−.01	−.01	−.01	−.01	−.00	−.01	.01	−.08	.04	−.02	−.07	.02	—							
23. % other races	5.16	6.63	.10	.11	.11	.19	−.03	−.19	.18	.07	.12	.09	.10	.12	.12	.13	.11	.05	−.33	.18	.18	−.04	.81	.12	—						
24. % some college or above	50.01	15.88	−.01	.00	.18	−.02	−.13	−.07	.01	.00	.04	.01	.02	.04	.06	.02	.06	.01	.16	.03	.34	−.21	−.16	−.05	−.15	—					
25. Income per capita ($1,000)	23.84	12.46	.06	−.02	.22	−.01	−.02	.04	.01	−.01	−.01	−.00	−.01	−.01	.00	−.00	.02	.04	.39	.02	.30	−.21	−.12	−.09	−.14	.73	—				
26. % population in poverty	15.58	9.41	−.15	−.05	−.28	−.03	−.01	−.08	−.09	.05	.06	.05	.05	.06	.04	.04	.01	.02	−.29	−.09	−.19	.43	.17	.10	.15	−.57	−.55	—			
27. % female unemployed	7.47	4.78	−.05	−.03	−.09	.03	.04	−.07	−.09	.04	.05	.04	.05	.06	.03	.05	.02	−.01	−.18	−.03	−.06	.34	.16	.04	.16	−.32	−.29	.51	—		
28. % male unemployed	8.18	5.22	−.09	−.08	−.08	−.02	.00	−.04	−.09	.04	.04	.04	.04	.05	.02	.04	.01	−.00	−.11	−.02	−.08	.32	.06	.07	.07	−.30	−.29	.48	.47	—	
29. % primary sector employees	2.58	4.41	−.13	.05	−.20	.03	−.21	−.17	.04	−.03	−.06	−.04	−.04	−.06	−.06	−.05	−.05	−.01	−.09	.12	−.13	−.05	.33	.10	.27	−.29	−.22	.24	.12	.04	—
30. % secondary sector employees	20.71	8.69	.05	.02	−.03	.02	.19	.02	−.05	−.04	−.07	−.05	−.05	−.07	−.07	−.05	−.06	−.03	−.10	.01	−.15	.00	−.08	−.07	−.05	−.47	−.31	.08	.10	.01	−.11

Note: Correlations with absolute values larger than .02 are significant at $p < .05$. CO = carbon monoxide; NO_2 = nitrogen dioxide; PM_{10} = particulate matter with aerodynamic diameter ≤ 10 μm; $PM_{2.5}$ = particulate matter with aerodynamic diameter ≤ 2.5 μm; SO_2 = sulfur dioxide; TSP = total suspended particulate.

Table 2. Study 1: Results From the Fixed-Effects Poisson Regression Models via Maximum Likelihood Estimation

	Murder		Rape		Robbery		Assault		Burglary		Larceny		Motor vehicle theft	
Variable	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Air pollution	0.399***	0.395***	0.064***	0.050***	0.079***	0.070***	0.132***	0.124***	0.040***	0.039***	0.008***	0.004***	0.056***	0.062***
(composite)	(0.012)	(0.014)	(0.006)	(0.007)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Log population	0.432***	0.647***	0.741***	0.766***	0.643***	0.588***	0.524***	0.538***	0.513***	0.470***	0.619***	0.594***	0.727***	0.631***
(100,000)	(0.049)	(0.061)	(0.022)	(0.025)	(0.011)	(0.013)	(0.007)	(0.008)	(0.004)	(0.005)	(0.002)	(0.003)	(0.006)	(0.007)
Law enforcement		0.068***		0.014***		−0.009***		−0.002*		−0.014***		0.002***		−0.001*
rate		(0.010)		(0.004)		(0.001)		(0.001)		(0.001)		(0.000)		(0.000)
Median age		0.009†		−0.002		0.000		−0.007***		−0.002***		−0.002***		0.002**
		(0.005)		(0.002)		(0.001)		(0.001)		(0.000)		(0.000)		(0.001)
% male		−0.004		0.002		−0.001		0.004***		0.003***		−0.003***		0.005***
		(0.006)		(0.002)		(0.001)		(0.001)		(0.000)		(0.000)		(0.001)
% Asian		−0.025***		−0.003†		0.006***		−0.003***		0.007***		0.008***		0.011***
		(0.005)		(0.002)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)
% Black		−0.001		0.007***		0.006***		0.008***		0.005***		0.005***		0.005***
		(0.002)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
% Hispanic		0.021***		−0.001		0.007***		0.006***		0.000*		0.001***		0.009***
		(0.003)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)
% Native American		0.081***		0.022***		0.003		0.010***		−0.002*		−0.007***		−0.008***
		(0.015)		(0.004)		(0.003)		(0.001)		(0.001)		(0.001)		(0.002)
% other races		−0.008***		0.005***		−0.001†		0.007***		−0.002***		0.002***		−0.012***
		(0.002)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
% some college or		0.001		−0.007***		−0.002**		0.003***		0.001***		0.000*		−0.007***
above		(0.003)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)
Income per capita		−0.014***		0.001		−0.000		−0.002**		−0.008***		−0.001***		−0.006***
($1,000)		(0.004)		(0.002)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)
% population in		0.010**		0.001		0.004***		0.006***		0.005***		−0.002***		−0.005***
poverty		(0.003)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)
% female		0.022***		0.000		0.012***		0.005***		0.004***		0.001***		0.003***
unemployed		(0.004)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)
% male		−0.000		−0.010***		0.001		−0.003***		−0.002***		−0.001***		−0.002***
unemployed		(0.003)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)
% primary sector		0.007		0.007*		−0.002		0.007***		0.000		−0.006***		0.004***
employees		(0.008)		(0.003)		(0.002)		(0.001)		(0.001)		(0.000)		(0.001)
% secondary sector		0.008*		−0.003*		−0.000		0.002***		−0.000		0.001***		−0.008***
employees		(0.004)		(0.001)		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)
Wald χ^2	1,955.1	2,277.5	1,949.4	1,850.8	8,444.5	8,577.1	21,820.5	20,571.5	17,720.8	20,644.6	158,525.5	138,164.1	174,717.9	113,165.5

Note: Unstandardized Poisson regression coefficients are displayed, with standard errors in parentheses. All models included city and year fixed effects. The reference category for race was White; the reference category for economic sector was the tertiary sector.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 3. Study 1: Results From the Fixed-Effects Poisson Regression Models via Maximum Likelihood Estimation (With Robust Standard Errors)

	Murder		Rape		Robbery		Assault		Burglary		Larceny		Motor vehicle theft	
Variable	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Air pollution	0.399†	0.395*	0.064*	0.050*	0.079**	0.070***	0.132**	0.124*	0.040*	0.039*	0.008	0.004	0.056*	0.062**
(composite)	(0.230)	(0.197)	(0.028)	(0.025)	(0.026)	(0.019)	(0.051)	(0.054)	(0.020)	(0.017)	(0.011)	(0.011)	(0.025)	(0.023)
Log population	0.432***	0.647†	0.741***	0.766***	0.643***	0.588***	0.524***	0.538***	0.513***	0.470***	0.619***	0.594***	0.727***	0.631***
(100,000)	(0.088)	(0.346)	(0.065)	(0.064)	(0.087)	(0.074)	(0.075)	(0.074)	(0.054)	(0.062)	(0.033)	(0.034)	(0.069)	(0.065)
Law enforcement		0.068		0.014		−0.009		−0.002		−0.014†		0.002		−0.001
rate		(0.130)		(0.009)		(0.009)		(0.008)		(0.008)		(0.002)		(0.003)
Median age		0.009		−0.002		0.000		−0.007		−0.002		−0.002		0.002
		(0.009)		(0.007)		(0.006)		(0.005)		(0.006)		(0.002)		(0.007)
% male		−0.004		0.002		−0.001		0.004		0.003		−0.003		0.005
		(0.010)		(0.006)		(0.006)		(0.005)		(0.005)		(0.002)		(0.006)
% Asian		−0.025		−0.003		0.006†		−0.003		0.007*		0.008***		0.011**
		(0.021)		(0.006)		(0.004)		(0.003)		(0.003)		(0.001)		(0.004)
% Black		−0.001		0.007*		0.006*		0.008**		0.005*		0.005***		0.005
		(0.010)		(0.003)		(0.003)		(0.003)		(0.002)		(0.001)		(0.004)
% Hispanic		0.021**		−0.001		0.007*		0.006		0.000		0.001		0.009**
		(0.007)		(0.003)		(0.003)		(0.004)		(0.003)		(0.001)		(0.003)
% Native American		0.081**		0.022**		0.003		0.010		−0.002		−0.007†		−0.008
		(0.025)		(0.008)		(0.012)		(0.009)		(0.007)		(0.003)		(0.013)
% other races		−0.008†		0.005*		−0.001		0.007*		−0.002		0.002†		−0.012***
		(0.005)		(0.002)		(0.002)		(0.003)		(0.002)		(0.001)		(0.003)
% some college or		0.001		−0.007**		−0.002		0.003		0.001		0.000		−0.007†
above		(0.007)		(0.003)		(0.004)		(0.004)		(0.002)		(0.001)		(0.004)
Income per capita		−0.014		0.001		−0.000		−0.002		−0.008***		−0.001		−0.006
($1,000)		(0.011)		(0.004)		(0.005)		(0.004)		(0.002)		(0.001)		(0.006)
% population in		0.010		0.001		0.004		0.006		0.005*		−0.002		−0.005
poverty		(0.009)		(0.003)		(0.004)		(0.005)		(0.002)		(0.001)		(0.004)
% female		0.022		0.000		0.012***		0.005*		0.004		0.001		0.003
unemployed		(0.016)		(0.003)		(0.003)		(0.003)		(0.003)		(0.001)		(0.004)
% male		−0.000		−0.010*		0.001		−0.003		−0.002		−0.001		−0.002
unemployed		(0.005)		(0.005)		(0.004)		(0.003)		(0.003)		(0.001)		(0.003)
% primary sector		0.007		0.007		−0.002		0.007		0.000		−0.006*		0.004
employees		(0.014)		(0.007)		(0.007)		(0.005)		(0.009)		(0.003)		(0.008)
% secondary sector		0.008		−0.003		−0.000		0.002		−0.000		0.001		−0.008†
employees		(0.007)		(0.003)		(0.003)		(0.003)		(0.003)		(0.001)		(0.005)
Wald χ^2	106.7	104.5	174.9	224.0	545.5	517.7	230.9	192.2	136.4	176.0	616.8	903.8	1,453.4	2,005.4

Note: Unstandardized Poisson regression coefficients are displayed, with robust standard errors in parentheses. All models included city and year fixed effects. The reference category for race was White; the reference category for economic sector was the tertiary sector.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 4. Study 1: Results From the Fixed-Effects Poisson Regression Models via Maximum Likelihood Estimation (With Robust Standard Errors), Balanced Panel

	Murder		Rape		Robbery		Assault		Burglary		Larceny		Motor vehicle theft	
Variable	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Air pollution (composite)	0.498†	0.483*	0.066*	0.055*	0.096**	0.082***	0.150*	0.149*	0.046†	0.044*	0.007	0.002	0.072*	0.080**
	(0.263)	(0.216)	(0.031)	(0.027)	(0.030)	(0.020)	(0.060)	(0.062)	(0.025)	(0.020)	(0.014)	(0.013)	(0.030)	(0.027)
Log population (100,000)	0.472**	0.739†	0.753***	0.774***	0.608***	0.596***	0.570***	0.587***	0.602***	0.558***	0.625***	0.608***	0.752***	0.662***
	(0.152)	(0.383)	(0.075)	(0.072)	(0.095)	(0.086)	(0.097)	(0.088)	(0.062)	(0.065)	(0.041)	(0.042)	(0.087)	(0.087)
Law enforcement rate		0.104		0.015		−0.007		−0.008		−0.017		0.001		−0.001
		(0.161)		(0.013)		(0.008)		(0.013)		(0.011)		(0.002)		(0.003)
Median age		0.008		0.001		0.001		−0.007		0.002		−0.001		0.002
		(0.011)		(0.009)		(0.007)		(0.006)		(0.004)		(0.002)		(0.009)
% male		0.014		0.005		0.008		0.009		0.005		−0.002		0.008
		(0.011)		(0.006)		(0.007)		(0.006)		(0.008)		(0.003)		(0.008)
% Asian		−0.023		−0.000		0.007†		−0.002		0.007*		0.007***		0.011**
		(0.020)		(0.005)		(0.004)		(0.003)		(0.003)		(0.001)		(0.004)
% Black		−0.008		0.004		0.003		0.006†		0.005*		0.005**		0.003
		(0.010)		(0.003)		(0.002)		(0.003)		(0.002)		(0.001)		(0.004)
% Hispanic		0.023**		0.002		0.008*		0.007		0.003		0.002		0.008*
		(0.007)		(0.003)		(0.003)		(0.005)		(0.003)		(0.002)		(0.004)
% Native American		0.084**		0.015		0.009		0.014		0.003		−0.004		−0.012
		(0.030)		(0.009)		(0.014)		(0.011)		(0.006)		(0.004)		(0.015)
% other races		−0.008		0.002		−0.001		0.007*		−0.004**		0.002		−0.012***
		(0.005)		(0.002)		(0.002)		(0.003)		(0.002)		(0.002)		(0.003)
% some college or above		0.007		−0.009**		0.000		0.005		0.004†		0.000		−0.010†
		(0.008)		(0.003)		(0.004)		(0.005)		(0.002)		(0.001)		(0.005)
Income per capita ($1,000)		−0.022†		−0.001		−0.005		−0.004		−0.009***		−0.000		−0.005
		(0.012)		(0.005)		(0.005)		(0.004)		(0.003)		(0.002)		(0.007)
% population in poverty		0.010		0.003		0.004		0.006		0.008**		−0.000		−0.006
		(0.011)		(0.004)		(0.005)		(0.006)		(0.002)		(0.002)		(0.005)
% female unemployed		0.025		0.004		0.013***		0.007*		0.004		0.002		0.005
		(0.019)		(0.004)		(0.004)		(0.003)		(0.003)		(0.002)		(0.005)
% male unemployed		0.001		−0.012†		0.001		−0.005		−0.004		−0.002		−0.002
		(0.007)		(0.007)		(0.004)		(0.003)		(0.004)		(0.001)		(0.004)
% primary sector employees		0.006		−0.007		−0.002		0.006		−0.009		−0.008*		0.002
		(0.016)		(0.007)		(0.009)		(0.006)		(0.008)		(0.004)		(0.011)
% secondary sector employees		0.011		−0.003		−0.000		0.003		0.002		0.001		−0.011†
		(0.008)		(0.004)		(0.003)		(0.004)		(0.004)		(0.002)		(0.006)
Wald χ^2	83.2	99.1	169.2	205.4	436.0	458.8	230.6	216.6	130.8	211.4	427.0	647.6	1,096.3	1,525.3

Note: City $N = 4{,}097$. Unstandardized Poisson regression coefficients are displayed, with robust standard errors in parentheses. All models included city and year fixed effects. The reference category for race was White; the reference category for economic sector was the tertiary sector.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 5. Study 1: Results From the Fixed-Effects Poisson Regression Models via Maximum Likelihood Estimation (With Bootstrapped Robust Standard Errors)

	Murder		Rape		Robbery		Assault		Burglary		Larceny		Motor vehicle theft	
Variable	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Air pollution (composite)	0.40† (0.21)	0.395† (0.225)	0.06** (0.02)	0.050* (0.024)	0.08** (0.03)	0.070*** (0.019)	0.13* (0.05)	0.124* (0.050)	0.04* (0.02)	0.039* (0.017)	0.01 (0.01)	0.004 (0.011)	0.06* (0.03)	0.062** (0.023)
Log population (100,000)	0.43*** (0.10)	0.647* (0.283)	0.74*** (0.07)	0.766*** (0.061)	0.64*** (0.08)	0.588*** (0.065)	0.52*** (0.09)	0.538*** (0.082)	0.51*** (0.05)	0.470*** (0.059)	0.62*** (0.03)	0.594*** (0.035)	0.73*** (0.08)	0.631*** (0.085)
Law enforcement rate		0.068 (0.092)		0.014 (0.009)		−0.009 (0.019)		−0.002 (0.011)		−0.014 (0.009)		0.002 (0.005)		−0.001 (0.016)
Median age		0.009 (0.011)		−0.002 (0.006)		0.000 (0.006)		−0.007 (0.005)		−0.002 (0.005)		−0.002 (0.002)		0.002 (0.007)
% male		−0.004 (0.011)		0.002 (0.006)		−0.001 (0.006)		0.004 (0.004)		0.003 (0.005)		−0.003 (0.003)		0.005 (0.006)
% Asian		−0.025 (0.027)		−0.003 (0.010)		0.006 (0.005)		−0.003 (0.006)		0.007 (0.005)		0.008*** (0.001)		0.011 (0.008)
% Black		−0.001 (0.010)		0.007** (0.003)		0.006† (0.003)		0.008** (0.003)		0.005** (0.002)		0.005*** (0.001)		0.005 (0.005)
% Hispanic		0.021** (0.007)		−0.001 (0.003)		0.007** (0.003)		0.006 (0.005)		0.000 (0.002)		0.001 (0.001)		0.009** (0.003)
% Native American		0.081*** (0.019)		0.022* (0.008)		0.003 (0.012)		0.010 (0.011)		−0.002 (0.008)		−0.007† (0.004)		−0.008 (0.014)
% other races		−0.008 (0.005)		0.005* (0.002)		−0.001 (0.002)		0.007* (0.003)		−0.002 (0.002)		0.002* (0.001)		−0.012*** (0.003)
% some college or above		0.001 (0.007)		−0.007** (0.002)		−0.002 (0.004)		0.003 (0.003)		0.001 (0.002)		0.000 (0.001)		−0.007* (0.004)
Income per capita ($1,000)		−0.014 (0.012)		0.001 (0.004)		−0.000 (0.005)		−0.002 (0.004)		−0.008*** (0.002)		−0.001 (0.001)		−0.006 (0.005)
% population in poverty		0.010 (0.010)		0.001 (0.003)		0.004 (0.004)		0.006 (0.005)		0.005* (0.002)		−0.002 (0.001)		−0.005 (0.003)
% female unemployed		0.022 (0.017)		0.000 (0.003)		0.012*** (0.003)		0.005* (0.002)		0.004 (0.003)		0.001 (0.001)		0.003 (0.004)
% male unemployed		−0.000 (0.005)		−0.010* (0.005)		0.001 (0.004)		−0.003 (0.003)		−0.002 (0.003)		−0.001 (0.001)		−0.002 (0.003)
% primary sector employees		0.007 (0.013)		0.007 (0.008)		−0.002 (0.006)		0.007 (0.005)		0.000 (0.009)		−0.006* (0.003)		0.004 (0.008)
% secondary sector employees		0.008 (0.007)		−0.003 (0.003)		−0.000 (0.003)		0.002 (0.003)		−0.000 (0.003)		0.001 (0.001)		−0.008* (0.004)
Wald χ^2	118.8	173.1	216.6	306.8	569.6	1,282.0	193.9	466.0	148.8	269.5	977.1	1,758.3	1,435.7	2,614.4

Note: Unstandardized Poisson regression coefficients are displayed, with bootstrapped robust standard errors in parentheses. All models included city and year fixed effects. The reference category for race was White; the reference category for economic sector was the tertiary sector.
†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

Study 2: Psychologically Experiencing Air Pollution Increases Unethical Behavior

To establish a causal connection between the experience of air pollution and unethical behavior, we used an experimental design in Study 2. Since it would be impractical and ethically controversial to randomly assign participants to physically experience air pollution (vs. no pollution), we investigated whether psychologically experiencing air pollution would result in a similar effect.

Method

Participants. We used G*Power to determine the sample size required for a small-to-medium-sized effect: 119 participants per condition were required for the study to be powered at 85%. On the basis of past experiences with Amazon Mechanical Turk (MTurk), we aimed to recruit 15 extra participants per condition. Participants qualified for the study only if they were located in the United States and had a nonduplicate Internet protocol (IP) address. In the end, 256 MTurk participants (54% female; age: M = 35.83 years, SD = 13.02) completed this study in exchange for $1 each.

Experimental manipulation. We randomly assigned participants to view a photo that featured either a polluted or a clean scene. While viewing the photo, participants were instructed to imagine that what they saw was their area of residence and to reflect on how they would feel as they walked around in this area and breathed the air.

Unethical-behavior measure. Next, participants completed a supposedly unrelated task—the Remote Associates Test (RAT; Mednick, 1962)—which presents three cue words and asks the participant to identify a fourth word associated with each of the three words (e.g., sore, shoulder, sweat → cold; see also Gino & Ariely, 2012; Lu, Akinola, & Mason, 2017; Lu, Brockner, Vardi, & Weitz, 2017; Lu, Hafenbrack, et al., 2017). Participants attempted five RATs in a fixed order after a practice trial. For each correctly answered RAT, participants received a bonus of $0.50. Adapting the commonly used computer-glitch cheating paradigm (e.g., Vohs & Schooler, 2008; von Hippel, Lakin, & Shakarchi, 2005), we informed participants that the program had a glitch that would allow the answer for each RAT to appear in a box below the three cue words if they hovered their mouse over the box. Participants were asked to attempt the RATs on their own without looking at the answers. In keeping with past research (e.g., Vohs & Schooler, 2008; von Hippel et al., 2005), we operationalized unethical behavior as the number of times a participant hovered the mouse over the answer box and thus allowed the correct answer to appear. On average, participants cheated on 2.77 out of 5 trials (SD = 1.92), which was analogous to stealing $1.39 from the researchers.

Results

Since unethical behavior in the current study was a count variable, we performed a Poisson regression. As predicted, participants in the polluted condition (M = 2.99, SD = 1.92) cheated significantly more times on the RATs than did those in the clean condition (M = 2.55, SD = 1.90), b = 0.16, SE = 0.07, p = .034, 95% CI = [0.012, 0.307].

Discussion

Conceptually replicating Study 1 but offering causal evidence, Study 2 revealed that psychologically experiencing air pollution increased individuals' tendency to behave unethically.

Studies 3a and 3b: Anxiety Mediates the Effect of Psychologically Experiencing Air Pollution on Unethical Behavior

Studies 3a and 3b extended Study 2 in four important ways. First, we aimed to shed light on why air pollution may increase unethical behavior. Given prior findings that air pollution can increase anxiety (Corrigan & Watson, 2005) and that anxiety can induce unethical behavior (Kouchaki & Desai, 2015), we tested anxiety as a potential mediator of the effect of air pollution on unethical behavior. Second, Study 3 addressed a methodological limitation of Study 2. In Study 2, the "polluted" photo and the "clean" photo featured different locations (e.g., the polluted photo contained factories and cars, whereas the clean photo did not). To address this shortcoming, Study 3 used photo pairs that featured identical locations in Beijing, except that photos in the polluted condition were taken on polluted days, whereas photos in the clean condition were taken on clean days. Third, to ascertain the robustness of the Study 2 finding, we used two different measures of unethicality in Study 3 (the die-roll task in Study 3a and the Self-Reported Inappropriate Negotiation Strategies scale in Study 3b). Fourth, we examined the generalizability of the Study 2 finding across two different population samples (American university students for Study 3a and Indian adults for Study 3b). In particular, we recruited Indian participants in Study 3b because India has severe air pollution (“Air Pollution in India,” 2015); thus, sampling Indian participants allowed us to test whether the experimental effect of psychologically experiencing air pollution would generalize to individuals who are exposed to high levels of air pollution on a regular basis.

Study 3a method

Participants. We used G*Power to determine the sample size for a medium-sized effect: 59 participants per condition were required for the study to be powered at 85%. We aimed to recruit 5 extra participants per condition. A total of 129 students (45% female; age: M = 27.97 years, SD = 8.82) from a northeastern university in the United States participated in exchange for $5 each. Participants qualified for our study only if they were fluent in English. Moreover, because we used photos of Beijing as our experimental materials (see Fig. 3), we did not recruit any East Asian participants to minimize any confounds due to familiarity. We excluded 3 participants who correctly guessed the purpose of the study and 2 other participants who failed to follow instructions.

Experimental manipulation. The experimental stimuli were 15 pairs of photos of contemporary Beijing (displayed on a computer screen). Importantly, each pair of photos featured both a polluted version and a clean version of the same geographical location. One photo was taken on a polluted day (e.g., smoggy sky, low visibility), whereas the other was taken on a clean day (e.g., blue sky, high visibility). Participants were randomly assigned to sequentially view either the 15 polluted photos or the 15 clean photos; each photo was displayed for 5 s. While viewing the photos, participants were asked to imagine currently living in this city. Next, participants were instructed to spend 5 min writing a detailed diary of living in this city: “Go through the day as if you were there as a local, taking a bus, riding a bike, breathing the air, talking with your friends, exploring the city . . .” (see the Appendix for sample essays). To help participants visualize the experience, we created a 3 × 3 collage using 9 of the 15 photos, which was positioned above the text box where participants typed their diary (see Fig. 3).

Unethical-behavior measure. After completing the diary-writing task, participants performed a second task that ostensibly assessed their luck but in reality measured cheating (e.g., Gächter & Schulz, 2016; Gino & Ariely, 2012; Lu, Quoidbach, et al., 2017; Shalvi, Dana, Handgraaf, & De Dreu, 2011). The task instructed them to roll a die and self-report the outcome, which we explained would determine the amount of bonus payment (i.e., $1 for 1, $2 for 2, . . . $6 for 6). If no participant cheated, the expected outcome of the die-roll task would be (1 + 2 + 3 + 4 + 5 + 6)/6 = 3.50. If psychologically experiencing air pollution increased unethical behavior, then the average self-reported die-roll outcome would be significantly higher in the polluted condition than in the clean condition.

Anxiety measure. Two coders who were blind to the study hypotheses and experimental conditions rated each participant’s diary on the following eight dimensions: distressed, irritable, nervous, scared, enthusiastic, excited, happy, relaxed (1 = *not at all*, 5 = *extremely*; all ICC2s > .85). We aggregated ratings of distressed, irritable, nervous, and scared as a measure of anxiety (α = .95) and aggregated ratings of enthusiastic, excited, happy, and relaxed as a measure of positivity (α = .97; Watson, Clark, & Tellegen, 1988).

Manipulation check. As a manipulation check, we examined the diaries to confirm that participants in the polluted condition indeed experienced the photos as scenarios of air pollution (as opposed to merely scenarios of modern cities), whereas participants in the clean condition did not (see the Appendix for sample essays).

Study 3a results

As predicted, participants in the polluted condition self-reported a significantly higher mean die-roll outcome (M = 4.46, SD = 1.60) than did those in the clean condition (M = 3.60, SD = 1.85), $t(122)$ = 2.75, p = .007, d = 0.50, 95% CI for the mean difference = [0.24, 1.48]. Whereas the mean die-roll outcome of the clean condition was not significantly different from the expected outcome of 3.50, $t(64)$ = 0.44, p = .67, the mean die-roll outcome of the polluted condition was significantly higher than 3.50, $t(58)$ = 4.60, p < .001.[2]

As predicted, diaries in the polluted condition were rated as significantly higher on anxiety (M = 3.16, SD = 1.20) than those in the clean condition (M = 1.60, SD = 0.84), $t(122)$ = 8.49, p < .001, d = 1.51, 95% CI for the mean difference = [1.20, 1.92]. Moreover, diaries in the polluted condition were rated as significantly lower on positivity (M = 1.74, SD = 0.98) than those in the clean condition (M = 3.03, SD = 1.05), $t(122)$ = −7.01, p < .001, d = −1.26, 95% CI for the mean difference = [−1.65, −0.92].

Bootstrapping analyses revealed that anxiety level mediated the effect of the polluted (vs. clean) condition on the die-roll measure of unethical behavior (bias-corrected 95% CI = [0.0065, 0.8984]). In contrast, positivity level was not a significant mediator (bias-corrected 95% CI = [−0.3041, 0.4677]).

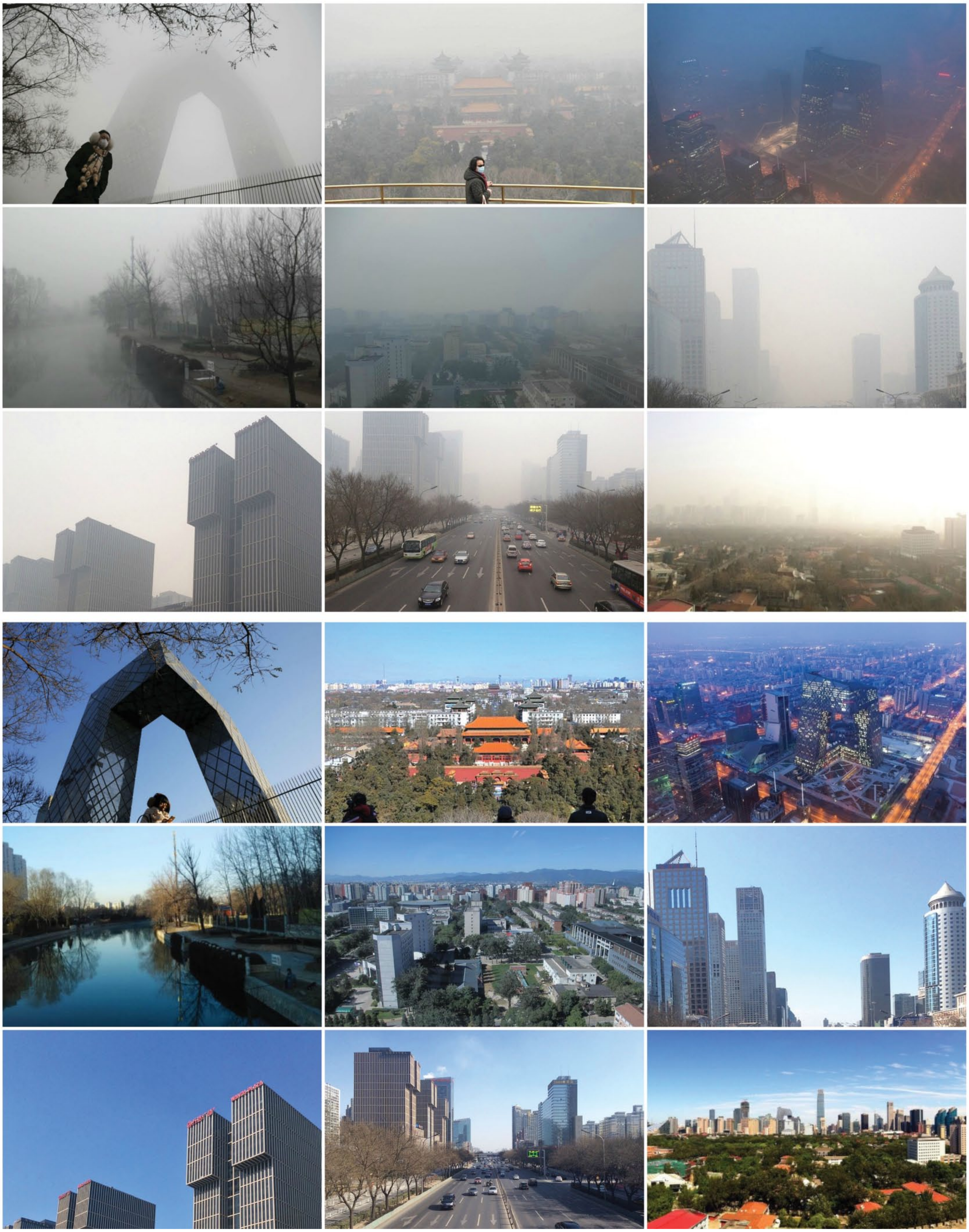

Fig. 3. Studies 3a and 3b: the collage of photos displayed while participants typed their diary. The top collage was shown in the polluted condition, and the bottom collage was shown in the clean condition.

Study 3b method

Participants. We used G*Power to determine the sample size for a small-to-medium-sized effect: 141 participants per condition were required for the study to be powered at 90%. Given past experiences with MTurk participants from India, we aimed to recruit 35 extra participants per condition. Participants qualified for the study only if they were fluent in English, located in India, had a nonduplicate IP address, and had an approval rate above 95% for their previously completed tasks on MTurk. The study was completed 356 times by participants in exchange for $1.50 each (30% female; age: M = 30.81 years, SD = 7.95). No participant correctly guessed the purpose of the study.[3]

Experimental manipulation and measures. The experimental manipulation was the same as in Study 3a. After participants completed the diary-writing task, we assessed their unethicality with five items from the widely used Self-Reported Inappropriate Negotiation Strategies scale (Lu, Quoidbach, et al., 2017; Robinson, Lewicki, & Donahue, 2000). Participants indicated the extent to which they would be willing to engage in unethical tactics in a negotiation (e.g., "intentionally misrepresenting factual information to support your negotiating arguments or position"; 1 = *definitely would not use*, 7 = *definitely would be willing to use*; α = .79). The presentation order of the items was randomized.

We next measured anxiety with six items adapted from the short Spielberger State–Trait Anxiety Inventory (Marteau & Bekker, 1992). Specifically, participants were asked to indicate the extent to which they would feel anxious, calm, neutral, relaxed, tense, and upset (1 = *not at all*, 5 = *very much*; α = .72) if they walked around in the photographed city. The presentation order of the six items was randomized.

Study 3b results

The results of Study 3b replicated those of Study 3a: Participants in the polluted condition were significantly more willing to use unethical negotiation tactics (M = 4.26, SD = 1.26) than those in the clean condition (M = 3.89, SD = 1.34), $t(354) = 2.69$, $p = .007$, $d = 0.29$, 95% CI for the mean difference = [0.10, 0.65]. Moreover, participants in the polluted condition also reported significantly higher anxiety (M = 2.67, SD = 0.90) than those in the clean condition (M = 2.24, SD = 0.61), $t(354) = 5.37$, $p < .001$, $d = 0.56$, 95% CI for the mean difference = [0.27, 0.59]. As in Study 3a, bootstrapping analyses revealed that anxiety level mediated the effect of the polluted (vs. clean) condition on the Self-Reported Inappropriate Negotiation Strategies score (bias-corrected 95% CI = [0.0204, 0.1771]).

Discussion

Studies 3a and 3b replicated the Study 2 finding with two different population samples, two different anxiety measures, and two different unethicality measures. In addition, both studies provided mediational evidence for the psychological mechanism of anxiety: The psychological experience of air pollution increased anxiety, which in turn increased people's tendency to behave unethically.

General Discussion

Using complementary methodologies of large-scale archival data and experiments, the present research revealed that air pollution predicts criminal and unethical behavior. In addition, we identified one mechanism—anxiety—that explains the effects of air pollution on unethical behavior: Air pollution heightens anxiety, which in turn increases unethical behavior. Furthermore, both the causal and mediation effects were consistent across American and Indian participant samples, thus demonstrating generalizability across both less and more polluted countries.

Importantly, we recognize that anxiety may not be the only mechanism linking air pollution to unethical behavior. The psychology and sociology literature has suggested other mechanisms through which air pollution may increase unethical behavior. For example, the broken-windows theory posits that environmental disorder (e.g., broken windows, graffiti) can induce social and moral disorder (Keizer, Lindenberg, & Steg, 2008; Vohs, Redden, & Rahinel, 2013; Wilson & Kelling, 1982). Indeed, individuals are more likely to litter and steal in dirtier environments (Keizer et al., 2008). This is partly because environmental disorder implies both a descriptive social norm that transgressing is common and an injunctive social norm that transgressing may be acceptable (Keizer et al., 2008). Thus, when individuals experience a polluted environment, their overall concern for moral appropriateness may diminish, which may make them more prone to unethical and unlawful acts. As another mechanism, the dark smog caused by pollutants (e.g., NO_2) lowers visibility. Just as criminal activities are more rampant at night (Doleac & Sanders, 2015), smog may induce a sense of anonymity that disinhibits self-interested and unethical acts (Zhong, Bohns, & Gino, 2010). For example, research has found that individuals are more likely to cheat in a dim versus bright room (Zhong et al., 2010). Such alternative mechanisms await future investigation.

Because it would be impractical and ethically controversial to randomly assign subjects to physically experience pollution (vs. no pollution), our experiments used photos to simulate the psychological experience of air pollution. We acknowledge that exposing individuals to air pollution photos is not the same as exposing them to actual air pollution. This represents a limitation of the current research and points to a fruitful future direction.

The present research offers several notable theoretical contributions. First, it has uncovered the ethical costs of air pollution beyond its well-known toll on health and the environment. Second, our findings extend the past research examining how polluted objects (e.g., dirty money; Q. Yang et al., 2013) and polluted social contexts (e.g., political fraud and tax evasion; Gächter & Schulz, 2016) increase unethical behavior. Our research thus contributes to the burgeoning literature on how the socioecological environment affects human behavior (e.g., Oishi, 2014; Wei et al., 2017). Third, by identifying the mediating mechanism of anxiety, we add to the literature on how anxiety can induce unethical behavior (Kouchaki & Desai, 2015; Lee et al., 2015). Fourth, we contribute to the behavioral ethics literature by assessing unethicality not only with three different tasks with high internal validity, but also with real-world criminal activities that are costly to society. Overall, the present findings connect the fields of environmental studies, socioecological psychology, criminology, and moral psychology.

The current findings have important implications for policymakers. On September 15, 2015, former president Barack Obama issued an Executive Order advocating the use of "behavioral science insights" to better serve the people. The present research responds to this call by revealing how air pollution may be an immoral nudge that affects numerous people around the world. We thus provide another compelling reason for policymakers to combat air pollution. A less polluted environment is not only a healthier one but also a safer one.

Appendix

An example of essays written by participants in the polluted condition of Study 3a:

> Another typical day in the city. I had to wear my mask because the air was thick with smog. I decided not to ride my bicycle and car pooled instead. In recent days I have noticed no one on bikes, no one walking, only workers on the streets. The air is so thick that it's impossible to breathe sometimes. I remember when the parks had people and I could take walks. When I see people now I think they're crazy or old or visiting and don't know the dangers. I stay inside at work and leave to go to my apartment. Exercising outside is almost impossible, my lungs hurt when I breathe and I get short of breath. I worry when I see children. The trees even look different, so many have died. The grass remains green but the flowers lose their color in the milky air. It's all we talk about these days: when will the smog lift? How much worse can it get?

An example of essays written by participants in the clean condition of Study 3a:

> I woke up and went for a walk along the river early in the morning. It's nice and quiet and I can take in the fresh air. Afterwards, I went and had breakfast with a friend at a local cafe. We parted ways, and it seemed like a beautiful day so I wanted to stay outside. I drove home to my apartment and got my yoga mat. Then I went to the park to practice yoga for an hour. Then I decided it was a nice day to go shopping since most people were at work this time of day. I walked along the streets and window shopped. I went back home to relax and freshen up for the night. I had plans with several friends to go out for drinks and dancing. We had such a great time.

Action Editor

Ayelet Fishbach served as action editor for this article.

Author Contributions

All authors developed the study concept and design. J. G. Lu and J. J. Lee collected and analyzed the data. J. G. Lu drafted the manuscript, and J. J. Lee, F. Gino, and A. D. Galinsky provided critical revisions. All authors approved the final version of the manuscript for submission.

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Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

Open Practices

All materials have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/6xd9w/. The design and analysis plans for Study 3b were preregistered at https://aspredicted.org/blind.php?x=x5w98e.

The complete Open Practices Disclosure for this article can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797617735807. This article has received badges for Open Materials and Preregistration. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

Notes

1. As an illustration of its comprehensiveness, this panel data set contained 17 different cities named "Springfield" located in different states.
2. Because the experiment did not include a baseline condition, it is possible that the clean condition led participants to act more ethically.
3. Careful inspection of the data revealed 41 problematic cases, where participants completed the study multiple times with different IP addresses, copied and pasted content directly from the Internet, or failed to follow instructions for the diary task. We did not exclude these cases from the analyses reported in the main text, because these exclusion criteria had not been mentioned in our preregistration. Importantly, all results remained substantively unchanged when we did apply these exclusion criteria. For the 315 participants (30% female; age: M = 31.31 years, SD = 8.21) who faithfully completed the study, the results were as follows—the direct effect of the polluted (vs. clean) condition on unethicality: $t(313) = 2.59$, $p = .010$, 95% CI for the mean difference = [0.09, 0.67]; the direct effect of the polluted (vs. clean) condition on anxiety: $t(313) = 6.07$, $p < .001$, 95% CI for the mean difference = [0.36, 0.71]; and the indirect effect of the polluted (vs. clean) condition on unethicality through anxiety: bias-corrected 95% CI for the mean difference = [0.0221, 0.2151].

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