Commentary

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On the Limited Generality of Air Pollution and Anxiety as Causal Determinants of Unethical Behavior: Commentary on Lu, Lee, Gino, and Galinsky (2018)

Daniel W. Heck[1,2], Isabel Thielmann[3], Sina A. Klein[3,4], and Benjamin E. Hilbig[3]

[1]Department of Psychology, Philipps-Universität Marburg; [2]Department of Psychology, University of Mannheim; [3]Department of Psychology, University of Koblenz-Landau; and [4]Alfred-Weber-Institute for Economics, Heidelberg University

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Lu, Lee, Gino, and Galinsky (2018) recently proposed a "causal effect of psychologically experiencing a polluted (vs. clean) environment on unethical behavior" (p. 340) and mediation of this effect by increased anxiety. Supporting their first hypothesis, Lu and colleagues reported a positive effect of air pollution on annual crime rates in 9,360 U.S. cities. Moreover, correlation analyses supported the proposed mediation by anxiety when dishonesty was measured after participants saw photographs of clean or polluted environments. Here, we argue that Lu and colleagues' theory is incompatible with other evidence on unethical behavior and thus overly broad.

First, the hypothesis that air pollution directly causes crime conflicts with ample evidence that crime rates are higher in summer than in winter (McDowall, Loftin, & Pate, 2012), plausibly because of higher temperatures increasing frustration and aggression and changes in individuals' activity patterns (Hipp, Curran, Bollen, & Bauer, 2004). In turn, air pollution is markedly higher in winter than in summer (Massey, Kulshrestha, Masih, & Taneja, 2012), which is mainly because of emissions from increased use of heating and vehicles. That seasonal trends of crime rates and air pollution are exactly opposed is difficult to reconcile with Lu and colleagues' hypothesis of a causal pollution–crime link.

A more restrictive version of Lu and colleagues' theory might be that pollution has incremental predictive validity for crime over and above seasonal trends. Indeed, Bondy, Roth, and Sager (2020) showed that the Air Quality Index (AQI) has incremental validity beyond temperature and other control variables on crime. However, the effect was confined to less severe offenses (e.g., pickpocketing), and null effects occurred for more severe offenses (e.g., murder). Moreover, the AQI includes ground-level ozone, which is negatively correlated with the pollutants used in Lu and colleagues' operationalization of pollution. Likewise, Herrnstadt, Heyes, Muehlegger, and Saberian (2018) showed incremental effects of ozone and particulate matter on crime rates when controlling for temperature. However, these effects were limited to specific pollutants and violent crimes (e.g., assault). The authors therefore concluded that "this seems to be a story about violence - not criminality in general" (p. 23). Overall, it thus remains unresolved whether pollution generally affects unethical behavior beyond seasonal trends. In Study 1, we addressed this question using monthly data on air pollution and crime rates.

Second, Lu and colleagues provide only limited evidence that anxiety causes unethical behavior. In their Studies 2 and 3, participants imagined living in a clean versus polluted city depicted on photographs. However, "experiencing" air pollution in this way might simply increase negative mood; thus, other emotional states (e.g., anger, negative affect, frustration) than anxiety may have increased unethical behavior. Indeed, "investigations of 'an emotion' are most probably investigations of several simultaneous emotions" (Polivy, 1981, p. 816). Thus, measuring both anxiety and dishonesty as dependent variables of the experimental manipulation

Corresponding Author:
Daniel W. Heck, Department of Psychology, Philipps-Universität Marburg, Gutenbergstraße 18, 35032 Marburg, Germany
E-mail: dheck@uni-marburg.de

and testing mediation can provide only weak evidence for the supposed mediator because of possible confounding variables (Fiedler, Schott, & Meiser, 2011). Other studies in which the causal effect of anxiety on unethical behavior was investigated by manipulating mood (e.g., H. Zhang, Shi, Zhou, Ma, & Tang, 2020) suffer from similar limitations.

Sidestepping the requirement for mood manipulations, we tested whether a stronger inclination toward experiencing anxiety is associated with increased unethical behavior. Specifically, in Study 2, we investigated whether trait anxiety as assessed by HEXACO Emotionality and its Anxiety facet (Ashton & Lee, 2007) is positively related to dishonesty. Originally, Lu and colleagues' theory was concerned with state anxiety, defined as distress or physiological arousal in reaction to the potential for undesirable outcomes (Brooks & Schweitzer, 2011). However, state anxiety is (by definition) what individuals high in trait anxiety should more likely experience across various situations. Thus, unless Lu and colleagues are referring to some form of state anxiety that is independent of trait anxiety, their reasoning implies a positive correlation between trait anxiety and dishonesty.

Indeed, Kouchaki and Desai (2015) showed that both state and trait anxiety are positively linked to unethical behavior at work. Nevertheless, they explicitly limited the generality of their conclusions, because "anxiety sometimes may act as a motivator of *ethical* [italics added] behavior" (p. 371). Likewise, mortality salience (linked to the potential of experiencing anxiety) reduced dishonest behavior when honesty was made salient (Schindler et al., 2019), and social anxiety correlated only with some types of unethical behavior (Wowra, 2007). Other studies provided further evidence against a relation of trait anxiety (operationalized by emotionality, neuroticism, or emotional stability) to hypothetical and actual criminal behavior (e.g., Aseltine, Gore, & Gordon, 2000; Rentfrow, Gosling, & Potter, 2008; van Gelder & de Vries, 2012). In Study 2, we tested whether trait anxiety is also unrelated to incentivized dishonest behavior using a large-scale reanalysis.

Study 1: Seasonal Trends of Air Pollution and Crime Rate

Method

To test the incremental effect of air pollution on crime rates over and above seasonal trends, we collected (a) archival data from openly accessible databases for monthly crime rates and air pollution and (b) yearly population sizes of 103 districts in England, Northern Ireland, and Wales from October 2015 to September 2018.[1] Of note, Lu and colleagues' data are on a yearly basis and thus entirely unsuited to control for seasonal trends. Following Lu and colleagues, we used a composite measure of air pollution per month defined as the mean of the z-standardized levels of particulate matter with aerodynamic diameter less than or equal to 2.5 µm ($PM_{2.5}$), particulate matter with aerodynamic diameter less than or equal to 10 µm (PM_{10}), and nitrogen dioxide (NO_2). Whenever data on some air-pollution indices were missing, the composite score was based on one or two indices only, a procedure justified given the high intercorrelations of indices (i.e., $r \geq .88$ between each index and the composite score). Lu and colleagues additionally included data on carbon monoxide (CO), sulfur dioxide (SO_2), and total suspended particulate (TSP), which were, however, mostly unavailable in the data set used here. Importantly, all these variables were strongly correlated (pairwise correlations of $r > .60$; Y. Y. Zhang, Jia, Li, & Hou, 2018). Moreover, since Lu and colleagues' theoretical predictions focused on air pollution in general (rather than specific pollutants in particular), the composite measure used in the current analysis provides an appropriate operationalization for testing the hypothesis in question. After exclusion of 16 outliers with total crime frequencies falling two interquartile ranges below the median per district, the merged data set contained 3,509 observations. The data and analysis scripts are available on the Open Science Framework (https://osf.io/k76b2/).

Results

Figure 1 shows the seasonal trends of air pollution and the total number of crimes. Replicating previous findings (Hipp et al., 2004; Massey et al., 2012; McDowall et al., 2012), our results showed that crime rates peaked in summer whereas air pollution peaked in winter, demonstrating that seasonal trends were exactly opposed to each other. To test whether air pollution has incremental validity over and above these opposing seasonal trends, we fitted generalized additive models (GAMs; Wood, 2011) predicting the number of crimes per district and month while accounting for nonlinear effects. To model crime frequency, we relied on a logarithmic link function and the negative binomial distribution, which is a less restrictive, more robust variant of the Poisson distribution used by Lu and colleagues. In addition to the fixed effect of air pollution, the model included log population as a predictor, which was the only control variable included in all of Lu and colleagues' analyses (whereas others such as gross domestic product per capita or unemployment rate were included merely as robustness tests, without having any consistent effect). Moreover, we added a nonlinear

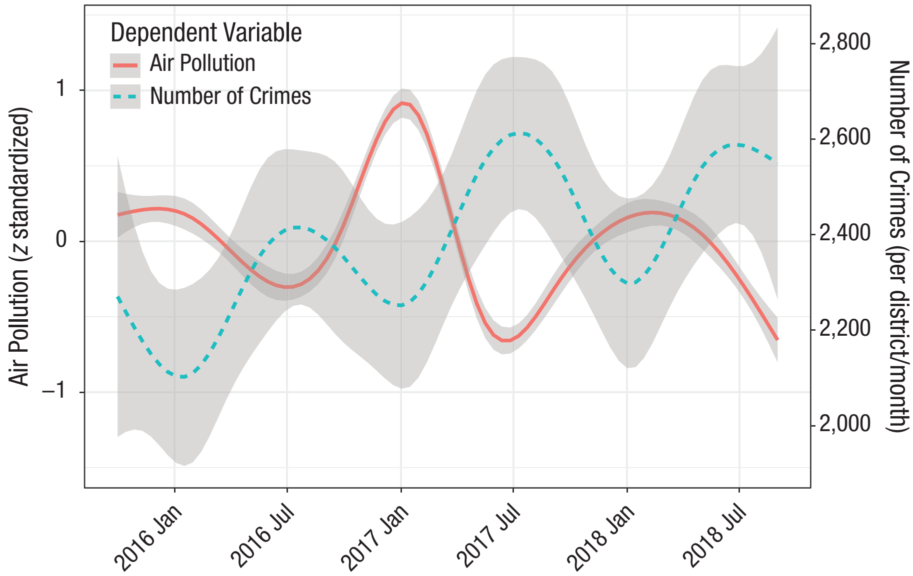

Fig. 1. Results from Study 1: smoothed seasonal trends of air pollution measured in *z* values (solid red line) and number of crimes per district and month (dashed blue line). Gray ribbons represent 95% confidence intervals of the smoothed trend estimates.

effect of time to account for circular seasonal trends in crime rates using a thin-plate smoothing spline (Wood, 2011). Paralleling Lu and colleagues, who used fixed effects for cities to control for unobserved heterogeneity, we used random effects for districts, thereby accounting for the nested data structure (i.e., repeated observations within district). Finally, we added a smoothed two-dimensional effect of longitude and latitude of the geometric centers of districts to account for spatial dependencies in the data (i.e., districts closer to each other are more likely to have similar crime rates).

To test the incremental effect of air pollution on crime rates, we approximated the Bayes factor BF_{01}, which quantifies the evidence for a null effect of pollution or, more precisely, for the nested model without pollution as predictor against the more general model with pollution as predictor. Importantly, Bayes factors take the sample size into account and thereby allow one to conclude whether a specific data set and sample size provide evidence for or against an effect ($BF_{01} << 1$ and $BF_{01} >> 1$, respectively) or whether they are uninformative ($BF_{01} \approx 1$). To obtain the BF_{01}, we fitted two GAM versions with and without pollution as a predictor, respectively, and transformed the corresponding values of the Bayesian information criterions (BICs) to Bayes factors (Kass & Raftery, 1995). Note that BF_{10} is equal to $1/BF_{01}$, which quantifies the evidence against the null hypothesis.

In line with Figure 1, monthly seasonal trends were extremely predictive (in all cases, $BF_{10} > 3.8 \times 10^6$) for the monthly frequencies of all 14 crime categories reported by the UK police (i.e., antisocial behavior, bicycle theft, burglary, criminal damage and arson, drugs, other crime, other theft, possession of weapons, public order, robbery, shoplifting, theft from the person, vehicle crime, and violence and sexual offenses). Most importantly, Table 1 shows the estimated odds ratios (*OR*s) of the *z*-standardized pollution variable, which ranged between 0.992 and 1.025 with a median of 1.008 across crime categories (including the total number of crimes), thus being practically indistinguishable from *OR*s of 1, which indicate null effects. This impression was confirmed by the BF_{01} which provided clear evidence against any incremental effect of air pollution (in all cases, $BF_{01} \geq 2.3$ with a median of 43.1 and a maximum of 100.8; see Table 1).

To facilitate a comparison with the original, frequentist analyses by Lu and colleagues, we also show *p* values based on Wald tests of the incremental effect of air pollution (Table 1). On the basis of the standard errors of the estimates, we also computed the approximate statistical power ($1 - \beta$) of these tests for a significance level (α) of 1% to allow evaluation of the conclusiveness of nonsignificant effects. As an effect size under the alternative hypothesis, the median *OR* reported by Lu and colleagues (*OR* = 1.065) was used for the power calculations. Strikingly, even though the power was above 96% for all 15 crime types, only the *OR* for antisocial behavior was significant (*OR* = 1.025, *p* = .005), which was the most prevalent type of crime in the data set and included offenses such as nuisance, inconsiderate neighbors, vandalism, street drinking,

Table 1. Results From Study 1: Incremental Effects of z-Standardized Air Pollution on Crime Rates

	Generalized additive model (GAM)						Generalized linear model (GLM)					
Dependent variable	b	SE	OR	p	$1 - \beta$	BF_{01}	b	SE	OR	p	$1 - \beta$	BF_{01}
Antisocial behavior (27.0%)	0.024	0.009	1.025	.006	> .99	2.3	0.021	0.009	1.021	.020	> .99	3.9
Bicycle theft (1.7%)	0.012	0.013	1.012	.382	.98	49.5	0.002	0.014	1.002	.854	> .99	58.3
Burglary (6.6%)	0.013	0.008	1.013	.091	> .99	20.6	0.003	0.009	1.003	.720	> .99	55.6
Criminal damage and arson (9.0%)	0.004	0.006	1.004	.494	> .99	57.0	0.001	0.006	1.001	.880	.98	58.6
Drugs (2.2%)	0.004	0.008	1.004	.638	> .99	68.7	0.005	0.011	1.005	.669	> .99	54.1
Other crime (1.3%)	0.008	0.011	1.008	.453	> .99	66.9	−0.007	0.013	0.993	.619	> .99	52.3
Other theft (8.3%)	0.011	0.006	1.011	.054	> .99	11.7	0.006	0.006	1.006	.330	> .99	36.8
Possession of weapons (0.6%)	0.006	0.014	1.006	.633	.98	64.6	0.001	0.016	1.001	.938	.99	59.1
Public order (5.4%)	0.008	0.012	1.008	.467	.99	100.8	0.000	0.012	1.000	.998	> .99	59.2
Robbery (1.2%)	0.000	0.011	1.000	.989	.99	51.1	−0.025	0.014	0.976	.076	.93	12.4
Shoplifting (6.0%)	0.009	0.007	1.009	.252	> .99	31.2	0.005	0.008	1.005	.529	.99	48.6
Theft from the person (1.8%)	−0.008	0.015	0.992	.592	.96	35.7	−0.023	0.015	0.977	.127	.98	18.7
Vehicle crime (6.8%)	0.022	0.009	1.022	.013	> .99	4.6	0.019	0.010	1.019	.058	> .99	10.0
Violence and sexual offenses (22.1%)	−0.002	0.006	0.998	.769	> .99	43.1	−0.007	0.006	0.993	.248	.94	30.4
Total number of crimes	0.008	0.003	1.008	.015	> .99	8.2	0.006	0.003	1.006	.052	> .99	9.0

Note: Percentages in the left-hand column refer to the relative frequency of the crime category relative to the total number of crimes. All models included log population as a predictor as well as random effects for districts. Moreover, the GAM used splines to model monthly seasonal trends and the geographic locations of districts, whereas the GLM assumed (discrete) fixed effects for months. b = estimate for the effect of the z-standardized pollution variable in a negative binomial regression; OR = odds ratio; $1 - \beta$ = approximate statistical power of the Wald test for a significance level (α) equal to 1% based on the median effect size reported by Lu, Lee, Gino, and Galinsky (2018; OR = 1.065); BF_{01} = Bayes factor against the incremental effect of air pollution.

littering, begging, or fireworks misuse. Overall, results thus clearly supported the conclusions from Bayesian analysis.

As a robustness check, we also fitted generalized linear models (GLMs) with a negative binomial link function and fixed effects for both date and districts while dropping longitude and latitude as predictors, thus exactly replicating Lu and colleagues' model specification (except for the link function). Again, the Bayes factors showed clear evidence against any incremental effect of air pollution (in all cases, $BF_{01} \geq 4.0$ with a median of 48.6 and a maximum of 59.2; see Table 1). Likewise, none of the frequentist Wald tests were significant at the nominal level (α) of 1% despite the high statistical power for all dependent variables ($1 - \beta \geq$ 93%).

It is important to highlight that both our and Lu and colleagues' Study 1 relied on correlational data. In a recent review on testing causal environmental effects, Bind (2019) emphasized that "significant results from observational studies should always be interpreted and evaluated with caution" (p. 38). While keeping this limitation in mind, we found that seasonal trends of air pollution and crime rates were exactly opposed to each other, which is difficult to reconcile with Lu and colleagues' general theory of a direct causal effect of air pollution on crime. Moreover, our results also provide clear evidence against the more restrictive hypothesis that air pollution has an incremental effect above seasonal trends.

Study 2: Linking Trait Anxiety and Dishonesty

Method

To test the link between trait anxiety and dishonest behavior, we performed a large-scale reanalysis based on 4,965 participants across 16 prior studies investigating the relation between personality traits and dishonest behavior (for details of the data and methods, see Heck, Thielmann, Moshagen, & Hilbig, 2018). In all studies, dishonest behavior was measured in binary versions of standard cheating tasks, namely, the dice-roll or coin-toss paradigm. In these paradigms, participants receive a fixed reward (e.g., 5€) if they report having obtained a prespecified result in a private coin toss or dice roll (e.g., "tails" or "side 5," respectively). Given that the experimenter cannot know the actual outcome of the private coin toss or dice roll, respectively, it is impossible to expose participants as cheaters. Nonetheless, the correlation of external covariates, such as personality traits, with the probability of dishonest behavior can be estimated using a modified logistic regression (Moshagen & Hilbig, 2017). The data and analysis scripts are available on the Open Science Framework (https://osf.io/k76b2/).

Results

We computed one-sided BFs to quantify evidence for a null effect versus a positive effect of HEXACO Emotionality (Cronbach's α = .76) and its Anxiety facet (α = .66) on dishonesty (see Heck et al., 2018). Using the modified logistic regression approach, we tested the first-order association of these two traits with dishonesty. The results provided strong evidence in favor of a null effect versus a medium-sized, positive effect for both HEXACO Emotionality (BF_{01} = 7.9) and its Anxiety facet (BF_{01} = 15.2).[2] As indicated by the larger Bayes factor, the evidence was particularly strong for the Anxiety facet. Similar conclusions were obtained when using frequentist Wald tests with a significance level (α) of 1%. That is, analyses of both Emotionality (p = .676) and its Anxiety facet (p = .652) clearly failed to reach statistical significance, whereas both tests had an approximate statistical power ($1 - \beta$) of 92% for detecting a small effect (i.e., an *OR* of 1.25 for a z-standardized predictor). The reanalysis thus showed a null effect of trait anxiety on dishonest behavior in standard cheating paradigms, thereby contradicting Lu and colleagues' hypothesis that anxiety (acting as a mediator) causes unethical behavior.

Conclusion

Our analyses and reanalyses provided consistent evidence against the generality of a causal effect of air pollution on unethical behavior via anxiety. First, pollution showed no incremental effect on crime rates above opposing seasonal trends. Second, trait anxiety was unrelated to dishonest behavior. These findings clearly conflict with Lu and colleagues' broad hypotheses, demonstrating that neither air pollution nor anxiety can be considered general causes of unethical behavior.

As a remedy, Lu and colleagues may specify more precisely which types of "air pollution" (e.g., experienced vs. objective, types of pollutants) and anxiety (e.g., specific versions of state anxiety, negative emotions) lead to different aspects of unethical behavior (e.g., dishonesty, violence). For instance, Lu and colleagues' theory could be restricted to (a) specific pollutants, (b) a 6-month lag between peaks in pollution and crime, (c) a subset of crimes (even though we consistently found null effects), (d) specific emotional states elicited by their experimental manipulation, or (e) specific types of state anxiety that are independent of trait anxiety.

Indeed, such restrictions and the fact that they require further theoretical justifications (e.g., why should there be a 6-month delay?) may not appear attractive. However, theory revision is the straightforward option that fosters scientific progress. Thus, we encourage Lu and colleagues to revise their claims in terms of generality and scope and thereby exclude those portions of the "empirical content" (in terms of falsifiability; Popper, 2002) of their theory that our and other evidence conflicts with.

Transparency

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Author Contributions
All of the authors contributed to the idea and theoretical background of the studies. D. W. Heck collected the data for Study 1 and performed all analyses. All of the authors contributed to writing the manuscript and approved the final version for submission.
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.
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Open Practices
All data and R code have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/z2bsa/. The design and analysis plans for the studies were not preregistered. The complete Open Practices Disclosure for this article can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797619866627. This article has received the badge for Open Data. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

ORCID iDs

Daniel W. Heck https://orcid.org/0000-0002-6302-9252
Isabel Thielmann https://orcid.org/0000-0002-9071-5709

Notes

1. Data were obtained from the UK police (https://data.police.uk), the UK Department for Environment, Food & Rural Affairs (https://uk-air.defra.gov.uk), and the Office for National Statistics (https://www.nomisweb.co.uk) under the Open Government License. Note that crime data were not available for Scotland. Moreover, several UK districts were not included in the analysis because of a lack of pollution-measurement sites. Since it is unlikely that the missingness mechanism depends on the substantive question of interest (i.e., the crime–pollution link), analyzing a subset of all existing districts did not threaten the validity of our data or analysis, respectively.
2. To check the sensitivity of our results with respect to the prior for the effect size, we also computed Bayes factors assuming small and very small effects by using scale parameters r = .35 and r = .25, respectively (whereas a medium effect size corresponds to r = .50; see the supplementary material of Heck et al., 2018). Importantly, these analyses led to the exact same conclusions for both Emotionality (BF_{01} = 5.6 and BF_{01} = 4.1, assuming a small and very small effect, respectively) and Anxiety (BF_{01} = 10.9 and BF_{01} = 7.8, respectively).

References

Aseltine, R. H., Gore, S., & Gordon, J. (2000). Life stress, anger and anxiety, and delinquency: An empirical test of general strain theory. *Journal of Health and Social Behavior*, *41*, 256–275. doi:10.2307/2676320

Ashton, M. C., & Lee, K. (2007). Empirical, theoretical, and practical advantages of the HEXACO model of personality structure. *Personality and Social Psychology Review*, *11*, 150–166. doi:10.1177/1088868306294907

Bind, M.-A. (2019). Causal modeling in environmental health. *Annual Review of Public Health*, *40*, 23–43. doi:10.1146/annurev-publhealth-040218-044048

Bondy, M., Roth, S., & Sager, L. (2020). Crime is in the air: The contemporaneous relationship between air pollution and crime. *Journal of the Association of Environmental and Resource Economists*, *7*, 555–585.

Brooks, A. W., & Schweitzer, M. E. (2011). Can Nervous Nelly negotiate? How anxiety causes negotiators to make low first offers, exit early, and earn less profit. *Organizational Behavior and Human Decision Processes*, *115*, 43–54. doi:10.1016/j.obhdp.2011.01.008

Fiedler, K., Schott, M., & Meiser, T. (2011). What mediation analysis can (not) do. *Journal of Experimental Social Psychology*, *47*, 1231–1236. doi:10.1016/j.jesp.2011.05.007

Heck, D. W., Thielmann, I., Moshagen, M., & Hilbig, B. E. (2018). Who lies? A large-scale reanalysis linking basic personality traits to unethical decision making. *Judgment and Decision Making*, *13*, 356–371.

Herrnstadt, E., Heyes, A., Muehlegger, E., & Saberian, S. (2018). *Air pollution as a cause of violent crime: Evidence from Los Angeles and Chicago*. Retrieved from http://www.evanherrnstadt.com/docs/Crime_and_Pollution.pdf

Hipp, J. R., Curran, P. J., Bollen, K. A., & Bauer, D. J. (2004). Crimes of opportunity or crimes of emotion? Testing two explanations of seasonal change in crime. *Social Forces*, *82*, 1333–1372. doi:10.1353/sof.2004.0074

Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association*, *90*, 773–795. doi:10.1080/01621459.1995.10476572

Kouchaki, M., & Desai, S. D. (2015). Anxious, threatened, and also unethical: How anxiety makes individuals feel threatened and commit unethical acts. *Journal of Applied Psychology*, *100*, 360–375. doi:10.1037/a0037796

Lu, J. G., Lee, J. J., Gino, F., & Galinsky, A. D. (2018). Polluted morality: Air pollution predicts criminal activity and unethical behavior. *Psychological Science*, *29*, 340–355. doi:10.1177/0956797617735807

Massey, D., Kulshrestha, A., Masih, J., & Taneja, A. (2012). Seasonal trends of PM10, PM5.0, PM2.5 & PM1.0 in indoor and outdoor environments of residential homes located in North-Central India. *Building and Environment*, *47*, 223–231. doi:10.1016/j.buildenv.2011.07.018

McDowall, D., Loftin, C., & Pate, M. (2012). Seasonal cycles in crime, and their variability. *Journal of Quantitative Criminology*, *28*, 389–410. doi:10.1007/s10940-011-9145-7

Moshagen, M., & Hilbig, B. E. (2017). The statistical analysis of cheating paradigms. *Behavior Research Methods*, *49*, 724–732. doi:10.3758/s13428-016-0729-x

Polivy, J. (1981). On the induction of emotion in the laboratory: Discrete moods or multiple affect states? *Journal of Personality and Social Psychology*, *41*, 803–817. doi:10.1037/0022-3514.41.4.803

Popper, K. (2002). *The logic of scientific discovery* (2nd ed.). London, England: Routledge.

Rentfrow, P. J., Gosling, S. D., & Potter, J. (2008). A theory of the emergence, persistence, and expression of geographic variation in psychological characteristics. *Perspectives on Psychological Science*, *3*, 339–369. doi:10.1111/j.1745-6924.2008.00084.x

Schindler, S., Reinhard, M.-A., Dobiosch, S., Steffan-Fauseweh, I., Özdemir, G., & Greenberg, J. (2019). The attenuating effect of mortality salience on dishonest behavior. *Motivation and Emotion*, *43*, 52–62. doi:10.1007/s11031-018-9734-y

van Gelder, J.-L., & de Vries, R. E. (2012). Traits and states: Integrating personality and affect into a model of criminal decision making. *Criminology*, *50*, 637–671. doi:10.1111/j.1745-9125.2012.00276.x

Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society B: Statistical Methodology*, *73*, 3–36.

Wowra, S. A. (2007). Moral identities, social anxiety, and academic dishonesty among American college students. *Ethics & Behavior*, *17*, 303–321. doi:10.1080/10508420701519312

Zhang, H., Shi, Y., Zhou, Z. E., Ma, H., & Tang, H. (2020). Good people do bad things: How anxiety promotes unethical behavior through intuitive and automatic processing. *Current Psychology*, *39*, 720–728. doi:10.1007/s12144-018-9789-7

Zhang, Y. Y., Jia, Y., Li, M., & Hou, L. A. (2018). Spatiotemporal variations and relationship of PM and gaseous pollutants based on gray correlation analysis. *Journal of Environmental Science and Health A: Toxic/Hazardous Substances & Environmental Engineering*, *53*, 139–145. doi:10.1080/10934529.2017.1383122