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Outdoor Air Pollution and Psychological Well-Being: A Meta-Analysis

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ABSTRACT

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Human life takes place as part of a global ecosystem, meaning that human mental health is at least partially tied to the health of the planet. Health experts who seek to promote psychological well-being should consider how changes to the broad ecological system may impact their efforts. Given the potential impact of the environment on human well-being, we conducted a meta-analysis to assess the impact of air pollution on subjective well-being. The goal of this project was to outline the current state of the research on these constructs and provide a clear framework for what research is still needed. Nonsignificant relationships were found for six out of seven of the measured pollutants. Overall, these results appear to indicate a nonsignificant negative relationship between our constructs; however, our model had significant heterogeneity which may impact the validity of these findings. Attempts to reduce statistical heterogeneity demonstrated the importance of complex measurement and study design when studying the impact of ecological environments on well-being.

Keywords: Subjective well-being, air pollution, life satisfaction, ecopsychology

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All of human life takes place as part of a global ecosystem: humans depend on the natural world for a livable climate, edible food, and breathable air (Y. Li et al., 2018; Romanelli et al., 2015). An adequately safe environment is necessary for human flourishing to be possible at the societal scale, which means that human mental health is in some ways tied to the health of the planet (Lomas, 2015; Nurse et al., 2010) Thus, psychologists and other health experts who seek to promote psychological well-being should consider how changes to the broad ecological system may impact their efforts (Berry et al., 2018). In 2015, the United Nations set out a global resolution with 17 sustainable development goals to support "people, planet, and prosperity" (Assembly, 2015). Included in this resolution were goals to promote health and well-being (goal 3) and to protect and restore global ecosystems (goal 15) (Assembly, 2015, p. 14). Human health is dependent on a stable climate, clean air and water, and food security; and natural ecosystems that provide these services are often damaged by problematic human behavior, therefore promoting human health and protecting natural ecosystems are complementary objectives (Nurse et al., 2010; Romanelli et al., 2015). To accomplish the sustainable development goals outlined above, research must address how alterations in global ecosystems may be impacting psychological functioning, and how human behaviors are impacting natural ecosystems.

The idea that individuals can achieve a meaningful and satisfying life is a core tenant of most modern societies, and yet policy makers often fail to consider how policy decisions will impact the well-being of citizens (Odermatt & Stutzer, 2017; Turner, 2018). Instead, much of public policy is currently guided by increasing gross domestic product (GDP), which is only associated with higher subjective well-being in poor countries while increases tend to plateau for rich countries (Proto & Rustichini, 2013). Subjective well-being measurement has been put forward as an alternative method to assess the progress of societies, with the severity of various environmental and social stressors measured against their impact on subjective well-being.

This thesis will focus specifically on the link between subjective well-being and outdoor air pollution using a systematic review and meta-analysis in order to understand how this environmental stressor impacts subjective well-being on a global scale. Researchers, psychologists, and policy makers would benefit from a big picture report on the connection between air pollution and well-being in order to address both of them more effectively.

The Impact of Air Pollution on Human Health

Air pollution as an important human health issue first entered the public psyche during the great smog of London in the 1950's which killed up to 12,000 people (Polivka, 2018). This event, along with other pollution disasters in the 1950's led to important air pollution reform, particularly in regard to limiting concentrations of sulfur dioxide which is responsible for acid rain (Stern & Professor, 1982). However, despite the success of these early efforts, ambient air pollution still causes more than nine million deaths annually (Burnett et al., 2018; Errigo et al., 2020; Lelieveld et al., 2019; Stern & Professor, 1982).

Ambient air pollution impacts physical health both acutely and chronically, with the health effect depending on the chemical make-up, size, and concentration of the particle. Understanding the physical health effects of air pollution is important because decreases in physical health may be a potential mediator between air pollution and subjective well-being (F.

Li & Zhou, 2020). Specific pollutants including Carbon monoxide (CO), Nitrogen oxides (NOx), Sulfur dioxide (SO2), Ozone (O3), and other micro pollutants have significant impacts physical health: these compounds largely build up as a result of the burning of fossil fuels and have been linked to increases in respiratory and cardiovascular disease, lung cancer, and all-cause mortality (Almetwally et al., 2020; Faustini et al., 2014; Kim et al., 2013; Meng et al., 2003; Robertson, 2006). Particulate matter (pm, pm10, pm2.5) is a mixture of every particle in the ambient air that humans breath: pm particles are classified by their diameter (pm10 = 10 μm, pm2.5= 2.5 μm, ultrafine pm= .01 μm) (Almetwally et al., 2020). The health effects of Pm2.5 particulates are more severe than larger molecules as they are small enough to reach the bronchial capillary wall in the lungs (Almetwally et al., 2020; World Health Organization, 2014). Overall, air pollution has a significant and well documented effect on physical health.

Along with the health effects of air pollution on physical health, the psychological effects of air pollution have also received considerable research attention. This research generally indicates that increased levels of PM, NO2, and SO2 are associated with poor mental health and the aggravation of existing mental disorders, although most of the current research has not sufficiently accounted for alternative explanations such as seasonality, medical difficulties, or wind direction (Buoli et al., 2018). These negative psychological effects are hypothesized to be a result of fine and ultra-fine particles' impact on the central nervous system (CNS) and cognitive systems (Buoli et al., 2018; Calderón-Garcidueñas et al., 2015; Gu et al., 2020). The exact mechanisms of neurodegeneration are not well-known but are likely related to neuroinflammation and oxidative stress (Calderón-Garcidueñas et al., 2015). Along with the physiological components of the air pollution/mental health interaction, there are also thought to be psychosocial components as well. Increased air pollution has been associated with decreased physical activity, which in turn has been associated with decreased mental health—thus decreased physical activity may mediate the relationship between the two variables (An et al., 2018; Tainio et al., 2021; Yang et al., 2021). Overall, air pollution has been associated with decreased mental health although the exact mechanisms for this relationship still deserve research attention and more alternative explanations for the association need to be ruled out.

The Impact of Air pollution on Psychological Well-being

An important component of mental health is subjective well-being, yet there is only a small body of research on the connection between air pollution and subjective well-being (Lomas, 2015; Nurse et al., 2010). Subjective well-being can be defined as either the subjective experience of positive emotional states (hedonic well-being) or the subjective experience of meaning and purpose (eudemonic well-being) (Henderson & Knight, 2012). Researchers may question why subjective well-being is worth studying as a construct given that it is a subjective evaluation measure rather than an objective indicator of happiness and prosperity; however, how individuals in a society personally view their subjective well-being (their personal ability to find joy and meaning in their life) may be an equally important indicator of the success of that society as objective measures of societal success such as GDP (Diener et al., 2018). The idea that well-being is a better indicator of societal success is particularly important when studying a topic like air pollution where personal beliefs about the well-being impact of air pollution are likely to change an individual's desire to mitigate that problem (Chen et al., 2019; Diener et al., 2018).

Although improvements in well-being are associated with lower all-cause mortality and a variety of other positive outcomes, improving population well-being may also be worthwhile in its own right as most individuals strive to experience meaning and joy in their own lives (Adler & Seligman, 2016; Bryndin, 2017; Martín-María et al., 2017). Diener et al (2018) specifies several main reasons for why subjective well-being is worth tracking on a global scale. First of all, tracking subjective well-being may help elucidate societal differences in quality of life: in regard to the current paper, measuring subjective well-being differences due to air pollution can help clarify the impact that air pollution is having on overall quality of life. Second, citizens highly value subjective well-being. Given that people want to live happy and fulfilling lives, measuring how air pollution is impacting their ability to do that will help encourage air pollution mitigation efforts (Diener et al., 2018).

A core goal of clinical psychology and science in general is to reduce suffering and improve quality of life for all people; understanding the impact air pollution is having on psychological well-being may help achieve that goal. In order to understand the relationship between subjective well-being and air pollution, it is important to assess the current state of the literature on these constructs.

This body of research is largely based on subjective well-being reports via national and international surveys correlated with air pollution levels at the time of the report, a method termed the life-satisfaction approach (Welsch, 2002). This research was originally created as a method of environmental evaluation to calculate the economic cost of air pollution on well-being. This paper will focus on clarifying the impact of air-pollution on well-being without making arguments about environmental market valuation.

Current research suggests a negative relationship between subjective well-being and increased ambient air pollution (Y. Li et al., 2018; Lu, 2020). These results have been found across pollutant type and geographical areas as noted in Li et al.'s (2018) review. Effects of pollution on SWB are not the same across groups, with older people and younger people being impacted more severely (Luechinger, 2010; Menz & Welsch, 2012). Along with physical measurement of air pollution, perceptions of air pollution have also been measured; in these studies, higher perception of air pollution is correlated with lower subjective well-being, this relationship is stronger for wealthier individuals and individuals who hold pro-environmental views (Ferrer-i-Carbonell & Gowdy, 2007; Hart et al., 2018; F. Li & Zhou, 2020; Rotko et al., 2002).

Despite the previous findings suggesting a negative impact of air pollution on well-being, several measurement problems inhibit conclusive findings, particularly because it is hard to match exact air pollution exposure on the individual level and because air pollution likely impacts individuals differently depending on their personal health history and beliefs about air pollution risks (Li et al., 2018; Lu, 2020). Therefore, matching individual exposure and recognizing heterogeneity in effects is particularly important. My thesis will seek to assess the severity of this problem by assessing the spatiality, temporality, and geographical location of air pollution measurement. We will reduce heterogeneity in our analysis by only including within country analyses.

Altering subjective well-being in the long-term (either negatively or positively) is difficult, which may lead some to wonder how air pollution could have a long-lasting impact on subjective well-being. Due to hedonic adaptation, people tend to return to a base level of happiness regardless of life circumstances. Even after large life events like getting married or winning the lottery people tend to return to their normal level of happiness after a relatively short period of time (Perez-Truglia, 2012). However, hedonic adaptation is a complex construct with many potential mechanisms and exceptions: individuals may adapt to changing life circumstances by increasing coping strategies, recontextualizing life circumstances, or by altering personal characterizations of happiness (Klausen et al., 2021). Given the complexity of the construct, avoiding promoting societal well-being based on the idea that people will return to their base level of happiness is both ill-conceived and unethical (Huang, 2018; Klausen et al., 2021).

Air pollution may be a construct that resists hedonic adaptation due to its gradual and varying impact on physical health and life opportunities, thus the continued impact of air pollution on well-being may depend on the specific characteristics of the individual and the environment (their personal valuation of air pollution, cultural adaptability, and person risk assessment) (Menz, 2011). Thus, for air pollution to significantly contribute to loss of well-being and happiness it would need to contribute a consistent but variable impact on life satisfaction.

There are several mechanisms that may contribute to this loss in satisfaction. The first relates to perceptions of air pollution, with the theory being that individuals experience decreases in life satisfaction and positive emotional states when they believe the air quality is poor (Du et al., 2018; Y. Li et al., 2018). A second potential process by which air pollution may impact SWB is through physical health, with physical health difficulties caused by air pollution leading to lower well-being (F. Li & Zhou, 2020). The final potential mechanism for air pollution to impact well-being is through lost engagement in meaningful life activities including physical exercise, and nature exposure (Chang et al., 2019; Wang et al., 2020).

Two systematic reviews of air pollution and subjective well-being data have already been conducted, although these reviews do not assess the overall between studies effect size or include comprehensive review criteria (Y. Li et al., 2018; Lu, 2020). Lu ‘s (2020) review assessed the overall psychological, economic, and social effects of air pollution and found a consistent effect for air pollution on life-satisfaction and happiness; however, this study failed to address specific differences in study design, did not address the quality of study design, did not include review search criteria, and did not offer comprehensive recommendations for future research. Li’s (2018) review on subjective well-being and air pollution more thoroughly assessed the impact of air pollution on subjective well-being, with a more comprehensive focus on the measurement, drivers, and outcomes of the current subjective well-being research. This study found consistent negative relationships between subjective well-being survey data and several pollutants, highlighted the difficulty of conducting high quality air pollution survey data, and recommended psychophysical research design as an alternative method. While this study addressed the difficulties of conducting survey well-being data, it did not systematically identify the quality of the current well-being data. It also did not include review search criteria and did not offer comprehensive recommendations for future research (Borenstein et al., 2021). Although published systematic reviews have contributed meaningfully to the current body of well-being research, more detailed reviews are needed that assess differences in study design, assess quality of data, and include comprehensive review criteria.

Along with a need for a more comprehensive systematic review, available research has also not addressed the meta-analytic effect of air pollution on subjective well-being. Meta-analytic reviews add important incremental value to systematic reviews by providing a synthesized overall effect size for the relationship (Borenstein et al., 2021). Non-meta-analytic reviews generally rely on statistically significance of individual studies to form conclusions about the quality of findings: however, this approach fails to analyze the clinical importance of effects and is prone to bias due to type 1 error and low power (Cheung & Lucas, 2014; Cooke et al., 2016; Kahneman et al., 2004). Meta-analytic research would be particularly useful for air pollution and well-being research as this field generally has small effect sizes which leads to increases in bias. Furthermore, meta-analytic analysis in this area could help explorer how temporal or spatial level of study analysis influences the effect between variables.

A final limitation in current well-being research relates to subjective well-being and air pollution measurement—currently there is poor consistency about the best length of well-being measures, and type of well-being construct measured. Subjective well-being is typically measured through a single item or multi-item self-report measure. Single-item measures have been shown to have similar construct validity to longer measures, although they are also prone to bias (Barrington-Leigh & Behzadnejad, 2017). This meta-analysis will help determine if current approaches to well-being measurement are providing a consistent measure of the impact of air pollution on well-being by assessing the relationship between well-being and air pollution on different temporal scales.

Present Study

Overall, measuring the impact of air pollution on subjective well-being is a promising line of research with important psychological and environmental implications. Three important areas need to be addressed to move forward effectively with air pollution and well-being research: 1. A systematic review that specifically focuses on future research needs, 2. A meta-analysis of air pollution effects in order to assess overall air pollution impact based on type of pollutant and in order to assess heterogeneity between studies, and 3. A general discussion and consensus on the best way to move forward with well-being and air pollution measurement. This study sought to address all three limitations through a systematic review and meta-analysis using the PRISMA guidelines for reviews (Page et al., 2021).

This study will seek to clarify the current research on air pollution and psychological well-being in order to promote more effective research and solutions by 1. calculating the across studies impact of air pollution, 2. determining how study design and type of pollutant influence the relationship between air pollution and well-being, and 3. Providing a clear idea of what research is needed in the future. Specifically, this systematic review will outline the state of the current research and discuss problems and solutions for calculating accurate correlation and causation for hypothetical psychological constructs such as well-being in complex ecological environments. To reduce heterogeneity and endogeneity the present study excludes all subjective well-being constructs besides life satisfaction in the meta-analysis.

Hypotheses

1. Across studies, life satisfaction will have a significant and meaningful negative relationship with both invisible and visible air pollution as indicated by a statistically significant beta (95% confidence interval does not include zero).

2. The effect of air pollution on wellbeing will be significantly larger on both smaller temporal scales and smaller spatial scales, with the mean beta on smaller scales falling below the 95% confidence interval of larger scales.

3. The effect of air pollution on well-being will differ significantly depending on the geographical region with higher beta in Asia than in other regions as indicated by the mean geographical region falling outside of the other region's 95% confidence intervals.

4. The effect of air pollution on well-being will differ significantly depending on the type of pollutant.

Method

Review and Selection Criteria

We conducted a systematic review and meta-regression to synthesize the result of related studies and identify the aggregated slope coefficient between studies (Standardized Beta = across studies relationship between one standard deviation increases of objective air pollutants on standard deviations of subjective life-satisfaction report). The formula for standardized beta was $B = \beta * x/y$ where x = the standard deviation of air pollution and y = the standard deviation of life satisfaction for a specific study as suggested by (Palmer & Sterne, 2016).

Error was computed by dividing the square root of the standardized beta coefficient by the square root of sample size (Lee et al., 2015).

Inclusion and exclusion criteria are outlined below.

- Population—Studies including general adult populations (≥18 years of age)
- Exposures — Studies of outdoor particles with mass < 10 μm in aerodynamic diameter (PM10) and outdoor particles < 2.5 μm in aerodynamic diameter (PM2.5), as outlined in (Braithwaite et al., 2019).
- Outcomes — studies had to be correlated with subjective measures of life satisfaction.
- Studies were peer reviewed and had to be published in a scientific journal
- Design — studies had to use a cross comparison or time series design

We excluded studies meeting the following descriptions:

- Design — correlation between life satisfaction and air pollution was measured between countries rather than within countries.
- Population —studies that assessed special populations (i.e., not a general adult sample)
- Exposures — studies that did not include observed air pollution exposure in natural environments (i.e., perceived risk of exposure, laboratory experiments)
- Outcomes —studies that used other methods for measuring subjective well-being.

We only included life-satisfaction in our meta-analysis due to heterogeneity problems associated with comparing different research designs and well-being variables. With studies that included other questions related to well-being and air pollution, we analyzed only the data regarding objective air pollution exposure and life-satisfaction. To avoid bias we checked for studies that were not written in English but did not find any. Studies that measured multiple pollutants simultaneously were included, which is feasible because meta-regression relies on individual beta coefficients rather than overall effect size. Therefore, we did not have to collapse data within studies. Studies were grouped together based on the type of pollutant assessed.

Organizational Framework

Both the systematic review and meta-analysis in this study were conducted and reported in accordance with the PRISMA guidelines (Borenstein et al., 2021), and a published guide to conducting meta-analyses (Schiavo, 2019). We were, however, unable to pre-register our study because new PROSPERO guidelines prevent registration after any data have been collected rather than before data extraction is complete (Palmer & Sterne, 2016). We had already started collecting data when we attempted to preregister our study because we did not realize that guidelines had changed.

Data Collection and Extraction

Study selection and retrieval

To identify studies which fit inclusion criteria we used the following electronic databases: EBSCO, Psych INFO, Web of Science, Academic search premier. We used the following criteria to identify pertinent studies and filter out irrelevant studies: Keywords: "Well-being" "Psychological Well-being" "Subjective well-being" "Eudemonic Well-being" "Hedonic Well-being" "Life Satisfaction"; and "Pollution" "Air Pollution"; and "pm2.5" "pm10" "so2" "particles" "api" "aqi" "03" "no2". We accessed these databases through Brigham Young

University's library website. We also checked google scholar for pertinent articles. The last search query was conducted on November 30th, 2021. We did not use a review protocol.

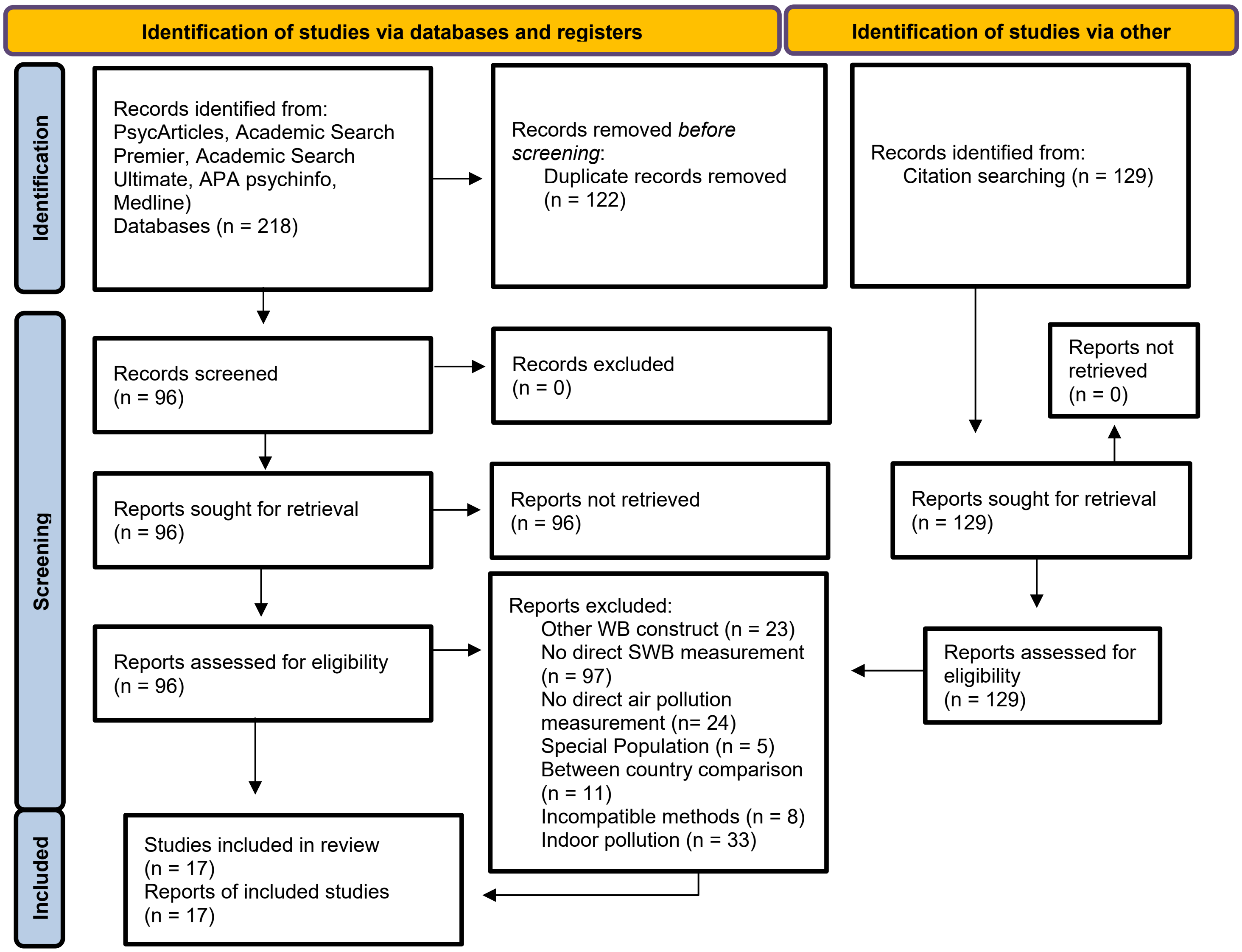
Data Extraction

The primary author aggregated the studies using a pre-prepared google doc template with the following terms: type of subjective well-being construct, mean and standard deviations of both well-being and air pollution data, sample size, research design, type of pollutant, spatial spread of research, temporal spread of study, beta coefficient, and standard error. The completed spreadsheet along with excluded studies are available on our OSF report: https://osf.io/7s96e/?view_only=8cce213e37604a9f9dcc67d7b18092be. The studies were then double checked by a research assistant, Across the study we found 37 inconsistencies which translated into an overall interrater reliability of 86%. All inconsistencies were resolved by the primary author. Given that only cross comparison studies were included, there was no need to transform beta coefficients. In order to accurately measure the relationship across studies we standardized beta coefficients by multiplying the coefficient by the standard deviation of the x and y variable (standard beta = beta*xsd/ysd) as recommended by Palmer & Sterne (2016). We calculated standard errors based on sample size and beta coefficient and then used these results for the meta-regression (Standard Error = sqrt of standardized beta/sqrt of sample size).

We collected data from 17 of which also met criteria for the meta-regression. To assess risk of publication bias we used a funnel plot (STATA command: metafunnel). To see a flow chart of our data extraction results, view the PRISMA chart below.

Figure 1. PRISMA Flow Diagram

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers, and other sources



From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated

guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71.

For more information, visit: http://www.prisma-statement.org/

Data coding

For the meta-analysis we coded well-being construct, study design, life satisfaction questions, mean and standard deviation of all pollutants, mean and standard deviation of life-satisfaction, temporal and spatial level of study design, sample size, type of air pollutant, beta coefficients, standard error, geographical region, and year published. We only sought data that included both subjective life satisfaction questions and objective air pollution measurement. For studies that included multiple equations with differing control variables we only included the result that included all controls. Coding for meta-analysis was checked for inconsistencies by a second reviewer, and any inconsistencies found were noted and resolved by the primary author. Two inconsistencies were found and corrected.

In our analysis there was only one missing data point. We contacted the author of this study and he responded with the missing information along with his STATA code for replication. Therefore, missingness impacting study results was not a concern for our meta-analysis.

Table 1. Study Information

Study	Temporal level of air pollution reporting	Spatial Level of air pollution reporting	Air Pollutants	Geographical Region	Year Published	Main Findings (*denotes significance at the .01 level, **denotes significance at the .005 level, and *** denotes significance at the .001 level)
(Ahumada & Iturra, 2021)	Yearly	City	PM2.5	South America	2021	Negative impact for PM2.5 (B = -.00591**)
(Barrington-Leigh & Behzadnejad, 2017)	Daily	Region	PM2.5, No2, So2, Co	North America	2016	Non-significant impact for all pollutants except So2 which had had a negative impact (PM2.5 B = -.0002, CO B = .0291, No2 B = .000074, So2 B = -.0053*)
(Dolan & Laffan, 2016)	Yearly	Region	PM2.5	Europe	2016	Negative impact with PM2.5 (B = -0.0181***)

(Dong et al., 2018)	Yearly	House	PM2.5	Asia	18-Feb	Negative impact with PM2.5 (B = -0.05**)
(Du et al., 2018)	Daily	House	PM2.5, PM10, No2, So2	Asia	2018	Negative impact for all pollutants in Beijing (SO2 = -.0109***, NO2 = −0.00612***, PM10 = −0.00612***, PM2.5 = −0.00283**) Negative impact for So2 and No2 (So2 = −0.0125** and No2 = -.00513**) but not PM10 and PM2.5 (PM10 = -.00184, PM2.5 = -.00245) for Shanghai Residents.
(Ferreira & Moro, 2010)	Yearly	Region	So2	Europe	2013	negative impact with So2 (B = −0.016*)
(Ferreira & Moro, 2010)	Yearly	Region	PM10	Europe	2010	Negative impact with PM10 (B = -0.043**)
(Goetzke & Rave, 2015)	Yearly	Region	Aggregate	Europe	2015	Negative impact with aggregate measure (B = -0.14**)
(Guo et al., 2021)	Quarterly	Region	Aggregate, PM10, Co	Asia	2021	Negative impact for CO but not PM10, and AQI (CO B = -0.1759**, PM10 B = -0.0038, AQI B = -0.0023)
(Liu & Hu, 2021)	Yearly	Region	Aggregate, PM10, No2, So2	Asia	2021	Negative impact for all pollutants (CO B = −0.0831**, No2 B = -0.1806***, PM10 B = -.2552***, AQI B = -.3179***)
(Liu & Hu, 2021)	Yearly	House	Aggregate, PM2.5, PM10, So2	Asia	2021	Negative Impact for all pollutants (So2 B = -.317**, PM 10 B = -.164*, AQI B = -0.284* PM2.5 B = -0.289*)

(Schmitt, 2013)	Daily, yearly	City	No2, OZ, CO	Europe	2013	Negative impact for O3 but no other pollutants (O3 B = -0.0015*, CO B = -0.0239, No2 B = -0.0010)
(MacKerron & Mourato, 2009)	Yearly	House	PM10, No2	Europe	2009	Negative impact for No2 but not PM10. (No2 B = -0.042*, PM10 B = -0.087)
(Mendoza et al., 2019)	Yearly	Region	PM2.5, PM10	South America	2019	Negative impact for both pollutants (PM10 B = − 0.0021*, PM2.5 B = − 0.0045**)
(Smyth et al., 2011)	Yearly	City	Aggregate, So2	Asia	2011	Negative impact for both pollutants (Aggr B = -0.001**, So2 B = -.002**)
(Luechinger, 2009)	Yearly	Region	So2	Europe	2009	Negative impact for So2 (B = -.005**)
(Shi & Yu, 2020)	Yearly	City	PM2.5	Asia	2020	Negative impact for PM2.5 (B =-.448***)
(Yuan et al., 2018)	Daily	Region	Aggregate	Asia	2018	Negative impact for aggregate (B = .0057**)

Study Quality Assessment

To assess for study quality, we used the OSQE for cross sectional studies (Drukker et al., 2021). This is a newly optimized quality criteria list specifically built for observational studies. A check on internal validity required assessment of both IV and DV with established measures and adequate control of confounds (i.e., controlled for at least age, income, and health). A check on external validity required including information about generalizability of results. A check on representativeness required inclusion of information about sample characteristics that demonstrated how the sample was representative. A check on IV required direct assessment of air pollution on at least the regional level, and a check on the DV required at least a single item life satisfaction self-report question. Optimal measurement of IV required measurement of pollution on the individual level at multiple time points. Finally, management of modifiers required adequate assessment of both endogeneity and multicollinearity.

Table 2. Study Quality Assessment

Study	Internal Validity	External Validity	Representativeness	Valid Measurement of IV	Optimal Measurement of IV	Valid Measurement of DV	Conflict of Interest	Confounders	Protocol	Managed Missing Data	Management of modifiers	Sample size
Ahumada & Iturra (2021).	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓
Barrington-Leigh & Behzadnejad (2017)	✓	✗	✗	✓	✗	✓	✓	✓	✓	✗	✗	✓
Dolan & Laffan (2016)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓
Dong et al. (2018)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓
Du et al. (2018)	✓	✗	✗	✓	✗	✓	✓	✓	✓	✗	✗	✓
Ferreira et al. (2013)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓
Ferreira et al. (2010)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓
Goetzke & Rave (2015)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓
Guo et al. (2021)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓
Liu & Hu (2021)	✓	✗	✗	✓	✗	✓	✓	✓	✓	✗	✗	✓
Liu et al. (2021)	✓	✗	✗	✓	✗	✓	✓	✓	✓	✗	✗	✓
Schmitt (2013)	✓	✗	✗	✓	✗	✓	✓	✓	✓	✗	✗	✓
MacKerron & Mourato (2009)	✓	✗	✗	✓	✗	✓	✓	✓	✓	✗	✗	✗
Mendoza et al. (2019)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓

Smyth et al. (2011)	✓	✗	✗	✓	✗	✓	✓	✓	✓	✗	✗	✓
Luechinger (2009)	✓	✗	✗	✓	✗	✓	✓	✓	✓	✗	✗	✓
Shi & Yu (2020)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓
Yuan et al. (2018)	✓	✗	✓	✓	✗	✓	✓	✓	✓	✗	✗	✓

Study quality assessment tool OSQE for cross sectional studies (Drukker et al., 2021)

Our study quality assessment (Figure 2) indicated broad difficulties with external validity, optimal measurement of air pollution, and problems with managing missing data and modifiers. The studies included did not demonstrate how their results would be representative of broader populations and did not assess air pollution with enough specificity. They also did not properly control for shared collinearity between independent variables and error terms.

Data Analytic Procedure

We analyzed the overall beta coefficient using Stata command: metareg, where beta indicated the across study slope coefficient weighted by sample size using a random effects design (Harbord & Higgins, 2008). To explore whether temporality or spatiality impacted the relationship between variables, we dummy coded studies based on their spatial and temporal characteristics. Spatial levels were regional, city, and house relating to whether comparisons were computed on the regional, city, or household level. Temporal levels were annual, quarterly, and daily, which related to whether studies measured pollution on the daily, quarterly, and annual level. We separated results by pollutant type using the STATA by command. We decided to compute separate meta-regressions for each pollutant type individually (rather than including them as moderators) as spatial and temporal relationships between variables likely depend on the pollutant in question.

To assess for total variation due to heterogeneity rather than chance we used the I^2 value, and then explored reasons for heterogeneity using subgroup analysis. The meta-regression study design allowed for accurate assessment for contributions of heterogeneity due to spatiality, temporality, and geography of data. We also used the Stata leaveoneout command to assess impacts of individual studies on heterogeneity.

Results

Study Characteristics

We extracted data and beta effects from 17 studies examining the relationship between air pollution and subjective report of life satisfaction. Robumeta controls for interstudy dependent effects by relaxing assumptions of normality (Hedges et al., 2010). Separately we also analyzed studies by type of pollutant which automatically controlled for aggregate effects as each analysis did not have multiple effect sizes from the same study. We also used standard error of the mean rather than standard deviation units for the analyses in order to control for differing sample sizes.

The total sample size across all studies was 599,043. In regard to air pollution, these studies included 7 aggregate effect sizes, 9 PM2.5 effect sizes, 8 PM10 effect sizes, 6 NO2 effect sizes, 8 SO2 effect sizes, 1 O3 effect size, and 3 CO effect sizes. In regard to geographical regions, these studies included 3 effect sizes from South America, 4 effect sizes for North America, 10 effect sizes from Europe, and 25 effect sizes from Asia. In regard to spatial measurement of air pollution, 4 effect sizes were calculated on the house level, 18 effect sizes were calculated on the city level, and 20 were calculated on the regional level. Finally, in regard to temporal measurement of well-being, 15 effect sizes were calculated on the daily level, 4 effect sizes were calculated on the quarterly level, and 23 were calculated on the annual level. Overall, data was spread fairly evenly across pollutant types, and the majority of effects were calculated in Asia at the regional level with annual life-satisfaction averages.

Influence Analysis

To assess the influence of individual studies on the overall effect we computed an influence analysis. An influence or "leave-one-out" analysis helps assess whether individual studies are responsible for large amounts of heterogeneity or effect (Baldwin & Shadish, 2011). An influence plot was commuted using the Stata Meta forestplot, leaveoneout command. Figure one outlines the result of this analysis.

Figure 2. Leave-one-out analysis

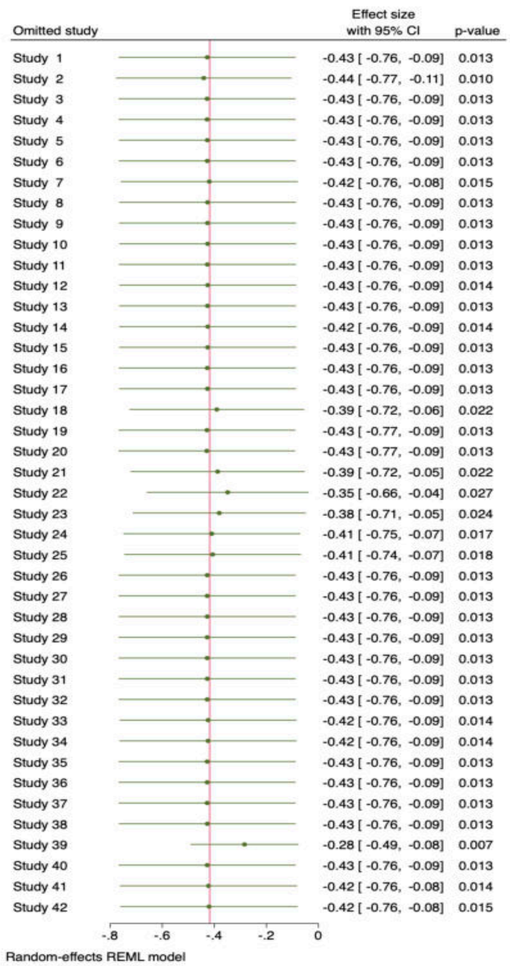


Figure 2: An influence plot from a "leave-one-out" analysis. The red line indicates the overall beta slope when all studies are included in the meta regression. The dots on the horizontal green line indicate the overall beta slope when those studies are removed from analysis (Baldwin & Shadish, 2011).

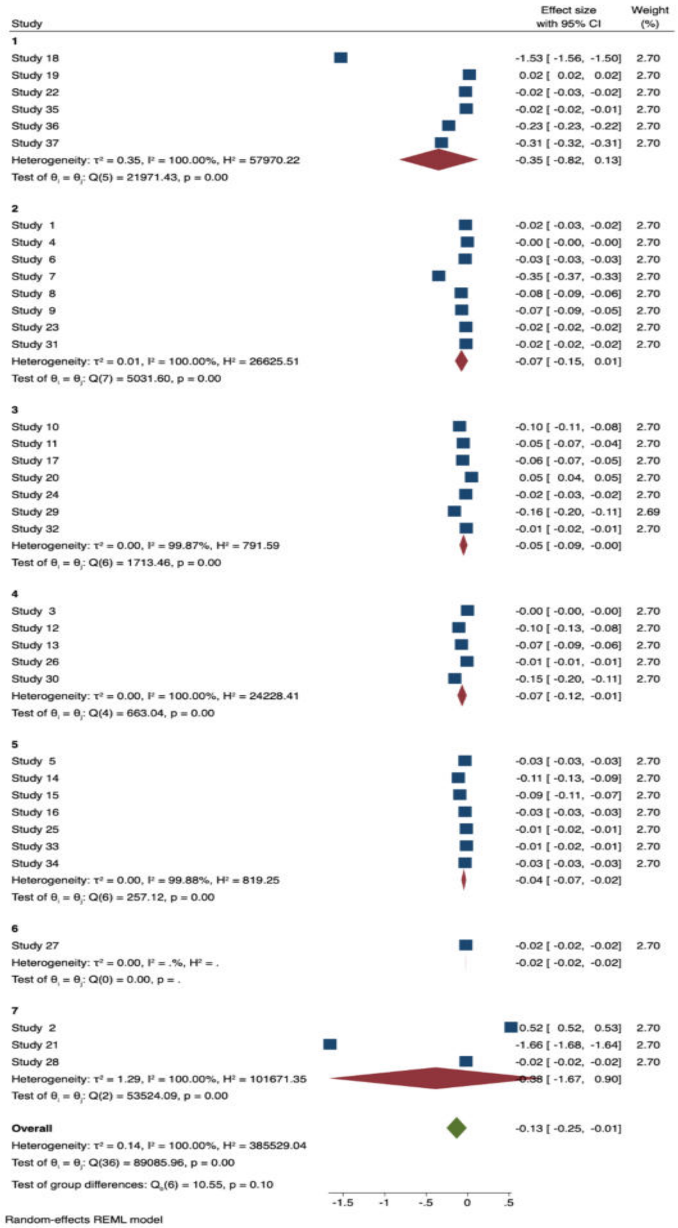
As indicated in figure 2., beta 39 (Shi & Yu, 2020) and beta 22-25 (Liu & Hu, 2021) had a large net negative effect on the overall regression slope. Dropping these studies decreased the Chi2 statistic by 500% (Chi2 = 420,000 to Chi2 = 83160). Even with this reduction, overall heterogeneity stayed extremely high (I2 = 100%, P > Q = .0000). We opted to remove both of these studies from the overall analysis, given their large impact on study results and because they dealt with endogeneity in a different way than all other studies which likely explains their larger beta coefficient. We did not remove any other studies from the analysis because there was no clear reason for their dismissal, and because removing further studies did not lead to a significant decrease in the I2 value.

Main Analysis

Is there a statistically significant negative relationship between increased ambient air pollution exposure and life satisfaction?

The overall regression coefficient for all pollutant types combined was nonsignificant (γ_1 = -.17, 95% CI = -.35 to .02, p =.07). We ran a multiple regression by pollution type to prevent inappropriately grouping of within study effect sizes. Nonsignificant relationships were found for all five measured pollutants except the aggregated pollution beta coefficient. Aggregate survey γ_1 = -.35, 95% CI = -.66 to -.04, p =.028. PM2.5 survey γ_1 = -.073, 95% CI = -.48 to .34, p =.189. PM10 survey γ_1 = -.05, 95% CI = -.47 to 37., p =.167. No2 survey γ_1 = -.07, 95% CI = -.47 to .39, p =.242. SO2 survey γ_1 = -.05, 95% CI = -.04 to .11, p =.161. CO survey γ_1 = -.384, 95% CI = -.92 to .152, p =.895. We could not compute an accurate effect size for OZ due to low sample size (>3). Besides the aggregate pollution effect, these results appear to indicate a nonsignificant negative relationship between subjective well-being and ambient air pollution, however, our model had significant heterogeneity (Q = 83160, p < .001, I^2 = 100%) which may explain the nonsignificant findings as broad heterogeneity reduces statistical power (Baldwin & Shadish, 2011). The statistical significance of the aggregate pollution effect should be interpreted with extreme caution due to the study's high heterogeneity, and thus this result does not indicate clinical significance. Furthermore, we found in exploratory analysis that dropping beta coefficient 18 renders the aggregate effect nonsignificant (γ_1= -.073, 95% CI = -.49 to -.34, p =.196). According to this meta-regression, neither our first hypothesis nor our fourth hypothesis were supported. In accordance with previous guidelines, we decided to analyze potential moderating variables that may explain heterogeneity.

Figure 3. Forest Plot



Moderating Analysis

We conducted a meta regression to assess for moderating influences from spatial and temporal measurement design and geographical region. Due to small sample size, we could not assess the impact of all moderating factors simultaneously. Variations in geography, temporality of air pollution measurement also could not be computed individually due to low sample size.

Heterogeneity Assessment

Heterogeneity is a measure of inconsistency across the study findings (Borenstein et al., 2021). We examined heterogeneity using subgroup meta-regression. Specifically, we checked whether spatial or temporal measurement or geographical region accounted for heterogeneity. Geographically, North America had the most heterogeneous results (h2 = 940,000, I^2 = 100%), followed up Europe (h2 = 640,000, I^2 = 100%), Asia (h2 =18684, I^2 = 99.99%), and South America (h2 = 48.59, I^2 = 97.94%). Overall, controlling for geographical heterogeneity reduced overall heterogeneity by as much as 2%, with studies in South America having the lowest heterogeneity. Spatially, measurement at the regional level had the most heterogeneous results (h2 = 1,300, I^2 = 100%) followed by city level (h2 = 1506.65, I^2 = 99.93%), and finally individual level (h2 = 136.92, I^2 = 99.27%) Overall, controlling for spatial characteristics reduced overall heterogeneity by as much as .07%, with air pollution exposure measured at the individual level having the lowest heterogeneity. Temporally, well-being measurement associated with quarterly measurement of air pollution had the highest heterogeneity (h2 = 150,000, I^2 = 100%) followed by daily measurement (h2 = 130,000, I^2 = 100%) and annual measurement (h2 = 97,613, I^2 = 100%) Overall, controlling for temporal characteristics reduced overall heterogeneity did not reduce heterogeneity. Despite attempts to control for study heterogeneity, no study characteristics accounted for enough variance in measurement to reduce heterogeneity to an appropriate level (Borenstein et al., 2021). Therefore, study results likely do not reflect the true relationship between ambient air pollution and life satisfaction. Hypotheses 1 through 4 could not be accepted or rejected due to broad heterogeneity. Heterogeneity may also be a result of true differences in study population effects rather than due to differences in measurement design as tau was large (T =.096), and thus the well-being of different populations may be impacted differently by air pollution. Due to this fact, the discussion section will focus on how to make studies amenable to better measurement in order to make a future meta-analysis possible.

Publication Bias

To assess for publication bias we used a funnel plot (Stata command: Metafunnel). The funnel plot showed substantial asymmetry, which may suggest publication bias although asymmetry may also be a result of measurement or true heterogeneity (see figure two) (Stuck et al., 1998; Tang & Liu, 2000). Given the broad heterogeneity of the study results, analysis of study bias is unwarranted, thus it is unclear whether publication bias impacted the results of this meta regression.

Figure 4. Funnel Plot

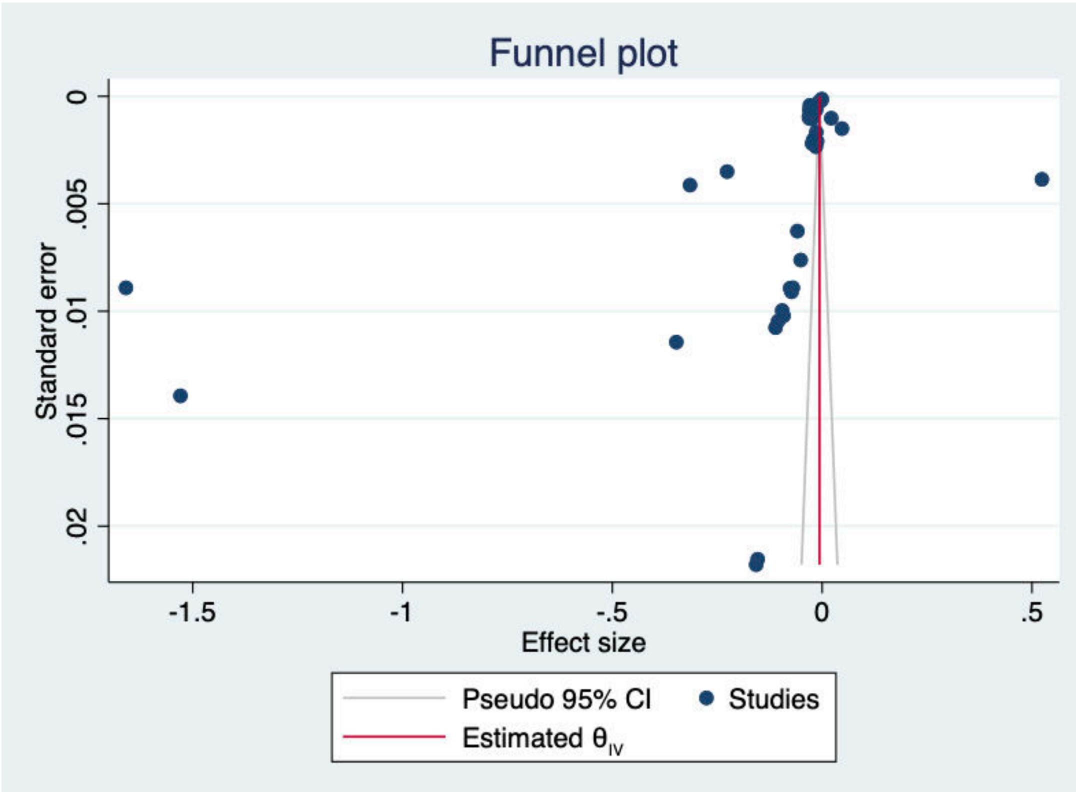
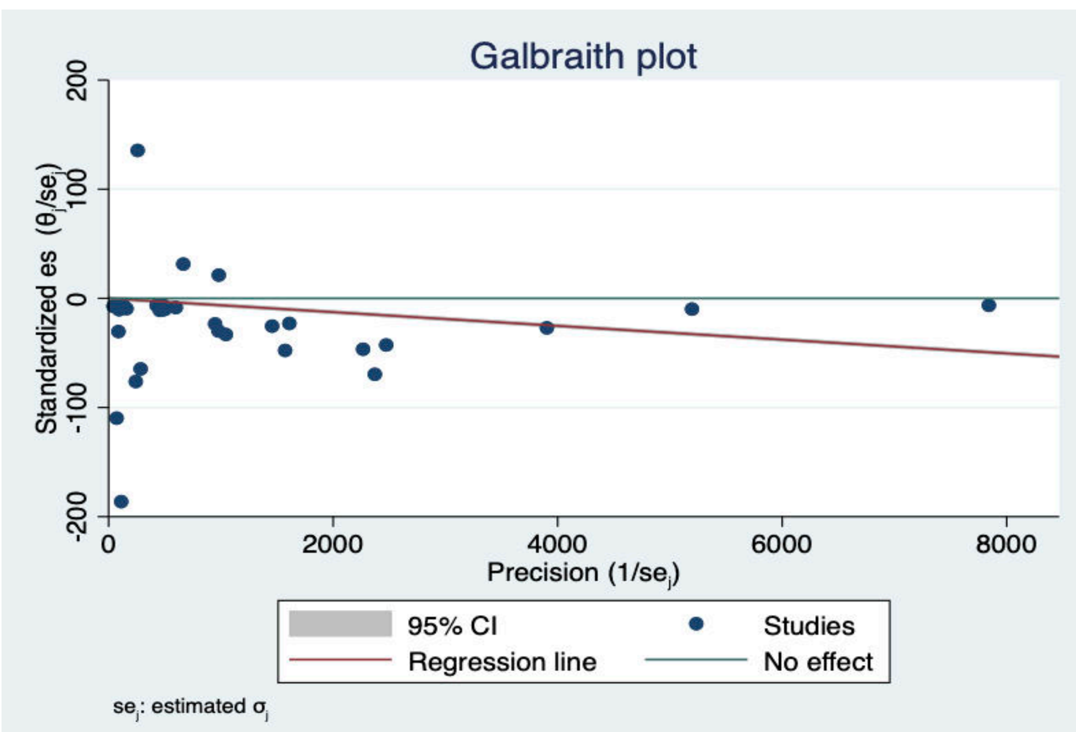


Figure 5. Galbraith Plot



Discussion

We conducted a meta-analysis (n = 17) to assess the relationship between subjective reports of life satisfaction and objective exposure to ambient air pollution. Results from our analysis indicate that there may be no significant relationship between these two variables across studies, although our results are largely inconclusive due to high heterogeneity and poor study design. These findings are contrary to our original hypotheses as we expected to find a significant relationship between air pollution and well-being.

In our analysis of heterogeneity, only measuring pollution exposure on the individual level began to reduce heterogeneity. This finding is important, because it indicates that many studies may not be assessing air pollution exposure with enough specificity, particularly given that amounts of exposure can vary significantly even across small geographical areas.

A second reason for high heterogeneity in our models may be a result of not controlling for subjective perceptions on air pollution exposure. There is ample research support that negative perceptions of air pollution impact the relationship between objective exposure to pollutants and well-being impact (Li & Zhou, 2020). The studies in our analysis did not control for subjective perceptions of exposure, which may help explain the wide variability in findings.

High heterogeneity may also be explained by subjective well-being measurement. As noted previously, all but one of our studies used a single item life satisfaction measure, often couched within a larger social survey. Some research has indicated that single item well-being measures have good psychometric properties; however, individuals in diverse cultures may answer these questionnaires differently and single item measures prevent deeper analysis of the well-being construct (Diamantopoulos et al., 2012)). Specifically, individuals may rate their life satisfaction higher or lower for different reasons and given the small effect sizes in ecological well-being research, these differences in responses may increase the heterogeneity across studies (Tov & Nai, 2018). Given the lack of multi-item measures included in current research, adequately assessing how well-being measurement impacts heterogeneity is not possible at this time.

Limitations

In addition to challenges with high heterogeneity, our research was also limited in several other ways. First of all, we only focused on meta-regression research due to a lack of studies with more complex study designs. This limitation limits the interpretability and generalizability of our results as we cannot compute an overall effect size or odds ratio. Multiple regression cross sectional study designs do not allow for complex understanding of the hierarchical relationships between variables. Therefore, our use of beta-coefficients limits the interpretability of our results.

Second, our study only focused on life-satisfaction as a measure of subjective well-being. We used life satisfaction to measure well-being because the majority of the research in this area has been done using life satisfaction measures, and because hedonic well-being measures have been shown to introduce bias into analysis. However, subjective well-being may be conceptualized more broadly than satisfaction with life. Other components of subjective well-being include present moment positive emotions, satisfaction with physical health, satisfaction with relationships, quality of life, and satisfaction with meaning and significance of life. Air pollution may influence these well-being areas differently, and therefore this study cannot make claims about the influence of air pollution on subjective well-being as a whole.

Future research

Future research on this topic should involve enhanced measurement, more complex study design, and better accounting of confounding variables. The goal of air pollution and well-being research in the first place is to assess how air pollution is actually impacting quality of life, yet current research does not have specificity or the complexity to actually understand the relationship between these variables. By enhancing complexity and specificity, future meta-analyses will be able to understand whether variability in results a result of true heterogeneity is actually or simply measurement error.

Methods have already been developed that will vastly improve the quality of air pollution and well-being measurement, however they are currently not being employed. In the last couple years, researchers have developed wearable air pollution trackers that are both accurate and cost effective (Park, 2021; Park et al., 2021). Future research could have participants wear these trackers for several months and measure subjective well-being at multiple time points. This research would allow for better understanding of individual exposure to air pollution over time and allow for more accurate assessment of the relationship between air pollution and well-being. Well-being measurement can be improved by using multi-faceted well-being measure such as the one used by (Smyth et al., 2011). Increasing measurement quality will greatly enhance future research and will allow for more specific measurement of the impact of air pollution on well-being.

Future research should also focus most explicitly on more complex statistical models assessing well-being and air pollution including hierarchical and SEM approaches. This research has already been started by Li & Zhou (2020), who have illustrated the hierarchical relationships between variables that influence air pollution and well-being in China. More research like this will allow meta-analyses of complex statistical models, which will likely help reduce heterogeneity and better analyze variance between populations. For example, research in this area may indicate an interstudy effect of age on air pollution perceptions and physical health problems that leads to decreased subjective well-being, alternatively this research may demonstrate a nonsignificant relationship across studies as indicated in our research. More complexity in future models will allow for more comprehensive analysis and a better understanding of the relationships between air pollution and well-being.

Future research should also include both perceptions of air pollution exposure and objective measurements of pollutants. Adding perceptions to statistical models will help limit heterogeneity. Completing a meta-analytic review assessing the specific effect of air pollution perceptions on well-being will help provide a quantitative analysis of this area of research. Perceptions are particularly important when analyzing impact on subjective reports of well-being, as individuals' who do not view air pollution as a health risk are unlikely to account for it when assessing their satisfaction with life.

Conclusion

Prior research on subjective well-being and ambient air pollution has indicated that there is a negative effect between increased ambient air pollution exposure and psychological well-being. Our paper sought to assess the magnitude of this relationship across studies, specifically focusing on the relationship between a standardized increase in air pollution and a standardized change in life satisfaction. Our analysis indicated a nonsignificant relationship between these two variables and did not find that this relationship was mediated by pollutant type, geographical location of study, or temporal or spatial specificity of air pollution exposure. Our study, however, had significant heterogeneity (>99%) that severely limited the interpretability of our findings.

Ultimately the goal of studying air pollution and well-being is to improve quality of life. Yet the current research does not provide clear answers on the relationship between these two constructs. Thus far we know that the effect of air pollution on well-being varies significantly between studies. However, this may be a result of either real differences in the subjective experience of air pollution exposure, measurement error, or a combination of the two. Separating measurement error from real variation should be the goal of future research, because at this point the quality of the literature does not offer definitive conclusions.

Understanding the overall impact of air pollution on well-being may require nuance because populations differ in their perceptions about air pollution, and some populations may adapt to higher pollution differently than others. Given that the ultimate goal of this research is understanding how well-being is impacted by a complex ecological environment, seeking to find universal dollar amounts or effect sizes for the relationship between these variables may be less productive than understanding the hierarchical relationships and mechanisms of change. Measuring mechanisms of change such as air pollution perception or impact on physical health will provide more fruitful areas for intervention, rather than simply quantifying the size of the relationship between variables.

Properly understanding mechanisms of change will require examining the constructs with enough specificity and complexity to actually understand how specific communities are being impacted. We hope our systematic review and assessment of heterogeneity will help provide a pathway to future successful meta-analytic and experimental research in this area. With more complex study designs and better measurement, future research will be able to better conceptualize the relationship between well-being and air pollution, and hopefully provide pathways for higher quality of life.

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