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How are you doing today? Air quality and subjective well-being across time and space in Germany

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Almut Balleer, Michael Hirsch, and Marvin Noeller*

How Are You Doing Today? Air Quality and Subjective Well-Being Across Time and Space in Germanys

Abstract

We present evidence that air pollution negatively affects current well-being. To do so, we create a new dataset, matching particulate matter concentration at the exact day and location with individual-level survey responses about current life satisfaction. The panel structure of our data allows us to overcome several identification challenges in the literature. Additionally, we show how aggregation of air pollution across time and space mis-measures the relevant exposure. Our results further suggest that air pollution affects current well-being mostly through negative emotions like sadness or worry. We estimate the willingness to pay for clean air that refers to the direct, immediate effects of air pollution and can be mapped well to economic models.

JEL-Codes: H41, I31, Q53

Keywords: Subjective well-being; air pollution; willingness to pay; compensating variation

July 2025

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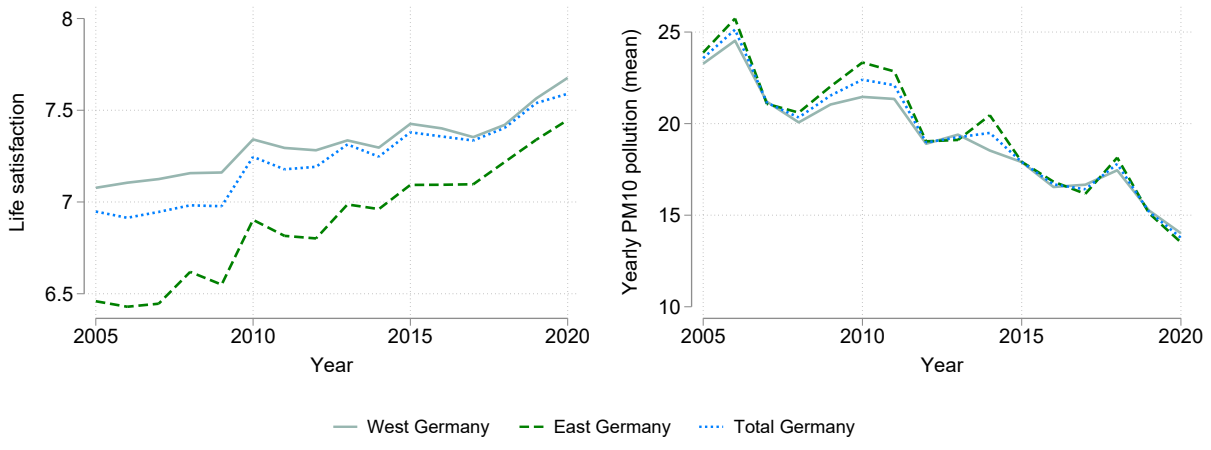
1 Introduction

How does air pollution affect current well-being? A growing body of medical research documents that poor air quality negatively affects mental health, especially anxiety and depression (see, e.g., Zhao *et al.*, 2020). At the same time, the psychological literature has shown that assessments of life satisfaction are often affect-contaminated, i.e., current (short-term) aspects play a disproportionately large role even when general well-being is inquired (Schwartz and Strack, 1991). This suggests a direct negative effect of air pollution on current well-being. In this paper, we combine survey information about current life satisfaction with measures of air pollution at the granular level across time and space. We therefore provide precise estimates of the short-term welfare costs of air pollution which allow us to measure the immanent immediate willingness to pay for improvements in air quality.

We utilize data from the Socio-Economic Panel (SOEP), an annual representative longitudinal survey on socio-economic characteristics of individuals and households in Germany. Individuals in the survey are asked about their current life satisfaction. Air pollution, measured as PM_{10} particulate matter, stems from the the German Federal Environment Agency. Simple aggregate correlations support a negative relationship between current life satisfaction and air pollution (see Figure 1). Crucially, for each individual we know the date and location (district) at which the survey took place. We then combine this information with measures of air pollution on that exact date in that exact location. We show that the granularity of this mapping is important as more aggregate measures across time or space misinform about the air pollution exposure an individual faces when being surveyed.

FIGURE 1: Current life satisfaction and air pollution in Germany over time



(A) Current life satisfaction (B) PM_{10} pollution

Notes: Panel (A) shows current life satisfaction from the Socio-Economic Panel (SOEP). Panel (B) shows PM_{10} pollution in $(\mu g/m^3)$ from the German Federal Environment Agency. Total Germany (blue dotted), East Germany (green dashed) and West Germany (green solid). Annual values for 2005 to 2020.

Exploiting the panel dimension of the survey data, we are able to overcome three obstacles faced by the existing literature on the relationship between air pollution and life satisfaction (cp. Levinson, 2020): First, omitted variable bias (OVB) may be due to many confounding factors that affect an individual's life satisfaction and pollution at the same time such as geographical aspects of the home location. Second, persons who care most about air pollution are likely to live in cleaner places, i.e. there is selection into home locations. Third, habituation makes individuals become accustomed to circumstances which leads them to over- or undervalue their general well-being. Due to the granular mapping and the use of appropriate fixed effects, we exploit variation in current life satisfaction and current local exposure to air pollution for the same individuals over time. This allows us to overcome any time-constant unobserved heterogeneity that results from OVB, selection or habituation. We further include important time-varying aspects such as changes in socio-economic characteristics, income or weather. Our approach therefore measures the direct impact of air pollution on current well-being rather than long-run changes in general well-being.

We find that lower air quality, i.e, higher levels of PM_{10} particulate matter concentration on the day of a survey interview, significantly reduces reported current life satisfaction. Specifically, an increase in daily particulate matter pollution by 10 ($\mu g/m^3$) leads to a reduction in life satisfaction by 0.005264 points on a eleven point-scale. We use these estimates to calculate a willingness to pay for a reduction in air pollution (see Levinson, 2012).[1] The ratio of the coefficients of air pollution and income provides an estimate of how much money compensates the average respondent for a one-unit increase in pollution. In our baseline specification, we estimate the willingness to pay for a reduction in PM_{10} pollution of one standard deviation per day to be \$4.31 in 2016 dollars. This value is among the lowest WTP in the literature according to the survey in Levinson (2020). This is not surprising, since our WTP measure refers to short-run, direct effects of air quality on current life satisfaction, while other measures do not separate these from long-run aspects. Long-run effects of air pollution are important, but do not relate well to economic modeling. Our measure of the immediate WTP corresponds to the characterization of the direct effect of air pollution on utility in economic models and is therefore useful to specify and calibrate utility functions in which air pollution plays a role.[2]

We address the potential endogeneity of income in our life satisfaction analysis by employing income predicted by observables only and document that our measured willingness to pay changes very little. We also show robustness with respect to the functional forms assumed in our regression equation. We estimate our baseline specification using linear OLS and ordered Probit estimation. We further emphasize the importance of our granular time-

[1] Ferreira *et al.* (2024) provide a recent survey on this approach, which can be used more generally to valuate public goods.

[2] See Michel and Rotillon (1995) for an example of a utility function with air pollution and Balleer and Endrikat (2023) for an application using a utility function with air pollution for welfare assessment.

location mapping by means of placebo exercises in which we assign future or past air pollution or air pollution at different locations to our respondents. The results are only significant if air pollution is measured close enough in time and space to the survey date.

As Levinson (2020) discusses, there are different concepts for measuring our well-being: happiness, subjective well-being, and life satisfaction. In a strict interpretation, happiness should refer to short-term circumstances, while life satisfaction should refer to long-term circumstances. However, psychologists find that people mix these terms up which leads to affect-contaminated reporting of life satisfaction. In our survey, people are asked how satisfied they *currently* are with their lives. Our results further support a role for current air pollution to affect stated current life satisfaction. To explore this issue further, we examine how daily variations in air pollution affect health and emotional outcomes. We show that air pollution has no statistically significant effect on reported health. It also does not affect happiness or anger. However, air pollution does have an effect on whether people are sad or worried, which is consistent with the medical literature that documents the link between air pollution, anxiety and depression. Our results therefore suggest that reported current life satisfaction is driven by these negative emotions.

Our study contributes to the broad literature on happiness and well-being in economics (see Clark (2018) for a recent survey). Here, we provide an estimate of to value of clean air as a public good. Doing so, we are by no means the first to study the relationship between air pollution and life satisfaction or happiness. By now there is a vast literature on this topic, surveyed by Frey *et al.* (2010) and more recently by Levinson (2020). Table A.1 in the Appendix contains an overview of the most important contributions. The overwhelming majority of studies is based on cross-sectional data or repeated cross-sections which faces the identification problems described in Levinson (2020). Only five papers use panel data for different countries (these include Abed Al Ahad (2024) and Saliba *et al.* (2023) for the UK, Giovanis and Ozdamar (2017) for Switzerland, Liu and Hu (2021), Zhang *et al.* (2017a), and Zhang *et al.* (2022) for China). There also exist panel data studies that address other aspects of air pollution such as NO_2 or SO_2 or measures of perceived air pollution. It is important to highlight the different environment in different countries. While air pollution is considered a major problem in China, Germany is a country with relatively moderate levels of air pollution, a topic which has received a lot less attention until recently. Studying the link between air pollution and well-being in the European context therefore allows to capture the unconscious link between air quality and life satisfaction. All of the existing studies use annual measures of particulate matter concentration and therefore suffer from the aggregation bias that we document in this paper. Most studies therefore focus on long-term effects of air pollution on general life satisfaction. We provide a more accurate short-term measure that links better to economic theory and enables a better calibration of economic

models of air pollution.[3]

We provide suggestive evidence that air pollution negatively affects life satisfaction by affecting negative emotions in the short-run. This is in line with evidence from Bellani *et al.* (2024), who show that higher levels of air pollution on election days in Germany reduce the voting share for incumbent parties and argue that this is due to more negative emotions. The same mechanism may be behind other outcomes such as productivity (Zivin and Neidell, 2012; Chang *et al.*, 2016; Lichter *et al.*, 2017; He *et al.*, 2019), investor's trading behavior (Huang *et al.*, 2020), or competition (Mo *et al.*, 2023).

The remainder of the paper is structured as follows. In Section 2 we describe our data. We discuss our empirical strategy, stressing the importance of our granular approach for identification, in Section 3. In Section 4 we present our results and Section 5 concludes.

2 Data

For our empirical analysis we combine three different datasets: Survey data from the German Socio-Economic Panel (SOEP), data on particulate matter from the German Environmental Federal Office, and meteorological data from the German Weather Service. Table B.1 provides a full list of all variables.

2.1 Current life satisfaction and individual characteristics

Data on current life satisfaction and individual characteristics are provided by the SOEP, an annual representative longitudinal survey on socio-economic characteristics of individuals and households in Germany (Goebel *et al.*, 2019). The survey is available since 1984 and contains information on roughly 15,000 households and 30,000 individuals for each wave. Due to the availability of data on air quality described below, we restrict the sample period to 2008 to 2020. In this period we observe an individual on average for approximately five waves of the survey, which provides a relatively long panel.

The main variable of interest for our application is a survey question on current life satisfaction (LS):

How satisfied are you currently with your life in general?

Respondents are asked to give their assessment on a scale from 0 to 10, where 0 indicates complete dissatisfaction and 10 indicates complete life satisfaction. This scale has not changed since 1984. The life satisfaction data obtained from the SOEP have been used in a large

[3]Closest to our setup is Zhang *et al.* (2017a) who combine three waves of the China Family Panel Studies (2010, 2012, and 2014) with daily and local data on air pollution, measured by means of an air pollution index. Schmitt (2013) uses a fixed effects estimation in an earlier sample of the SOEP ending in 2008 to measure how life satisfaction is affected by CO, NO_2 and O_3 outcomes.

number of studies to measure subjective well-being (e.g. Luechinger, 2009; Sarmiento *et al.*, 2023). Besides the assessment of current life satisfactions, the SOEP also contains questions with respect to affective well-being since 2007. Specifically, individuals are asked how often they felt angry, sad, happy and worried in the past four weeks. Answers can be given according to a five-point scale, where 1 equals very rarely and 5 equals very often. If life satisfaction is driven by short-run aspects of mental health, it should be related to these measures of affective well-being.

Two aspects of the survey are key for our analysis: First, during the interview, no questions are asked about perceived air quality, satisfaction with air quality or perceived pollution levels.[4] Thus, the interview takes place in a completely framing-free context. Moreover, the questions on life-satisfaction and affective well-being do not refer to environmental aspects or aspects of air quality. Individuals therefore have no incentive to overestimate or underestimate their life satisfaction with regard to their own air quality preferences in a strategic context (Frey *et al.*, 2004). Second, the SOEP provides both the district number of the respondent's registration address and the survey date.[5] This allows to match data on air quality and other weather conditions at the district level for the exact survey date. Interviews take place all year, but more often in the first half of the year (see Figure B.1).

In addition to the data on life satisfaction, we include survey data both from the household and individual panels as additional control variables in our analysis. These questions cover age, marriage status, the number of children, nationality, the level of education, whether or not an individual is unemployed, subjective health status, disability status, as well as environmental and economic concerns. Moreover, we have information on income at the household level, which is crucial to calculate willingness to pay from our regressions. We use the German Consumer Price Index to calculate real income in 2020 terms. Table B.2 shows summary statistics for all variables in our dataset. Individuals in our survey data are between 16 and 105 years old, with an average of 47.46 years. Approximately 60% of the respondents are married and 10.59% of the participants have a disability. With respect to the economic situation, the average monthly net household income is €3,299.06 and 8.03% of the individuals were registered as unemployed. 94.19% of the participants have a school-leaving certificate and 23.38% have a university degree. The average life satisfaction in our sample is 7.31.

[4]Note that every five years there is a question on perceived air quality included in the survey. However, this question is part of the household survey only, is asked in a section about regional characteristics, and is only answered by one person of each household. By contrast, the question on life satisfaction is asked to every survey participant in the section on personal information.

[5]The respective districts are recorded using a recoded district code. This is the status as of 31 December 2017. Districts that merged during the observation period are included with the status as of 2017 (e.g. city of Aachen and district of Aachen to form the StädteRegion Aachen).

2.2 Air quality

Air pollution is measured in PM_{10} which describes airborne particles with a diameter of less than or equal to 10 μm.[6] The data on particulate matter pollution concentration measured as $\mu g/m^3$ is provided by the German Federal Environment Agency (UBA). The UBA provides data on particulate matter since the mid 1990s.[7] However, the number and the geographical distribution of the measuring stations was rather small until 2008. At the beginning of 2000, particulate matter was measured at 197 stations across Germany. However, large parts of Germany were not covered by these stations, for example the majority of North Rhine-Westphalia, the most densely populated federal state. This did not change until 2008, when the EU Air Quality Directive 2008/50/EC and the resulting recommendations for assessing and monitoring air quality introduced standardized requirements for the number and location of monitoring stations (European Parliament, 2008). These regulatory changes led to an increase in both the number and the geographical variation of measuring stations (see Figures B.2 and B.3 for the number and distribution of measuring stations over time.). To keep our sample as representative as possible with respect to regional coverage we restrict ourselves to the period from 2008 to 2020.

We merge the data on air quality with our survey data at the survey day-district level. To this end, we have to aggregate daily data from individual stations to the district level.[8] There is at least one measuring station in 255 of 401 districts (294 rural districts and 107 urban districts). If measuring stations are located within a district, the district-level PM_{10} pollution is calculated as the daily mean within a district. If no data are available for a district, the missing value is interpolated as the mean value of the neighboring districts. According to Schmitt (2013), the calculation of mean values for a district has a significant advantage due to the use of measured values from rural and urban stations. In urban areas, the stations are closer to the main roads and generally have higher pollutant values. These higher values are offset by the inclusion of rural stations, which generally measure lower values. 68 percent of the survey responses relate to direct district-level air quality measures, the remaining responses are merged to interpolated measures. In a robustness check, we investigate whether this interpolation affects our results. The average PM_{10} in our sample is 21.3 $\mu g/m^3$. This is well above the desired limit value of 15 $\mu g/m^3$ as recommended by the WHO (2021).

2.3 Meteorological data

As described by Mukherjee and Agrawal (2017), the formation and accumulation of particulate matter is influenced by the amount of precipitation, the duration of sunshine, the

[6]For more information, see `https://www.epa.gov/pm-pollution`
[7]For more information, see `https://www.umweltbundesamt.de/daten/luft/feinstaub-belastung`
[8]Some of the stations measure air quality hourly. We take the daily average for these stations.

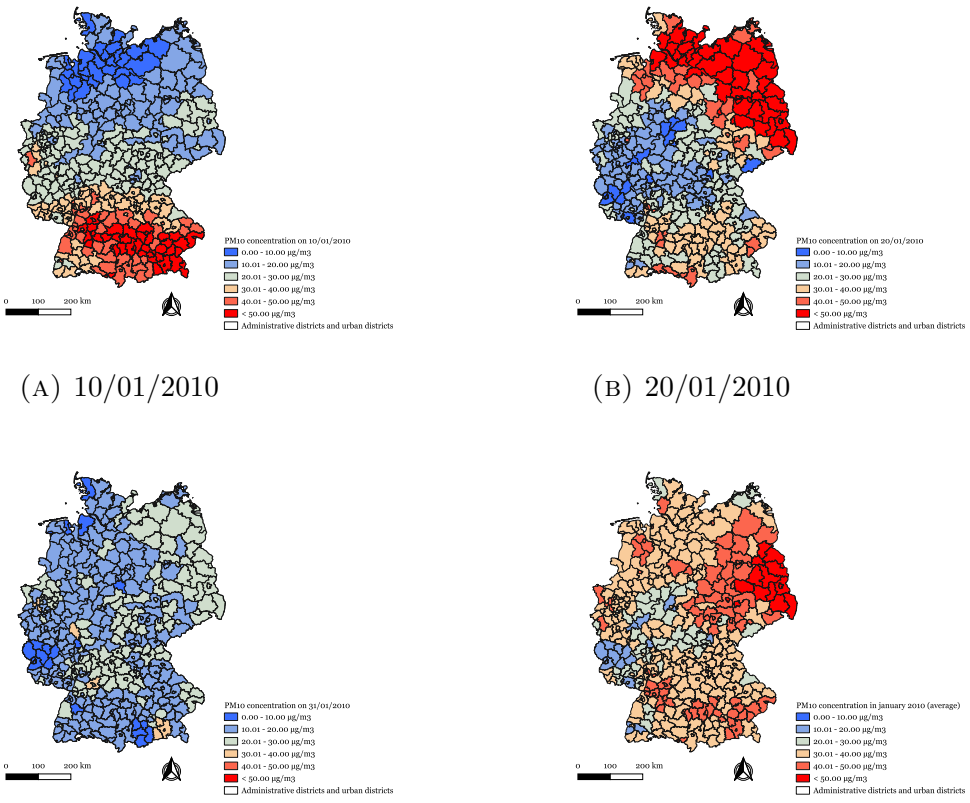
temperature and the wind speed. Therefore, we collect the corresponding meteorological measures from the the German Weather Service.[9] We aggregate meteorological measures in accordance to air pollution. If measuring stations are missing, we apply the corresponding interpolation procedure described above.

3 Empirical strategy

We merge information on current life satisfaction and air pollution exposure at the day-district level. We then exploit time variation within individuals to estimate a causal relationship between air pollution and life satisfaction conditional on other control variables. Below, we describe our identification strategy and estimation approach in detail.

3.1 Identification

FIGURE 2: PM_{10} pollution during January 2010



(A) 10/01/2010 (B) 20/01/2010

(C) 31/01/2010 (D) January 2010 (mean)

Notes: Particulate matter pollution from the German Federal Environment Agency. GIS data from `https://www.bkg.bund.de/DE/Home/home.html`. The administrative boundaries are as of 31 December 2017.

[9]For more information, see: `https://cdc.dwd.de/portal/`

Three aspects are important for identification. First, our granular day-district match is important as aggregation across time and/or across regions leads to mis-measured exposure of air pollution of the individuals in the survey. Second, individual fixed effects address time constant unobserved heterogeneity. Third, time-varying aspects that affect both current life satisfaction and air pollution are appropriately controlled for.

To investigate the role of aggregation of air pollution across time and space, Figure 2 plots daily particulate matter pollution for the 401 districts in our sample over the course of January 2010. Overall, the distribution of high and low particulate matter pollution varies a lot within a month. For example, on January 10 (Figure 2a) pollution is particularly high in the south of Germany. On January 20 (Figure 2b) air pollution is very high in the north eastern part of Germany. On January 31 (Figure 2c), air pollution is at a low to moderate level in all parts of Germany. When we calculate the monthly average of air pollution (Figure 2d), these regional differences vanish and we see a relatively high degree of air pollution across Germany. In addition to the within month variation, we also see a lot of within year variation in air pollution. This variation throughout the year can be observed in almost every district. We depict two examples. Figures B.4 and B.5 plot daily levels of air pollution over the years 2008, 2012, 2016, and 2020 for the districts "Altenburger Land", a more rural district in the eastern part of Germany and "Karlsruhe", a more urban district in the south-western part of Germany, respectively. For both regions we observe the classic U-shaped pattern over the course of the year, with high levels of particulate matter in the winter months and low levels in the summer month.[10] This pattern over the year also illustrates why calculating annual averages of air pollution as done in previous studies might be misleading. Due to the observed seasonal trend, annual averages would not adequately reflect the fluctuations in air pollution and their impact on life satisfaction. Also, annual measures include future particulate matter exposure at dates after the interview and not known to the respondent.

In addition to the temporal variation within districts, aggregation in space is equally problematic. Take the example of the "StädteRegion Aachen". The particulate matter pollution fluctuates within the month of January 2010 from 27.36 ($\mu g/m^3$) (on the 10th) to 17.04 ($\mu g/m^3$) (on the 20th) to 14.31 ($\mu g/m^3$) (on the 31st). That is we see a steady decline in air pollution over the course of the month. If we aggregate to the state of North Rhine-Westphalia, the corresponding pollution levels are 22.88645 ($\mu g/m^3$), 18.76526 ($\mu g/m^3$), and 20.31247 ($\mu g/m^3$). Thus, we first see a decrease in the level of air pollution and then an increase. This, again, is different from the dynamics at the country level (28.69393 ($\mu g/m^3$), 30.24084 ($\mu g/m^3$), and 19.212345 ($\mu g/m^3$)), where we first observe an increase and then a decrease. The use of data at a more aggregate regional level would therefore not capture the

[10] The higher concentration of particulate matter during the winter months is due to increased emissions from anthropogenic sources (heating systems) and the meteorological conditions prevailing at that time (Czernecki *et al.*, 2017).

actual pollution level and variation of this experienced by survey participants.

In our analysis below, we estimate placebo specifications in which we assign future or past air pollution to the survey respondents. We also assign air pollution in far away districts. This enables us to show whether and how the granular time-location measurement of current life satisfaction and air pollution matters for the results.

A large part of life satisfaction is genetically determined. Therefore, subjective answers of survey respondents are affected by unobserved, temporally persistent characteristics like intelligence, extraversion, or optimism (Diener *et al.*, 2018). These characteristics are roughly constant over time and can thus be captured by individual level fixed effects (Ferrer-i Carbonell, 2013; Nikolova and Graham, 2021). In fact, Ferrer-i Carbonell and Frijters (2004) note that ignoring such individual effects leads to biased estimates of the determinants of happiness. In addition, characteristics specific to the home location may affect both general life satisfaction and air pollution, e.g. the geographic location. Estimating individual fixed effects requires sufficient variation within individuals over time. Both current life satisfaction and PM_{10} pollution exhibit substantial within variation within individuals as Table B.2 in the Appendix documents. For air pollution, the within variation is larger than the between variation and is only 15 percent smaller than the overall variation. Current life satisfaction and air pollution are negatively correlated at the individual level both overall and within individuals over time.[11]

Existing studies document the influence of the meteorological data on life satisfaction (e.g., Schmitt (2013), Levinson (2013), or Barrington-Leigh and Behzadnejad (2017a)). Du *et al.* (2018) and Sanduijav *et al.* (2021), however, find no significant correlation between meteorological variables and life satisfaction. Barrington-Leigh and Behzadnejad (2017b) explicitly recognize that meteorological variables are important confounders when estimating the impact of air pollution on life satisfaction. As meteorological variables vary with time, they are not captured by the above-mentioned fixed effects. We therefore need to control for these variables in our estimation. Another potential concern to our identification strategy are persons that move between districts between two surveys. We address this issue in a robustness check based on a sample without movers.

3.2 Baseline regression

We estimate the following equation:

$$LS_{ijt} = \alpha P_{jt} + \gamma \ln Y_{ijt} + \beta_1 X_{ijt} + \beta_2 W_{jt} + \delta_i + \eta_s + c_j + \varepsilon_{ijt}. \quad (1)$$

[11] The overall correlation is -0.035 and the correlation of the variation within individuals over time is -0.0036.

Here, LS_{ijt} measures current life satisfaction of individual i in district j at survey-date t. Our treatment variable is P_{jt}, which measures particulate matter pollution (measured in PM_{10} in $\mu g/m^3$) within the district area j at survey-date t. Y_{ijt} is the net household income, defined as the income of the household in which individual i is registered.[12] We include income in logarithms to capture the decreasing marginal utility of income on life satisfaction (Jebb *et al.*, 2018). Ahumada and Iturra (2021), Levinson (2012), or Schmitt (2013) use a related approach. X_{ijt} is a vector of various socio-economic and demographic factors, namely age, age squared, nationality, martial status, children under 14, unemployed, disability, college, and subjective health status. W_{jt} is a vector of meteorological variables that were measured in the district j at survey-date t. We add individual level fixed effects δ_i. η_s includes year, month, and week-day fixed effects, respectively. c_j is a location specific fixed effect. We adjust error terms ε_{ijt} for heterogeneity and autocorrelation. Generally, our specification closely follows Levinson (2012), except that we estimate a panel with individual-level fixed effects.

We estimate Equation (1) using OLS. This follows most of the literature (e.g. Levinson, 2012; Mendoza *et al.*, 2019; Frey and Steiner, 2012; Sanduijav *et al.*, 2021; Ahumada and Iturra, 2021). Ferrer-i Carbonell and Frijters (2004) and Ferrer-i Carbonell (2013) show that estimated effects on life satisfaction in ordered Probit models are very similar to those obtained from an OLS estimation. We estimate our model by means of a Probit model as a robustness check.

Our coefficient of interest is α, which measures the change in life satisfaction on a eleven point scale in response to a change in experienced air pollution P. However, this coefficient is hard to interpret. Since income is included in our regression, we follow Levinson (2012) and use the estimated coefficients to calculate the willingness to pay for individuals to reduce PM_{10} exposure by one unit. To this end, after estimation we can fully differentiate Equation (1) to obtain

$$\frac{\partial LS \;/\; \partial P}{\partial LS \;/\; \partial Y} = \left.\frac{\mathrm{d}Y}{\mathrm{d}P}\right|_{\mathrm{d}LS=0} = -Y\frac{\hat{\alpha}}{\hat{\gamma}} \tag{2}$$

which provides the marginal rate of substitution (MRS) between pollution and income: $\mathrm{d}Y/\mathrm{d}P$. Here, $\hat{\alpha}$ and $\hat{\gamma}$ are the estimated coefficients of particulate matter pollution and household income based on estimating Equation (1). Y is the average monthly net household income. As in Levinson (2012) we interpret the MRS as willingness to pay for a change in air quality of 1 ($\mu g/m^3$) PM_{10}. It therefore reflects the amount of income that one would need to pay agents at higher levels of air pollution when life satisfaction should remain constant.

[12] This follows Levinson (2012) and Schmitt (2013). We also estimate equation 1 using net labour income in a robustness check.

4 Results

This section documents our baseline results and an extensive set of robustness checks. We also explore heterogeneity in the estimated effects across different sub-groups in our data. Finally, we shed some light on a potential mechanism underlying our estimated relationship between air quality and life satisfaction.

4.1 Baseline results

TABLE 1: Life satisfaction and air pollution

	Pollution and Income (1)	Add time and local fixed effects (2)	Including demographic variables (3)	Baseline Specification (4)	Instrument for income (5)
Daily PM_{10} pollution ($\mu g/m^3$)	-0.0044129**	-0.0004137*	-0.0004068**	-0.0005264**	-0.000574*
	(0.0002207)	(0.0002464)	(0.0001899)	(0.0002119)	(0.0003419)
ln(household income)	0.6235703***	0.6340879***	0.1907975***	0.1907774***	0.2051628***
	(0.005171)	(0.0053956)	(0.0110668)	(0.0110675)	(0.0655286)
Demographic covariates	No	No	Yes	Yes	Yes
Meteorological covariates	No	No	No	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes
Location fixed effects	No	Yes	Yes	Yes	Yes
Person-fixed effects	No	No	Yes	Yes	Yes
Observations	337,416	337,416	316,385	316,385	135,093
Adjusted (*within*) R^2	0.0500	0.0795	0.0700	0.0700	0,0587
Observation period	2008-2020	2008-2020	2008-2020	2008-2020	2013-2020
Average income	€3,285.67	€3,285.67	€3,394.84	€3,394.84	€3,046.32
SD of PM_{10}	13.18301	13.18301	13.31754	13.31754	11.81988
WTP for a reduction of ($\mu g/m^3$) for one year	€279,03	€25,72	€86,86	€112,41	€102,28
WTP for a reduction in the SD by one day	€10,08	€0,93	€3,17	€4,10	€3,31

Notes: Columns (1) and (2) are estimated with Pooled OLS. Columns (3) to (5) are estimated with fixed effects estimation. The dependent variable is individual current life satisfaction measures on a scale of 0 to 10. Demographic control variables: age, age squared, nationality, region, martial status, children under 14, unemployed, disability, college, subjective health status. Meteorological control variables: precipitation, average temperature, average temperature squared, temperature difference, hours of sunshine and wind speed. All specifications use robust standard errors. Statistical significance is indicated by ***p < 0.01; **p < 0.05. and *p < 0.10. SD: standard deviation. WTP: willingness to pay. In column (5), WTP is calculated using the average household income estimated in equation (3). The average household income of the sample is €3,804.33.

Table 1 presents results of estimating Equation (1). In column (1) we estimate a version of Equation (1) without any fixed effects, socioeconomic controls, or weather controls. In column (2), we add time and location fixed effects, in column (3) we add individual fixed effects and demographic variables. Throughout we find a statistically significant negative effect of air pollution on current life satisfaction. As expected the estimated coefficient gets smaller

once we introduce fixed effects. The point estimate hardly changes, however, when we control for demographic variables. We estimate our baseline specification in column (4), where we add meteorological covariates. According to this estimate, life satisfaction significantly decreases with daily pollution and increases with monthly net household income. Concretely, an increase in daily particulate matter pollution by 10 ($\mu g/m^3$) leads to a reduction in life satisfaction by 0.005264 points. Interestingly, the estimated coefficient for particulate matter pollution increases compared to the model without meteorological data. This confirms the importance of these variables to control for the correlation between weather, air pollution, and life satisfaction (Ahumada and Iturra, 2021).

The coefficient of income on life satisfaction is positive and significant. Based on the coefficients of air pollution and income, we calculate the willingness to pay for a reduction in air pollution according to Equation (2). The average income in this sample is €3,394.84. Together with the estimated values for $\hat{\alpha}$ and $\hat{\gamma}$ this implies a willingness to pay for a reduction in PM_{10} pollution in terms of average income for our sample period of €112.41 in 2020 terms. However, as the PM_{10} coefficient is determined on the basis of daily varying pollution values, Levinson (2012) recommends determining the marginal willingness to pay for a reduction in particulate matter pollution by one standard deviation for one day. Accordingly, we divide the WTP in terms of annual income by 365 days and multiply with the standard deviation of PM_{10} pollution, which is 13.31754 ($\mu g/m^3$). This results in a willingness to pay for a one-standard deviation reduction in PM_{10} pollution for one day of €4.10. To compare our resulting WTP to the literature, we calculate it in terms of 2016 US-Dollars. We use the Consumer Price Index to convert our WTP into 2016 terms and then use the average Euro-Dollar exchange rate for the year 2016 to arrive at WTP of roughly $4.31. This value is among the lowest WTP in the literature according to the survey in Levinson (2020). This is not surprising, since our WTP measure refers to short-run effects of air quality on current life satisfaction, while other measures do not separate these from long-run aspects.

One important concern in estimating willingness to pay is the endogeneity of income (Levinson, 2012). People are more satisfied with their life when they earn more (Kaiser, 2020). At the same time, people earn more because they are more satisfied with their life in general (Elsas, 2021). To deal with this endogeneity problem, we estimate a version of our model in which we instrument for income. The literature typically follows the approach of Luttmer (2005) who predicts the income of an individual based on observable characteristics which excludes variation based on life satisfaction.[13] We predict income based on the following regression

$$\begin{aligned} Y_{ijt} = \alpha + \beta_1 Male_i + \beta_2 Age_i + \beta_3 {Age_i}^2 + \delta Industry_i \\ + \theta Occupation_i + \gamma(Industry_i \times Occupation_i) + \epsilon_{ijt}, \end{aligned} \tag{3}$$

[13] Due to the limitations of Luttmer's approach, we also tested a second instrument based on Huang *et al.* (2018) approach. Results are available upon request.

where Y_{ijt} is income of individual i, in region j in year t, $Male$ is a dummy indicating gender, Age measures individual i's age in years, $Industry$ is the NACE Rev. 2 industry code for individual i's industry and $Occupation$ is the ISCO08 occupational classification. Since the required industry and occupation classifications are only available since 2013, the sample size is reduced considerably. We delete negative income predictions from our sample and, following Kaiser (2020), aggregate the remaining incomes to the household level. Then, we use the predicted income as our instrument in a two-stage least square estimation.[14] Column (5) in Table 1 shows the results. The estimated coefficients from the IV regression hardly differ from the baseline OLS estimates for both air pollution and income. The willingness to pay for a reduction in particulate matter pollution by one standard deviation is now €3.31.

4.2 Robustness

We perform three groups of robustness checks. First, we address whether the specification of Equation 1 affects our results. Second, we run a set of placebo regressions in order to address the importance of our granular mapping across time and space. Third, we investigate the role of the interpolation, subsamples and location specific trends.

Table 2, Panel A, shows estimates of Equation 1 using different functional forms. In Column (1) we estimate the model with income as a linear function, i.e. household income enters the estimation in levels not in logarithms. As before, we find that daily PM_{10} exposure has a negative and statistically significant effect on life satisfaction, with an estimated coefficient very close to our baseline regression. Also the effect of income on life satisfaction remains positive and significant. Due to the different functional form the MRS is the result of the division of the two coefficients $\hat{\alpha}$ for particulate matter pollution and $\hat{\gamma}$ for income by each other. This implies a willingness to pay of €1,545.08 of annual net household income for a reduction in particulate matter pollution by 1 ($\mu g/m^3$), or a willingness to pay of €56.37 for a reduction in PM_{10} pollution by one standard deviation. These implausibly high numbers are due to the fact that in this specification we do not take into account the decreasing marginal utility of income on life satisfaction. Jebb *et al.* (2018) show that annual income saturation of evaluative well-being occurs at $60,000 - $75,000. In Column (2) we therefore estimate a model with income as a linear function restricting our sample to individuals with reported annual incomes of maximal €72,000. The resulting willingness to pay of €82.40 of annual net household income and €3.02 for the reduction of particulate matter pollution by one standard deviation are more reasonable. In Column (3) we estimate a version of our model in which we take logarithms of both air pollution and income. The annual willingness

[14]The F-Statistic for the first stage is 2,755.25

Table 2: Robustness

A: Functional forms

	Linear income (1)	Linear income (up to €72,000) (2)	log(income) & log(PM_{10}) (3)	Probit model (4)
Daily PM_{10} pollution ($\mu g/m^3$)	-0.0005073**	-0.0004434**	-0.0088425*	-0.0029646***
	(0.0002121)	(0.0002249)	(0.0053147)	(0.0001337)
ln(household income)	0.00000417*	0.0000743***	0.1929497***	0.34672***
	(0.00000211)	(0.00000471)	(0.0115739)	(0.00289)
Observations	316,403	289,407	316,633	337,416
Adjusted (*within*) R^2	0.0685	0.0707	0.0141	0.0119
Observation period	2008-2020	2008-2020	2008-2020	2008-2020
Average income	€3,394.65	€2,895.19	€3,394.81	€3,285.67
SD of PM_{10}	13.31746	13.35762	13.31694	13.18301
WTP for a reduction of ($\mu g/m^3$) for one year	€1,459.86	€71.61	€86.70	€337.13
WTP for a reduction in the SD by one day	€53.26	€2.62	€3.16	€12.18

B: Placebo

	Time placebo (t_{+270}) (5)	Time placebo (t_{-270}) (6)	Time placebo (t_{-2}) (7)	Time placebo (t_{-1}) (8)	Local placebo (9)
Daily PM_{10} pollution ($\mu g/m^3$)	-0.00014	-0.0001185	-0.0001197	-0.0005654***	-0.000071
	(0.0002078)	(0.0003639)	(0.0002081)	(0.0002105)	(0.0002167)
ln(household income)	0.1904231***	0.1906855***	0.1907013***	0.1906839***	0.1907151***
	(0.010727)	(0.0110749)	(0.0110667)	(0.0110681)	(0.0110747)
Adjusted (*within*) R^2	0.0700	0.0700	0.0701	0.0701	0.0700
Observations	316,196	316,218	316,357	316,357	316,218
Observation period	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020
Average income	€3,394.74	€3,394.681	€3,394.82	€3,394.82	€3,394.68
SD of PM_{10}	13.60298	8.754095	13.28868	13.2774	12.34552
WTP for a reduction of ($\mu g/m^3$) for one year	€29.95	€25.32	€25.57	€120.79	€15.17
WTP for a reduction in the SD by one day	€1.12	€0.61	€0.93	€4.39	€0.51

Notes: All models except the Probit model use fixed effects estimation. The dependent variable is individual current life satisfaction scaled from 0 to 10. Except for the Probit model, all models use the covariates and fixed effects of our baseline specification. Demographic control variables: age, age squared, nationality, region, martial status, children under 14, unemployed, disability, college, subjective health status. Meteorological control variables: precipitation, average temperature, average temperature squared, temperature difference, hours of sunshine and wind speed. Robust standard errors were used. Statistical significance is indicated by ***p < 0.01; **p < 0.05. and *p < 0.10. SD: standard deviation. WTP: willingness to pay. The results shown in the Probit model (4) merely describe the direction and significance of the effect. They should not be compared with the marginal effects from the fixed effects model. In Columns (5) to (9), air pollution at the correct date and location is replaced with the respective placebo measure.

to pay is now €99.08 and thus almost unchanged compared to the baseline estimate.[15]

In Column (4) we estimate equation (1) as an ordered probit model. As described above, by estimating an ordered probit model we rely less on the assumption of cardinality.[16] We confirm the result in previous studies (e.g. Ambrey *et al.*, 2014; Levinson, 2012; Ferrer-i Carbonell and Frijters, 2004) that the significance and sign of the main coefficients remain unchanged. Life satisfaction decreases with increasing particulate matter pollution and increases with disposable income.

Table 2, panel B, addresses the importance of the exact mapping of air pollution to the survey responses in time and space. First, we run a placebo test by estimating the effect of air pollution in the same region 270 days in the future (Column (5)) and 270 days in the past (Column (6)) on life satisfaction. In both cases we do not find any significant impact of air pollution on current life satisfaction. In Columns (7) and (8) we consider air pollution closer to the day of the interview. Up until two days before the survey date, we do not find any significant effect. However, if we consider the pollution level one day before the survey takes place, the negative effect of air pollution on current life satisfaction is significant and very similar to the one from our baseline estimation. This suggests a delayed and very short-lived effect on life satisfaction. This seems plausible as there is a strong correlation of 0.75 between PM_{10} pollution measured on the day of the interview and measured on the day before, which already decreases to 0.53 between the day of the interview and two days before. In column (9), we run a placebo test in which we assign survey participants to the level of air pollution measured on the day of the interview in the most distant district.[17] As expected, we do not find any significant effect of air pollution in a different region on current life satisfaction.

We also estimate our baseline regression focusing only on individuals who live in a county for which we do not have to rely on interpolated values. We still find a significant negative effect of air pollution on current life satisfaction, and the estimated coefficient is fairly similar to the one we get from our baseline regression (see Column (6) in Table C.1). We further investigate if movers between districts drive our results by estimating a model in which we only consider individuals that did not move between counties in our sample period. Note that in this estimation our regional fixed effects are not identified anymore and fully absorbed by the individual level fixed effects. Even without movers we find a statistically significant negative effect of air pollution on current life satisfaction with an estimated coefficient which

[15]The MRS is now calculated using the formula:

$$\left.\frac{\partial Y}{\partial P}\right|_{\mathrm{d}LS=0} = \frac{\hat{\alpha} \times Y}{\hat{\gamma} \times P} \tag{4}$$

[16]For more information, see Ferrer-i Carbonell and Frijters (2004) or MacKerron (2012).

[17]Due to the arrangement of the districts within Germany, five districts are the most distant districts for all districts in Germany (1001 "Flensburg Stadt", 1054 "Nordfriesland", 9172 "Berchtesgadener Land", 13073 "Vorpommern-Rügen", and 13075 "Vorpommern-Greifswald").

is again very close to the one from our baseline estimation (see Column (7) in Table C.1). In a final robustness check we include a year-county fixed effect to our estimation as in Levinson (2012). Again the results hardly differ from our baseline estimates (see Column (8) in Table C.1).

4.3 Heterogeneity

Having established that air pollution has on average a negative impact on reported life satisfaction, we now address heterogeneity. Table 3 shows results for a specification in which we interact air pollution with income (Column (1)), health status (Column (2)), stated concerns about the economy or the environment (Columns (3) and (4)), and living in urban districts (Column (5)). Air pollution affects life satisfaction less when income is high. This suggests the possibility to offset adverse effects of air pollution with higher income (potentially through expenses for leisure activities or avoidance of pollution effects). Air pollution also affects life satisfaction less when in poor health or living in urban districts. This is surprising at first. Poor health itself has a strong effect on life satisfaction and may, as a consequence, make respondents less sensitive to additional, short-run deterioration of pollution. In urban districts, air pollution is generally high which may result in smaller adverse effects of additional pollution. With respect to economic and environmental concerns we do not detect any meaningful heterogeneity in the effect of air pollution on current life satisfaction. Personal aspects rather than general concerns therefore play a much more central role for the relationship between air pollution and life satisfaction.[18]
We also investigated interactions with gender and different age groups. We do not find any heterogeneity with respect to these demographic characteristics (see Table C.2 in the Appendix).

4.4 Towards a potential mechanism

One may argue that survey questions about life satisfaction refer to life in general and should therefore not be influenced to a large extend by current aspects such as air pollution on the day of the interview. How can it be that such a short-lived experience as high levels of air pollution influences the evaluation of a live as a whole? The psychological literature has shown that a number of daily events such as finding a coin (Schwartz and Strack, 1991) or the victory of one's favourite sports team can have an impact on the assessment of our life in general (Janhuba, 2019; Schwarz *et al.*, 1987). Put differently, how individuals assess their life can be influenced by an affect-contaminated component. These affect-contaminated components can be either physical or psychological. Regarding our research question, this

[18]Interestingly, economic and environmental concerns do significantly relate to other affections. Table C.3 in the Appendix shows the regressions corresponding to Table 3 using annoyance, i.e. having been angry for more than 4 weeks, as an outcome variable.

TABLE 3: Heterogeneity

	Income	Poor state of health	Economic concerns	Environmental concerns	Urban districts
	(1)	(2)	(3)	(4)	(5)
Daily PM_{10} pollution ($\mu g/m^3$)	-0.0004049*	-0.0007456***	-0.0005467**	-0.0003831	-0.0008312***
	(0.0002101)	(0.000215)	(0.0002255)	(0.0002429)	(0.0002491)
Interaction term	0.0005875*	0.0011413**	-0.0001083	-0.0000463	0.0008655**
	(0.0003249)	(0.0005548)	(0.0004546)	(0.0003875)	(0.00038)
Interacting variable		-0.2094546***	-0.101479***	0.0056577	0.04514364
		0.0175145	0.0128712	0.0111763	0.5307806
Covariates of the base model	Yes	Yes	Yes	Yes	Yes
Fixed effects of the base model	Yes	Yes	Yes	Yes	Yes
Person-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	316,385	316,385	305,997	285,622	316,385
Adjusted (*wihtin*) R^2	0.0701	0.0712	0.0721	0.0722	0.0701
F test PM_{10} and interaction = 0	4.03**	6.67***	3.6**	1.67	5.76***
Observation period	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020

Notes: All columns use fixed effects estimation. The dependent variable is individual current life satisfaction scaled 0 to 10. Demographic control variables: age, age squared, nationality, region, martial status, children under 14, unemployed, disability, college, subjective health status. Meteorological control variables: precipitation, average temperature, average temperature squared, temperature difference, hours of sunshine and wind speed. Robust standard errors were used. Statistical significance is indicated by ***p < 0.01; **p < 0.05. and *p<0.10.

means that air pollution can have a negative effect on an individual's (subjective) health status or can affect certain aspects of our mood, which in turn changes our assessment of life satisfaction, especially current life satisfaction. The SOEP provides information about an individual's subjective health status. Respondents are asked "How would you describe your current health?" with answering options ranging from "bad" to "very good" on a five-point scale. The SOEP also asks survey participants separately if they feel happy, sad, worried, or angry. Answers can be given according to a five-point scale, where 1 equals very rarely and 5 equals very often.

Table 4 documents the results from estimating Equation (1) where we replace the dependent variable with health and emotional variables. In Column (1) we estimate the effect of air pollution on subjective health status and do not find any significant effect, suggesting that the effect of air pollution on overall life satisfaction is not driven by a short-term change in subjective health. We also estimate our baseline regression with life satisfaction without controlling for health and show results in Column (2). Our estimated coefficients hardly change compared to our baseline estimates. In Columns (3) to (6) we estimate Equation 1 with emotional assessments. While we do not find any significant effect of daily exposure to particulate matter on being happy (Column (3)) or being angry (Column (6)), we do find that air pollution has a significant positive effect on both being sad (Column (4)) and being worried (Column (5)). This is at least suggestive evidence that exposure to higher levels of air pollution causes individuals to evaluate their overall life more negatively because they feel sad or worried (or both) as a result of this exposure. This finding is consistent with medical

TABLE 4: PM_{10} pollution, health outcomes and affections

	Health	LS w/out health	Happy	Sad	Worried	Angry
	(1)	(2)	(3)	(4)	(5)	(6)
Daily PM_{10} pollution ($\mu g/m^3$)	-0.0001203	-0.0004776**	-0.0000956	0.0002618*	0.0002721**	0.0000176
	(0.0001145)	(0.0002184)	(0.0001177)	(0.0001492)	(0.0001381)	(0.0001467)
ln(household income)	-0.0039306	0.1930028***	0.034222***	-0.0812464***	-0.0634647	0.0072219
	(0.0057439)	(0.011574)	(0.0059353)	(0.0073712)	(0.0069507)	(0.0072381)
Covariates of the base model	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects of the base model	Yes	Yes	Yes	Yes	Yes	Yes
Person-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	316,385	316,633	285,125	285,143	285,026	285,258
Adjusted (*within*) R^2	0.0196	0.0141	0.0294	0.0323	0.0332	0.0206
Observation period	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020

Notes: All columns use fixed effects estimation. The dependent variable is the subjective health status (1), life satisfaction (2) or a measure of current affections. Demographic control variables: age, age squared, nationality, region, martial status, children under 14, unemployed, disability, college, subjective health status. Health status is excluded in column (2). Meteorological control variables: precipitation, average temperature, average temperature squared, temperature difference, hours of sunshine and wind speed. Robust standard errors were used. Statistical significance is indicated by ***p < 0.01; **p < 0.05. and *p < 0.10. SD stands for standard deviation.

studies like Casas *et al.* (2017) or Vert *et al.* (2017) on particulate matter exposure and mental health. According to these studies particulate matter pollution has a direct impact on the psyche and can lead to mental disorders, anxiety and depression. This is because PM_{10} can cause inflammation and hormonal changes, which can promote anxiety and depression (Zhao *et al.*, 2020). The results are also consistent with the study by Bellani *et al.* (2024). They also find a negative influence of PM_{10} on components of affective well-being.

5 Conclusion

In this paper we provide novel evidence on the relationship between air pollution and life satisfaction in Germany. We combine data on life satisfaction and air pollution at the exact day and location (district) and show how aggregation across time and/or space may mismeasure the relevant air pollution exposure of survey respondents. Our research design then exploits time variation in current air pollution exposure for individuals over time and allows us to tackle several identification challenges of the literature on air pollution and life satisfaction simultaneously (Levinson, 2020). We show significantly negative effects of higher particulate matter concentration on life satisfaction in the short-run. To shed some light on the underlying mechanism, we provide suggestive evidence that, at least at the daily frequency we consider, health and air pollution are not significantly related. Instead, our results suggest that air pollution affects negative emotions that can be related to anxiety or depression. This is in accordance to the psychological literature which argues that a short-term change in affective well-being can influence the assessment of overall life satisfaction.

Based on our estimates we calculate a willingness to pay for a one-standard deviation reduction in air pollution on one day of $4.31 in 2016 terms. This willingness to pay represents a measure of the direct, immediate effect of air pollution on current well-being. It is therefore at the lower range of existing estimated. It can directly be used to inform economic modeling, i.e., the specification and calibration of utility functions with air quality. This is useful for model-based welfare assessment of air pollution and the possibility to perform counterfactual exercises with such as model. Our results therefore have implications for current policy debates. The European Commission's "Beyond GDP" program, for example, aims at identifying what affects prosperity over and above GDP.

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A Literature overview

TABLE A.1: Literature review: pollution and well-being

	Title	Authors	Sample	Number of observations	Happiness data	Air quality
1	Air Pollution Reduces the Individuals' Life Satisfaction Through Health Impairment	Abed Al Ahad (2024)	Panel	347,377	Life satisfaction (1-7)	$PM_{2.5}$, PM_{10}, NO_2 and SO_2 (yearly concentrations)
2	If the air was cleaner, would we be happier? An economic assessment of the effects of air pollution on individual subjective well-being in Chile	Ahumada and Iturra (2021)	Cross section	22,202	Life satisfaction (1-5)	$PM_{2.5}$ (annual concentration)
3	Estimating the cost of air pollution in South East Queensland: An application of the life satisfaction non-market valuation approach	Ambrey *et al.* (2014)	Cross section	919	Life Satisfaction (0-10)	PM_{10} (Number of days per year on which the average daily PM_{10} concentration exceeds 50 ($\mu g/m^3$)
4	Evaluating the short-term cost of low-level local air pollution: a life satisfaction approach	Barrington-Leigh and Behzadnejad (2017a)	Repeated cross section	34,587	Life satisfaction (1-5) Life satisfaction (1-10)	SO_2, NO_2, CO and $PM_{2.5}$ (daily concentrations)
5	Subjective well-being approach to environmental valuation: evidence for greenhouse gas emissions	Beja (2012)	Cross section	12,211 (Europe and USA), 8,469 (Latin America), 13,978 (Asia and Pacific), 8,750 (Sub-Sahara and Africa)	Life satisfaction (1-10)	Million tons of CO_2, N_2O, CH_4 and other greenhouse gas emissions (SF_6, HFC, PFC) Five-year average
6	Environment and Happiness: New Evidence for Spain	Cuñado and De Gracia (2013)	Cross section	2,565	Happiness (1-10)	NO_2, CO_2 (emissions in tons per regional area (in km^2)) (annual average) PM_{10} (Number of days per year on which the average daily PM_{10} concentration exceeds 50 ($\mu g/m^3$)
7	Gross national happiness as an answer to the Easterlin Paradox?	Di Tella and MacCulloch (2008)	Repeated cross section	344.294 (Europe), 371.149 (Europe and US)	Life satisfaction (1-10)	SOx emissions in kg per capita
8	Bad air days: The effects of air quality on different measures of subjective well-being	Dolan and Laffan (2016)	Cross section	129,393	Life Satisfaction (0-10) Happiness (0-10) Anxiety yesterday (0-10) Worthwhileness of activities (0-10)	$PM_{2.5}$ (annual local mean)
9	Geografically weighted regression models for ordinal categorical response	Dong *et al.* (2018)	Cross section	2,656	Life satisfaction (1-5)	$PM_{2.5}$ (annual average)

	variables: An application to geo-referenced life satisfaction data					
10	Variability in impact of air pollution on subjective well-being	Du *et al.* (2018)	Cross section	958 (Beijing) 878 (Shanghai)	Life satisfaction (0-10)	SO_2, NO_2, PM_{10} and $PM_{2.5}$ (daily concentrations)
11	On the use of subjective well-being data for environmental valuation	Ferreira and Moro (2010)	Cross section	1,184	Subjective well-being (1-7)	PM_{10} (annual local mean)
12	Income and preferences for the environment: evidence from subjective well-being data	Ferreira and Moro (2013)	Cross section	1,063	Life satisfaction (1-7)	PM_{10} (annual local mean)
13	Life satisfaction and air quality in Europe	Ferreira *et al.* (2013)	Repeated cross section	43,874	Life satisfaction (0-10)	SO_2 (annual regional mean)
14	Environmental degradation and happiness	Ferrer-i Carbonell and Gowdy (2007)	Cross section	8,910	Life satisfaction (1-7)	Perception of pollution, grime or other environmental problems at home
15	Neighborhood Determinants of Quality of Life	Gandelman *et al.* (2012)	Cross section	1,248	Quality of life (1-4)	Perceived absence of air pollution
16	Workplace environmental conditions and life satisfaction in Spain	García-Mainar *et al.* (2015)	Repeated cross section	32,317	Life satisfaction (0-10)	Number of days per year in which PM_{10} exceeds 50 ($\mu g/m^3$)
17	Structural Equation Modelling and the Causal Effect on permanent Income on Life Satisfaction: The Case of Air Pollution Valuation in Switzerland	Giovanis and Ozdamar (2017)	Panel	71,084	Life satisfaction (0-10)	O_3, SO_2, NO_2, CO and PM_{10}
18	Unhappy cities	Glaeser *et al.* (2016)	Cross section	261,987	Life satisfaction (1-7)	PM_{10} (annual mean)
19	Regional Air Quality and Happiness in Germany	Goetzke and Rave (2015)	Cross section	7,802	Life satisfaction (0-10) Perceived air pollution (1-5)	SO_2, NOx and PM_{10}
20	Effect of ambient air quality on subjective well-being among Chinese working adults	Guo *et al.* (2021)	Cross section	12,859	Life satisfaction (0-5) Happiness (0-5)	Quarterly PM_{10}, CO and AQI values
21	Happiness and Air Pollution	Jidong and Yiran (2015)	Cross section	6,626	Happiness (1-5)	NO_2 (annual local mean)
22	Can clean air make you happy? Examining the effect of nitrogen dioxide (NO_2) on life satisfaction	Knight and Howley (2017)	Panel	199,602	Life satisfaction (1-7)	NO_2 (annual mean at lower super output areas)
23	A Bayesian Model Averaging Approach to the Transfer of Subjective Well Being Values of Air Quality	León and Araña (2015)	Cross section	3,830	Life satisfaction (1-5)	NO_2, SO_2 (Air pollution within a 50 km × 50 km cell at the time of survey)
24	Valuing public goods using happiness data: The case of air quality	Levinson (2012)	Repeated cross section	6,035	Happiness (1-3)	PM_{10}, OZ, SO_2 and CO (daily concentrations)
25	Environmental quality and life satisfaction: Subjective versus objective measures of air quality	Liao *et al.* (2015)	Cross section	1,055	Life satisfaction (1-5)	Percent days in June 2010 when local pollution index below "good"
26	Happiness and air quality:	Limayani and Tanur (2024)	Cross section	74,684	Happiness (1-4)	SO_2 and NO_2 (annual

	microdata analysis in Indonesia					concentration measured with IKU)
27	How does air quality affect residents' life satisfaction? Evidence based on multiperiod follow-up survey data of 122 cities in China	Liu and Hu (2021)	Panel	25,247	Life satisfaction (1-5)	SO_2, NO_2, PM_{10} AQI and API (annual concentrations)
28	Effect of time-varying exposure to air pollution on subjective well-being	Liu *et al.* (2021)	Cross section	2,901	Subjective well-being (1-5)	PM_{10}, $PM_{2.5}$, SO_2 and AQI (hourly concentrations)
29	The Influence of Air Pollution on Happiness and Willingness to Pay for Clean Air in the Bohai Rim Area of China	Liu *et al.* (2022)	Cross section	6,552	Happiness (1-5)	$PM_{2.5}$ measured as number of days exceeding 75 ($\mu g/m^3$)
30	Valuing air quality using the Life Satisfaction Approach	Luechinger (2009)	Panel	227,789	Life satisfaction (0-10)	SO_2 (annual concentration)
31	Life Satisfaction and Transboundary Air Pollution	Luechinger (2010)	Repeated cross section	223,982	Life satisfaction (1-4)	SO_2 (annual concentration)
32	Life satisfaction and air quality in London	MacKerron and Mourato (2009)	Cross section	331	Life satisfaction (0-10)	$NO2 and PM10$ (annual concentration)
33	Valuation of the air quality in Chile: The life satisfaction approach	Mendoza *et al.* (2019)	Cross section	37,315	Life satisfaction (1-10)	Annual average of PM_{10} and $PM_{2.5}$
34	Do people habituate to air pollution? Evidence from international life satisfaction data	Menz (2011)	Repeated cross section	249	Life satisfaction (1-4)	PM_{10} (annual average)
35	Population aging and environmental preferences in OECD countries: The case of air pollution	Menz and Welsch (2010)	Repeated cross section	136	Life satisfaction (1-4)	PM_{10} (urban population weighted annual country averages)
36	Life-cycle and cohort effects in the valuation of air quality: evidence from subjective well-being data	Menz and Welsch (2012)	Repeated cross section	59,437	Life satisfaction (1-4)	SO_2 and NO_2 (annual means)
37	Well-being and environmental quality: Does pollution affect life satisfaction?	Orru *et al.* (2016)	Repeated cross section	3,770	Life satisfaction (0-10)	PM_{10} (annual concentration)
38	Exposure to air pollution and crime in the neighbourhood: Evidence from life satisfaction data in Turkey	Ozdamar (2016)	Repeated cross section	36,322	Life satisfaction (1-5)	Self-reported air pollution (1-3; severely exposed, somewhat exposed, not exposed)
39	The Causal Effects of Income Support and Housing Benefits on Mental Well-Being: An Application of a Bayesian Network	Ozdamar and Giovanis (2017)	Panel	7,848	Mental well-being (0-12)	NOx, O_3, CO (weekly local average)
40	Examining air pollution (PM_{10}), mental health and well-being in a representative German sample	Petrowski *et al.* (2021)	Cross section	3,020	Life satisfaction (1-5)	PM_{10} (annual average)
41	Local environmental quality and life-satisfaction in Germany	Rehdanz and Maddison (2008)	Panel	23,014	Subjective well-being (0-10)	Perceived air pollution (1-5; 1=not at all affected by

						air pollution , 2=slightly, 3=bearable, 4=strongly, 5=very strongly)
42	Willingness to Pay for Clean Air: Evidence from the UK	Saliba *et al.* (2023)	Panel	201,129	Life Satisfaction (1-7) Hedonic happiness (0-36)	NO_2, $PM_{2.5}$ and PM_{10} (annual mean at lower super output areas)
43	Air pollution and happiness: Evidence from the coldest capital in the world	Sanduijav *et al.* (2021)	Cross section	771	Life satisfaction (0-10)	PM_{10} and $PM_{2.5}$ (daily concentrations)
44	Subjective well-being and air quality in Germany	Schmitt (2013)	Panel	105,575	Life satisfaction (0-10)	CO, NO_2 and O_3 (daily county concentrations)
45	Reevaluating the subjective welfare loss of air pollution	Shi and Yu (2020)	Repeated cross section	33,737	Happiness (1-5)	$PM_{2.5}$ (annual concentration)
46	Objective air quality index versus subjective perception: which has a greater impact on life satisfaction?	Shi *et al.* (2022)	Cross section	396	Life satisfaction (1-5)	Objective air pollution: $PM_{2.5}$, NO_2, SO_2 and AQI (monthly average concentration); Subjective Perception of air pollution (1-5)
47	Environmental Quality and Life Satisfaction: Evidence Based on Micro-Data	Silva *et al.* (2012)	Cross section	4,880	Life satisfaction (satisfied vs. dissatisfied)	PM_{10} (annual average concentration)
48	The environment and well-being in urban China	Smyth *et al.* (2008)	Cross section	8,890	Subjective well-being (1-5)	SO_2 emissions (tons per capita)
49	A Study of the Impact of Environmental Surroundings on Personal Well-Being in Urban China Using a Multi-Item Well-Being Indicator	Smyth *et al.* (2011)	Cross section	2,741	Personal well-being index (1-10)	SO_2 (kgs per capita in 2007)
50	Assessing the effects of haze pollution on subjective well-being based on Chinese General Social Survey	Song *et al.* (2019)	Cross section	9,561	Subjective well-being (1-5)	$PM_{2.5}$ (average annual concentration)
51	Monetary valuations of life conditions in a consistent framework: The life satisfaction approach	Tsurumi and Managi (2017)	Cross section	29,921	Life satisfaction (0-10)	SPM (Suspended PM) at time of survey
52	Health-related and non-health-related effects of $PM_{2.5}$ on life satisfaction: Evidence from India, China and Japan	Tsurumi and Managi (2020)	Cross section	5,988 (India), 15,515 (China), 8.983 (Japan)	Life satisfaction (1-5)	$PM_{2.5}$ (average annual concentration)
53	Life Satisfaction and Air Pollution in Latin America	Vienne	Repeated cross section, Panel, Cross section	19,715 81 716	Life satisfaction (1-4)	$PM_{2.5}$, PM_{10} and CO_2 (annual average)
54	Preferences over Prosperity and Pollution: Environmental Valuation Based on Happiness Surveys	Welsch (2002)	Cross section	54	Happiness (1-4)	SO_2, NO_2, PM and Phosphorus (annual mean)
55	Environment and Happiness: Valuation of Air Pollution Using	Welsch (2006)	Cross section	80	Life satisfaction (1-4)	NO_2, PM and lead (annual)

	Life Satisfaction Data.					
56	Environmental welfare analysis: A life satisfaction approach	Welsch (2007)	Cross section	54	Happiness (1-4)	NO_2 (annual concentration)
57	Tax Payment, Social Copntribution For Pollution Prevention and Happiness	Xu and Li (2016)	Cross section	1,991	Happiness (1-4)	Perceived seriousness of pollution (1-4) (yearly)
58	Subjective well-being and environmental quality: The impact of air pollution and green coverage in China	Yuan *et al.* (2018)	Cross section	18,441	Life satisfaction (0-10)	Air quality index (SO_2, NO_2, PM_{10}, CO, O_3, $PM_{2.5}$)
59	Happiness in the air: How does a dirty sky affect mental health and subjective well-being?	Zhang *et al.* (2017a)	Panel	49,333	Life satisfaction (1-5) Hedonic unhappiness (0-4)	API (air pollution index: SO_2, NO_2, PM_{10})
60	Valuating Air Quality Using Happiness Data: The Case of China	Zhang *et al.* (2017b)	Cross section	21,589	Hedonic happiness (0-4)	$PM_{2.5}$, PM_{10}, CO, NO_2, O_3, SO_2 (daily concentrations)
61	The impact of air pollution on individual subjective well-being: Evidence from China	Zhang *et al.* (2022)	Panel	63,340	Life satisfaction (1-5)	$PM_{2.5}$ (annual concentration)
62	Air pollution lowers Chinese urbanities' expressed happiness on social media	Zheng *et al.* (2019)	Cross section	39,529	Happiness index (0-100)	$PM_{2.5}$ (daily concentration)

Notes: Source: Authors. In line number **53**, the repeated cross section took place at individual and country level. The panel only took place at country level. The cross section part consisted of an investigation at individual city level. Studies that are close to ours are marked in gray. In particular line **44** and **59**.

B Data Appendix

Table B.1: Variable list

Variable	Description
Life satisfaction	Indicated life satisfaction on a scale from 0 to 10
ln(household income)	Ln of the real net household income of the previous month in € converted to 2020
Net income	Real net income of the previous month of a working person in € converted to 2020
Gender	Gender-specific information, where 1 means a man, 0 means a woman and 3 means other
Age	Age of the individual in years
Age squared	Age squared
Married	Dummy variable equals one if the person is currently living in a partnership
Children under 14	Number of children under 14 living in the household
Nationality	Dummy variable equals one if the person is a German citizen
College degree	Dummy variable equals one if the person has a university degree
Unemployment	Dummy variable equals one if the person is currently registered as unemployed
Subjective health status	Self-assessed health status from 1 (very good) to 5 (very poor)
Disability	Dummy variable equals one if the person is disabled, unable to work
Poor state of health	Dummy variable equals one if the self-assessed health status from a person is 4 (poor) to 5 (very poor)
65 years and older	Dummy variable equals one if the person is 65 years or older
Environmental concerns	Dummy variable equals one if the person is very concerned about the environment
Economical concerns	Dummy variable equals one if the person is very concerned about economic development
Region	Dummy variable equals one if the person currently lives in East Germany
Urban	Dummy variable equals one if the person currently lives in a urban district
Happy	Frequency of being happy in the last 4 weeks from 1 (very seldom) to 5 (very often)
Sad	Frequency of being sad in the last 4 weeks from 1 (very seldom) to 5 (very often)
Worried	Frequency of being worried in the last 4 weeks from 1 (very seldom) to 5 (very often)
Angry	Frequency of being angry in the last 4 weeks from 1 (very seldom) to 5 (very often)
PM_{10}	Daily PM_{10} pollution in ($\mu g/m^3$)
Wind speed	Average wind speed at a height of approx. 10 m in m/s
Precipitation amount	Daily precipitation in mm
Sunshine hours	Daily sunshine duration in hours
Average Temperature	Daily mean air temperature at 2 m altitude in °C
Average temperature squared	Squared daily mean air temperature at 2 m altitude in $^{C}\circ$
Temperature difference	Difference between maximum and minimum air temperature

Notes: Sample 2008 - 2020. Life satisfaction, demographic variables, concerns and emotional variables from SOEP. Air pollution and meteorological variables from German Federal Environment Agency.

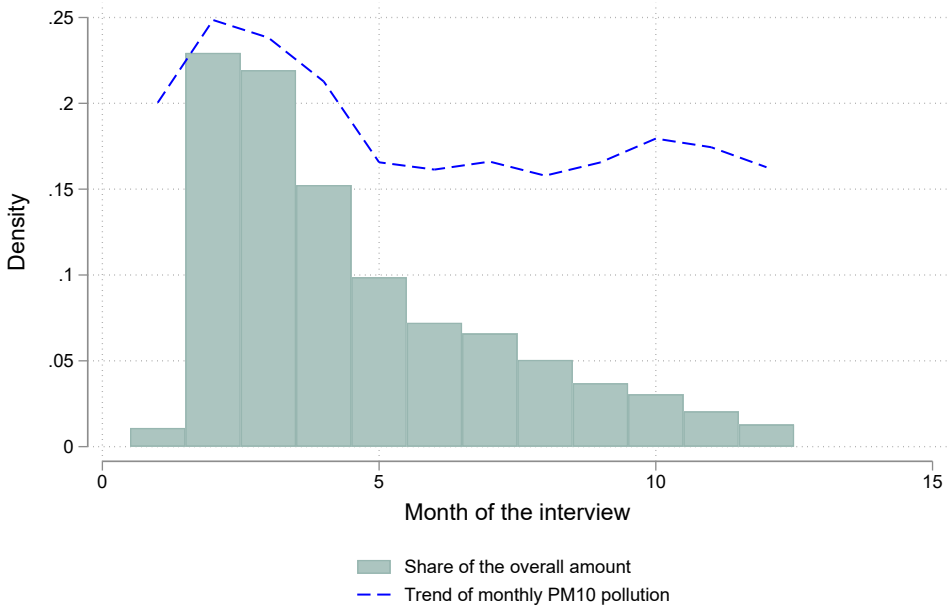
TABLE B.2: Descriptive statistics

	N	Mean	Std. Dev.	Min	Max
Life satisfaction	355,564	7.306881	1.751631	0	10
Within	74,312		1.08734	-1.593119	14.94325
Between	74,312		1.546228	0	10
Happy	302662	3.576931	0.8456737	1	5
Within	59,591		0.5593235	-0.115377	6.993597
Worried	302,542	2.336285	1.014517	1	5
Within	59,586		0.656989	-1.511443	5.625309
Sad	302,693	2.336285	1.014517	1	5
Within	59,585		0.704969	-1.027352	6.028592
Angry	302,811	2.765114	1.003938	1	5
Within	59,583		0.6940741	-0.9271935	6.310569
Monthly real net household income	337,448	3,299.059	4,817.182	0	1,732,926
Within	71,765		2,241.312	-522,523.5	529,121.6
Gender	335.660	0.4762379	0.4994358	0	1
Within			0.0084594	-0.3987621	1.351238
Age	355,562	47.45769	17.35834	16	105
Within	74,310		2.592953	39.31484	55.70769
Married	353,947	0.5922045	0.4914255	0	1
Within	73,929		0.1592277	-0.3308724	1.515281
Children under 14	355,564	0.6052525	1.0077	0	10
Within	74,312		0.3595405	-4.061414	5.105253
Nationality	355,553	0.8435508	0.3632812	0	1
Within	74,309		0.0557543	-0.0795262	1.766628
School degree	342,469	0.9419568	0.2338255	0	1
Within	71,164		0.0670592	0.0188799	1.77529
College degree	354,312	0.2338532	0.4232805	0	1
Within	74,079		0.076612	-0.6892237	1.15693
Unemployment	346,123	0.0803096	0.2717723	0	1
Within	70,573		0.1705094	-0.8427673	1.003387
Subjective health status	355,248	2.548186	0.9863018	1	5
Within	74,295		0.5659856	-0.8803854	6.048186
Disability	335,520	0.1059341	0.3077537	0	1
Within	67,888		0.1373431	-0.8171429	1.029011
Environmental concerns	303,264	1.824094	0.6354695	1	3
Within	61,870		0.3192414	-0.6177423	1.228412
Economical concerns	324,631	0.2048326	0.4035798	0	1
Within	62,700		0.306134	-0.7182444	1.127909
Region	355,564	0.2109184	0.4079612	0	1

Within	74,312		0.0550636	-0.7121585	1.133995
PM_{10}	355,564	21.30773	13.17321	0.12	208.97
Within	74,312		11.1927	-72.71727	154.0762
Between	74,312		8.092494	0.97	114.945
Wind speed	355,564	3.502685	1.712632	0.3	24.4
Within	74,312		1.361561	-4.097315	19.75653
Precipitation amount	355,564	1.82774	4.006857	0	133.1
Within	74,312		3.488976	-33.19726	120.3157
Sunshine hours	355,564	4.990163	4.313013	0	16.5
Within	74,312		3.670131	-6.36198	18.06209
Average Temperature	355,564	8.791939	7.03748	-19.1	31.6
Within	74,312		4.948519	-18.66806	32.24622
Average temperature squared	355,564	126.8242	143.6923	0	998.56
Within	74,312		104.1487	-373.5389	840.4425
Temperature difference	355,564	9.275952	4.338478	0.0369999	25.45
Within	74,312		3.545165	-4.624047	24.67595

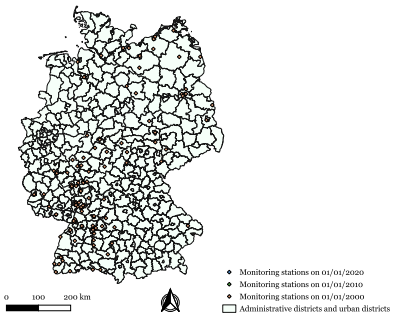
Notes: Sample 2008 - 2020. Life satisfaction, demographic variables, concerns and emotional variables from SOEP. Air pollution and meteorological variables from German Federal Environment Agency.

FIGURE B.1: Survey months and PM10 exposure

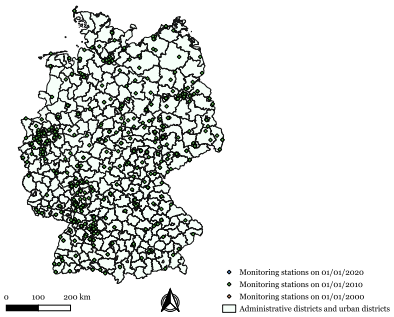


Notes: Sample 2008 - 2020. Interview months from SOEP (1= January and 12=December). PM_{10} pollution (blue line) from German Federal Environment Agency measured as average monthly PM_{10} pollution in the respective month over the entire period. The y-axis reflects the density of interviews conducted in the respective month. 356,160 observations.

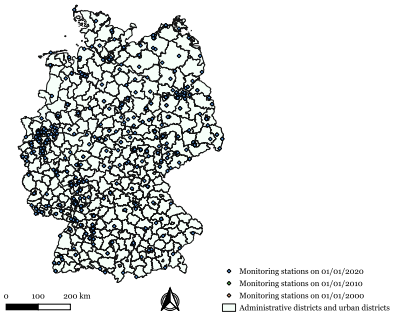
FIGURE B.2: Monitoring stations in Germany



(A) Monitoring stations on 31/12/2000



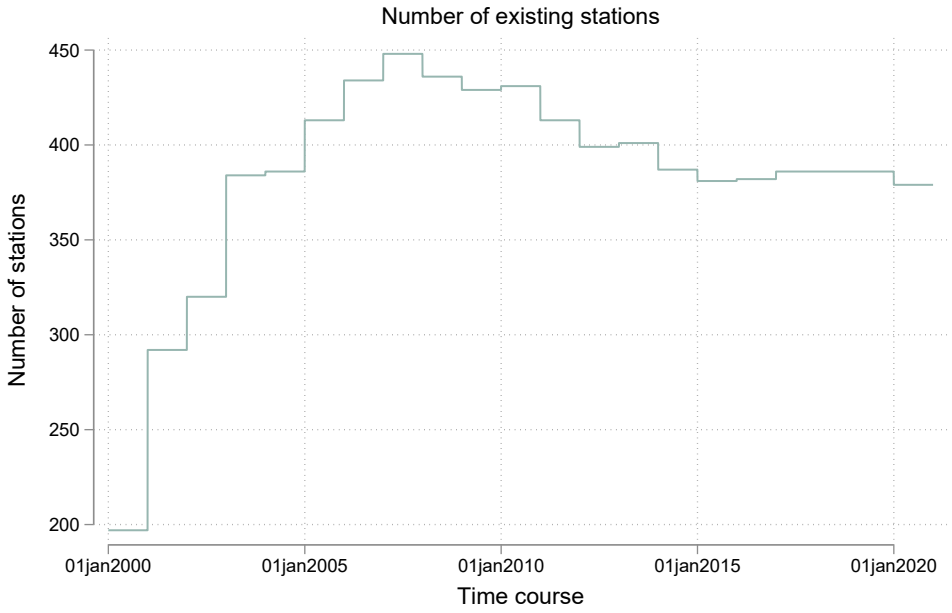
(B) Monitoring stations on 31/12/2010



(C) Monitoring stations on 31/12/2020

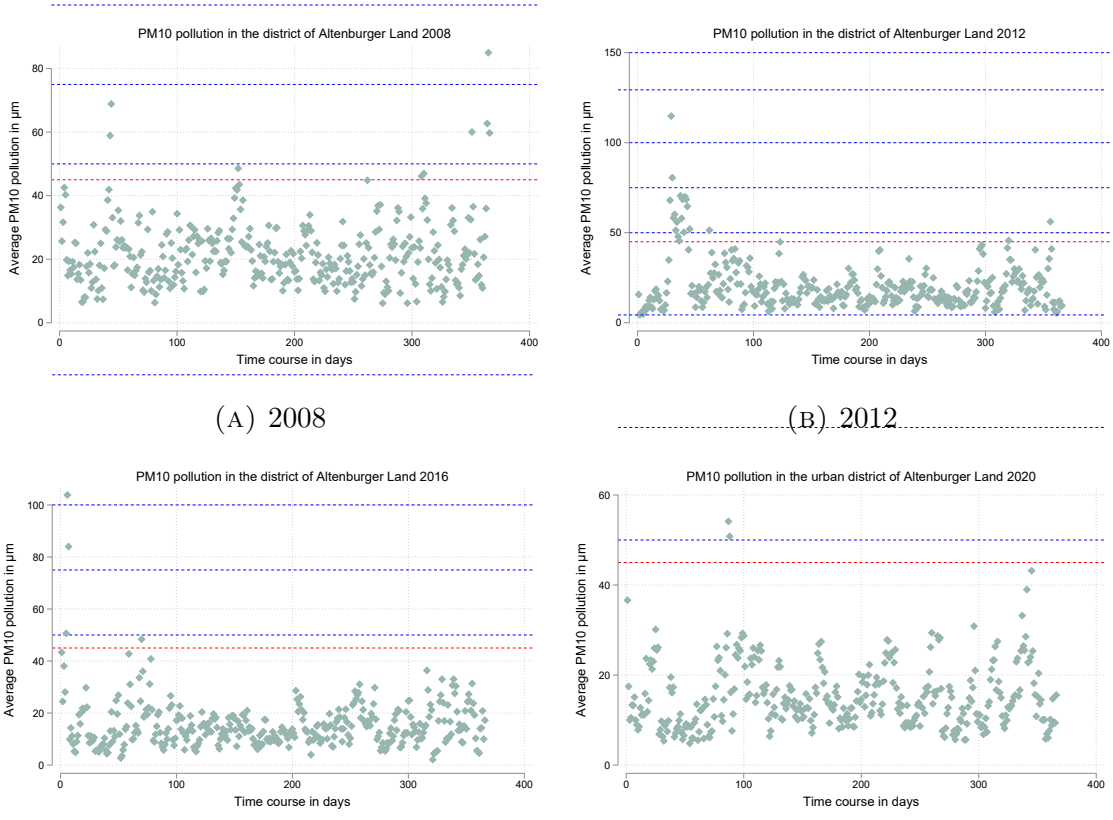
Notes: Source: German Federal Environment Agency. GIS data from `https://www.bkg.bund.de/DE/Home/home.html`. The administrative boundaries are as of 31 December 2017.

FIGURE B.3: Number of PM_{10} measuring stations in Germany over time



Notes: Source: German Federal Environment Agency. The x-axis shows the course of time from 1 January 2000 to 31 December 2020. The Y-axis shows the number of stations that measured particulate matter on the specific day. The graph has not been adjusted for stations that recorded an incorrect value on that day.

FIGURE B.4: PM_{10} pollution in Altenburger Land (district 16077)

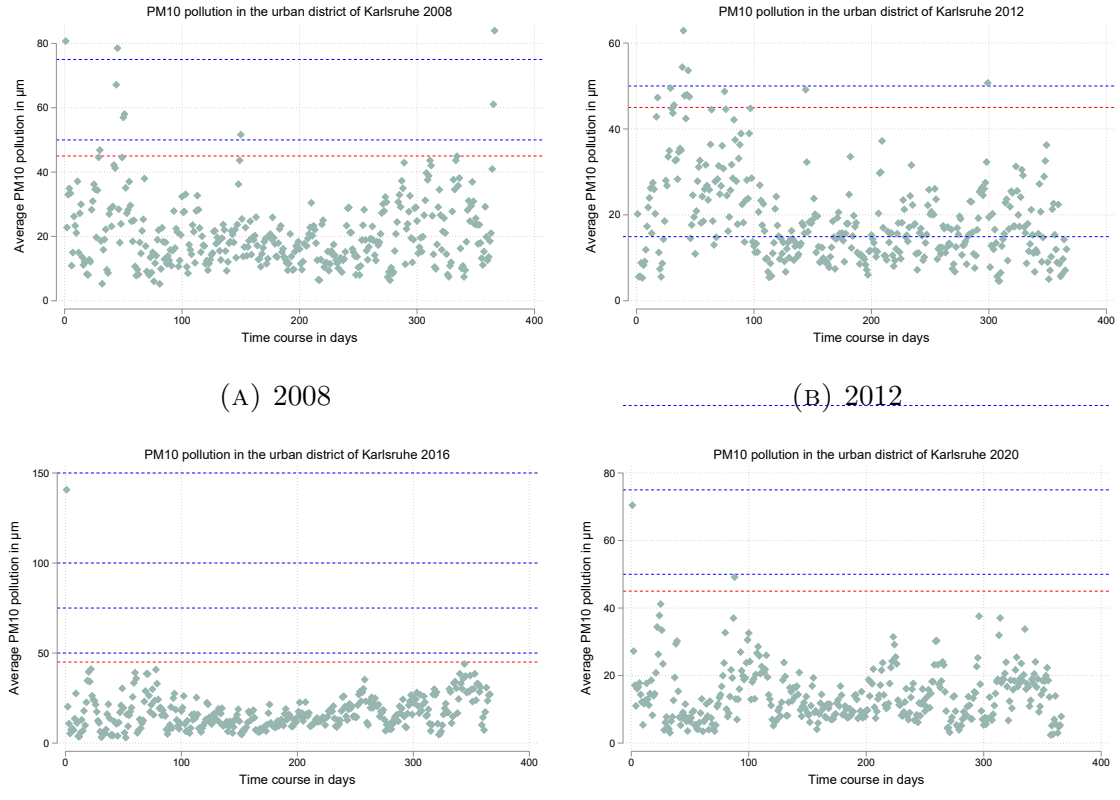


(A) 2008 (B) 2012

(C) 2016 (D) 2020

Notes: PM_{10} pollution from the German Federal Environment Agency. Administrative district 16077 Altenburger Land. The x-axis counts the days from 01.01 to 31.12. The y-axis indicates the level of PM_{10} pollution in ($\mu g/m^3$). The reference lines shown correspond to the WHO (2021) recommendations for daily particulate matter levels. The desired limit value for daily exposure should be 45 ($\mu g/m^3$) (red).

FIGURE B.5: PM_{10} pollution in Karlsruhe (district 8212)

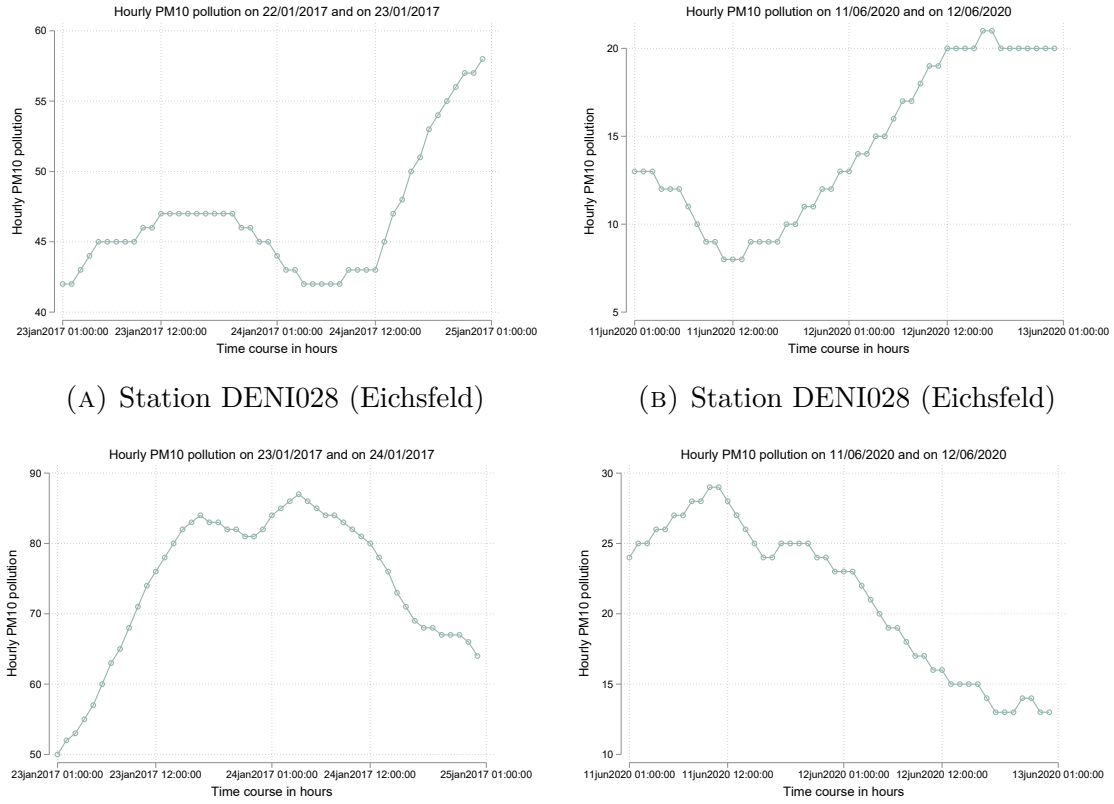


(A) 2008 (B) 2012

(C) 2016 (D) 2020

Notes: PM_{10} pollution from the German Federal Environment Agency. Urban district 8212 Karlsruhe. The x-axis counts the days from 01.01 to 31.12. The y-axis indicates the level of PM_{10} pollution in ($\mu g/m^3$). The reference lines shown correspond to the WHO (2021) recommendations for daily particulate matter levels. The desired limit value for daily exposure should be 45 ($\mu g/m^3$) (red).

FIGURE B.6: Three-day variation in hourly PM_{10} pollution



(A) Station DENI028 (Eichsfeld)

(B) Station DENI028 (Eichsfeld)

(C) Station DENW207 (Aachen)

(D) Station DENW207 (Aachen)

Notes: Source: PM_{10} pollution from the German Federal Environment Agency. The hourly PM_{10} pollution measured at station DENI028 (Eichsfeld) and at station DENW207 (Aachen). The x-axis counts the hours from 01:00:00 on the first day of the period until 00:00:00 one day later. The y-axis indicates the level of the hourly PM_{10} pollution in $(\mu g/m^3)$.

C Additional Results

TABLE C.1: Placebo test and other heterogeneity controls

	Time placebo (t_{+270}) (1)	Time placebo (t_{-270}) (2)	(t_{-2}) pollution (3)	(t_{-1}) pollution (4)	Local placebo (5)	Without Interpolation (6)	Without Movers (7)	Location specific trend (8)
Daily PM_{10} pollution ($\mu g/m^3$)	-0.00014	-0.0001185	-0.0001197	-0.0005654***	-0.000071	-0.0004924*	-0.0004951**	-0.0004914**
	(0.0002078)	(0.0003639)	(0.0002081)	(0.0002105)	(0.0002167)	(0.0002539)	(0.0002229)	(0.0002203)
ln(household income)	0.1904231***	0.1906855***	0.1907013***	0.1906839***	0.1907151***	0.1869745***	0.2035435***	0.1886796***
	(0.010727)	(0.0110749)	(0.0110667)	(0.0110681)	(0.0110747)	(0.0135391)	(0.012958)	(0.0111461)
Covariates of the base model	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects of the base model	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Person-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted (*within*) R^2	0.0700	0.0700	0.0701	0.0701	0.0700	0.0680	0.0650	0.0948
Observations	316,196	316,218	316,357	316,357	316,218	214,372	283,287	316,385
Observation period	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020
Average income	€3,394.74	€3,394.681	€3,394.82	€3,394.82	€3,394.68	€3,333.32	€3,401.76	€3,394.84
SD of PM_{10}	13.60298	8.754095	13.28868	13.2774	12.34552	13.76077	13.32508	13.31754
WTP for a reduction of ($\mu g/m^3$) for one year	€29.95	€25.32	€25.57	€120.79	€15.17	€105.34	€99.29	€106.10
WTP for a reduction in the SD by one day	€1.12	€0.61	€0.93	€4.39	€0.51	€3.97	€3.62	€3.87

Notes: All columns use fixed effects estimation. The dependent variable is individual current life satisfaction scaled 0 to 10. Demographic control variables: age, age squared, nationality, region, martial status, children under 14, unemployed, disability, college, subjective health status. Meteorological control variables: precipitation, average temperature, average temperature squared, temperature difference, hours of sunshine and wind speed. Robust standard errors were used. Statistical significance is indicated by ***p < 0.01; **p < 0.05. and *p < 0.10. SD: standard deviation. WTP: willingness to pay.

TABLE C.2: PM_{10} pollution and interaction terms: Sex and Age

	Sex	$Age \leq 30$	$30 < \text{Age} \leq 64$	$\text{Age} > 64$
	(1)	(2)	(3)	(4)
Daily PM_{10} pollution ($\mu g/m^3$)	-0.0008327***	-0.0005096**	-0.0003883	-0.0006219***
	(0.0002832)	(0.0002218)	(0.0003074)	(0.0002389)
Interaction term	0.0005277	-0.0001299	-0.0002322	0.0003604
	(0.0003654)	(0.0005396)	(0.0003666)	(0.0004084)
Interacting variable	0.1396909	0.0315318	-0.0767174***	0.1202938***
	(0.1855904)	(0.0222032)	(0.0154665)	(0.0203081)
Covariates of the base model	Yes	Yes	Yes	Yes
Fixed effects of the base model	Yes	Yes	Yes	Yes
Person-fixed effects	Yes	Yes	Yes	Yes
Observations	297,392	316,385	316,385	316,385
Adjusted ($wihtin$) R^2	0.0707	0,0701	0.0702	0.0703
F test PM_{10} and interaction = 0	4.51**	3.11**	3.33**	3.45**
Observation period	2008-2020	2008-2020	2008-2020	2008-2020

Notes: All columns use fixed effects estimation. Demographic control variables: age, age squared, nationality, region, martial status, children under 14, unemployed, disability, college, subjective health status. Meteorological control variables: precipitation, average temperature, average temperature squared, temperature difference, hours of sunshine and wind speed. All specifications use robust standard errors. Statistical significance is indicated by ***p < 0.01; **p < 0.05. and *p<0.10.

TABLE C.3: PM_{10} pollution, annoyance and interaction terms

	Poor state of health	Gender	Economic concerns	Environmental concerns	Urban districts
	(1)	(2)	(3)	(4)	(5)
Daily PM_{10} pollution ($\mu g/m^3$)	0.0001894	0.0001723	0.0003227**	0.0002933*	0.0002654
	(0.0001576)	(0.0001895)	(0.0001565)	(0.0001652)	(0.000171)
Interaction term	-0.0000696	-0.0000572	-0.0006659**	-0.0004678*	-0.0002533
	(0.0003157)	(0.0002477)	(0.0003032)	(0.0002656)	(0.0002617)
Interacting variable	0.0077007	-0.2543325	0.0731495***	0.0267712***	0.1658901
	(0.0106537)	(0.2487905)	(0.0086231)	(0.0075863)	(0.2756632)
Covariates of the base model	Yes	Yes	Yes	Yes	Yes
Fixed effects of the base model	Yes	Yes	Yes	Yes	Yes
Person-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	285,258	278,806	284,057	277,696	285,258
Adjusted ($wihtin$) R^2	0.0207	0.0206	0.0213	0.0207	0.0207
F test PM_{10} and interaction = 0	0.75	0.51	3.36**	2.16	1.22
Observation period	2008-2020	2008-2020	2008-2020	2008-2020	2008-2020

Notes: The estimation was based on a panel data model with fixed effects. The regression controls for the following demographic covariates: age, age squared, nationality, region, martial status, children under 14, unemployed, disability, college, subjective health status. In addition, the regression controls for the following meteorological covariates: precipitation, average temperature, average temperature squared, temperature difference, hours of sunshine and wind speed. Robust standard errors were used. The dependent variable is the frequency of being angry in the last 4 weeks. Statistical significance is indicated by ***p < 0.01; **p < 0.05. and *p<0.10. Statistical significance is indicated by ***p < 0.01; **p < 0.05. and *p<0.10.