Make Sure the Kids are OK: Indirect Effects of Ground-Level Ozone on Well-Being

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Julia Rechlitz* Luis Sarmiento† Aleksandar Zaklan‡

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We posit that pollution affects welfare outcomes directly, through a person's health, and indirectly, through their children's health. This paper is the first to consider the indirect channel to welfare losses from pollution by analyzing the effect of ozone on subjective health and life satisfaction, using a panel of German individuals and highly granular pollution data. Individuals with children suffer losses in life satisfaction, while those without do not. Ozone does not affect the health satisfaction of either group. We show that ozone leads to losses in workdays to care for a sick child, providing evidence on the mechanism.

JEL codes: Q53, I31, I18, J22

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*DIW Berlin. E-Mail: jrechlitz@diw.de

†DIW Berlin. E-Mail: asarmiento@diw.de. Corresponding Author

‡DIW Berlin. E-Mail: azaklan@diw.de

1 Introduction

Understanding the link between local air pollution, human health, and well-being is a relevant issue for economists. Air pollution causes a variety of economic costs, through losses in well-being (Luechinger, 2009; Levinson, 2012), increased expenditures on health services (**?**Barwick et al., 2018), disruptions to human capital formation through school absenteeism (Currie et al., 2009; Chen et al., 2018), shocks to labor supply (Hanna and Oliva, 2015; Aragon et al., 2016), and negative effects on labor productivity (Zivin and Neidell, 2012; Chang et al., 2019).

In this paper, we consider the effect of air pollution on well-being for the case of ground-level ozone in a panel of German individuals. Based on substantial epidemiological evidence that ozone exposure decreases objective health outcomes for both adults and children, we posit that ozone affects well-being directly, through a person's health,[1] and indirectly, through the health of her children. We test for the existence of the indirect channel to losses in well-being. To our knowledge, this paper is the first to analyze the indirect channel to losses in well-being due to air pollution. Specifically, we compare whether ozone exposure affects the subjective health and life satisfaction of individuals with and without children in different ways. We consider the mechanism linking ozone and well-being through children's health by evaluating if ozone exposure causes losses in workdays due to child sickness. Our main contributions to the literature are: First, we add to the literature on the effects of pollution on well-being by focusing on the mechanisms through which pollution affects the well-being of adults. Second, we contribute to the more general literature on the effects of pollution on economic outcomes by focusing on family effects of pollution on adults, via their children. Third, to our knowledge, this is the first paper to analyze the impact of ozone on subjective health satisfaction.

Ground-level ozone[2] is an aggressive pollutant leading to increases in the mor-

[1] Additional direct losses in well-being may occur through aesthetics effects, e.g., foggy air due to pollution (Levinson, 2012).

[2] In contrast to ground-level ozone, which is mostly human-made and harmful to flora and fauna, the bulk of ozone in the earth's atmosphere occurs naturally in the stratosphere, between about 10 km and 50 km above the earth's surface. This ozone layer is vital for protecting life from the sun's ultraviolet radiation. In the remainder of the paper, we write ozone instead of ground-level ozone for brevity.

bidity and mortality of affected persons (Schwela, 2000; Chay and Greenstone, 2003; Knittel et al., 2016). Short-term effects include decreases in lung capacity, inflammations of the respiratory tract, and a higher frequency of asthma attacks, while long-term exposure increases the risk of developing chronic lung disease (EPA, 2016), and potentially increase in the probability of developing cancer (Rocks et al., 2017; Kim et al., 2018). The health effects of ozone are most potent among high-risk populations, such as children, the elderly, outdoor workers, and individuals suffering from respiratory ailments. Ozone is a secondary pollutant formed through the reaction of nitrous oxides (NO_x) and volatile organic compounds (VOC), mainly emitted by motor vehicles and combustion plants, in combination with sunshine. In our sample, average annual ozone concentrations have been stable. However, current levels of atmospheric ozone are likely to increase due to climate-change-associated growth of heatwaves (Rosenzweig et al., 2004; Selin et al., 2009).[3]

We analyze the effects of ground-level ozone on two measures of subjective well-being: satisfaction with one's health, and satisfaction with one's life in general. Health satisfaction targets the health channel of air pollution, while the broader measure of life satisfaction encompasses further factors affecting an individual's well-being, such as indirect welfare effects stemming from the impact of ozone on the environment, the family, and the community. Evaluating subjective welfare outcomes is informative, especially in contexts of moderate ozone concentrations and healthy populations. In such settings, economic costs will be realized in the short to medium term when individuals *feel* less well due to exposure to ozone. In these situations, they may be expected to increase their demand for health services, decrease their labor supply, or suffer losses in productivity. Conversely, a moderate deterioration in objective outcomes may not lead to economic costs in short to medium terms, if the individual generally *feels* well.[4] We are mindful of the need to ascertain

[3]Heat waves diminish wind flows that disperse ozone precursors, while increasing the use of air conditioning and cooling devices that emit these same precursors. Mitigating climate change by decreasing the combustion of fossil fuels, e.g., through large-scale electrification of road transport or decommissioning of fossil-fuel power generation is likely to reduce current ozone levels.

[4]Validating the results for the subjective outcomes (well-being and health) using objective data is beyond the scope of this paper, due to data availability. However, we refer the reader to the extensive body of literature linking air pollution and objective outcomes.

that estimations are robust to the cardinalization of the ordinal well-being outcomes (e.g. Bond and Lang, 2018) and perform appropriate checks in this paper (Section 6.2).

This paper identifies the effect of ozone on individuals from short-term variation in ozone levels. Specifically, it combines geo-coded data on daily ozone levels from measuring stations across Germany with geo-coded individual-level data on subjective health and life satisfaction between 2005 and 2015 from the German Socio-Economic Panel Study (SOEP), a representative survey of German individuals. We exploit information on the precise date of the SOEP interview to assign daily, weekly, monthly, and quarterly exposure levels to each individual. The individual level of exposure comes from inverse distance weighting techniques that determine exposure at the exact coordinates of the households by weighting the values of ozone at neighboring monitoring stations. Having individual exposure levels across space and time allows us to exploit the variation in ozone across Germany and throughout the study period.

Our main analysis estimates the effects of ozone on the health and life satisfaction of adults with and without children through a set of multi-pollutant fixed-effects regressions, controlling for time and individual fixed effects, individual-level covariates, county-level macro variables, weather-related data, and additional pollutants relevant for the formation of ozone: carbon monoxide (CO), particulate matter (PM_{10}), nitrous dioxide (NO_2), and sulfur dioxide (SO_2). This study also explores a potential channel for losses in life satisfaction: Decreases in labor supply for people with children through increases in missed workdays because their child was sick due to ozone exposure. After our primary analysis, we examine the sensitivity of our results through several robustness tests. First, randomizing our pollution exposure variables across individuals and across time allows us to check for spurious causality. Second, we re-formulate the 11-point outcome scales for life and health satisfaction as binary variables and re-estimate our main specification using a probit model to check whether our results depend on the ordinal nature of the well-being outcomes.

Results show statistically and economically significant adverse effects of ozone on the life satisfaction of adults sharing their household with children. The economic significance increases with the length of exposure: point estimates grow in absolute value between daily, weekly, monthly, and quarterly time-windows. On the other hand, there is no effect for individuals living in children-less households. This result suggests that – under the assumption that the sensitivity of individuals' life satisfaction to ozone is not affected by childbirth – ozone pollution diminishes the welfare of adults with children while not significantly affecting childless persons. Ozone exposure leads to a significant increase in workdays lost because a child was sick, confirming the negative consequences of ozone for the health of children in our sample and providing evidence on the mechanism of losses in well-being due to ozone through people's children. In contrast to our results on life satisfaction, we do not find any effect of ozone on health satisfaction, neither for persons without children nor for individuals sharing their households with children. Our findings suggest that ozone concentrations in Germany are not high enough to affect the subjective health of adults in general, but are suggestive regarding the negative consequences of ozone on the health of children, and their associated and indirect effect on the life satisfaction of the adult population. Our results show that the indirect influence of ozone on persons with children should be taken into account in further research and policy debates regarding the costs and benefits of reducing air pollution. On the policy side, this study suggests that more stringent regulation of ozone is needed to account for the greater vulnerability of children to this pollutant and its indirect effect on the well-being and labor supply of adults with children.

In our view, the two contributions most relevant to ours are Luechinger (2009) and Levinson (2012). Luechinger (2009) analyzes the effect of SO_2 on subjective life satisfaction in Germany using a quasi-experimental design and finds a significant negative impact of SO_2 pollution on the life satisfaction of individuals, also using SOEP data. Using U.S. survey data, Levinson (2012) shows that PM_{10} pollution diminishes the life satisfaction of individuals. Our paper adds to the literature compared to Luechinger (2009) and Levinson (2012) in several respects: First, it studies the effects of a different pollutant, ozone. Second, it explores the channels through which pollution affects life satisfaction. Third, it leverages the higher quality of our data, mainly better coverage compared to Levinson (2012) and better regional granularity compared to Luechinger (2009), to pursue a more precise identification. Fourth, it explores how different time aggregations of pollution affect the coefficients of our causal variable, and fifth, it controls for the potentially confounding pollutants using multi-pollutant models.

Further studies on the link between air pollution and life satisfaction provide additional evidence on the relationship between these variables: Rehdanz and Maddison (2008) use SOEP data to find a negative association between people's claim to be affected by higher air pollution and their levels of life satisfaction. Ferreira and Moro (2010) use the same method at the level of Irish electoral districts and find similar results. Cunado and De Gracia (2013), Ferreira et al. (2013) and Ambrey et al. (2014) also find a negative association between life satisfaction and air pollution. However, to our knowledge, this literature does not explicitly explore channels through which air pollution affects well-being.

Additionally, there is a significant number of complementary literature on the *direct* impacts of local air pollution on objective health outcomes. Moretti and Neidell (2011) and Barwick et al. (2018) show that air pollution leads to greater expenditure on health services. Chay and Greenstone (2003), Jayachandran (2009) and Knittel et al. (2016) show that local pollution increases the mortality of children. Concerning the link between exposure to atmospheric contaminants and children's health, several articles show that pollution-related health problems can disrupt human capital formation through school absenteeism and decrease human capital outcomes, even in the long term. Currie et al. (2009) find that exposure to carbon monoxide increases school absences. Chen et al. (2018) find that ozone, particulate matter, and a composite pollution index decrease the health of school children and lead to greater school absenteeism. Gilliland et al. (2001) conclude that an increase of 20 ppm in ozone levels raises respiratory-health-related school absences by 84 %, while the peak of absenteeism is reached about five days after a high-ozone episode. Using exogenous variation from Indonesian forest fires, Rosales-Rueda and Triyana (2018) find that children exposed to air pollution exhibit disruptions to human capital formation several years after exposure, in particular through shorter stature and lower lung capacity. Those exposed in utero show persistent effects, being shorter than other children a decade and more after exposure. Sanders (2012) also shows long-term effects on human capital formation: In-utero exposure to total suspended particles (TSP) significantly decreases high school grades many years later. However, to our knowledge, this literature – unlike our paper – has not yet linked children being affected by pollution to economic outcomes for adults.

The remainder of this paper is structured as follows: Section 2 presents the epidemiological evidence on the effects of ozone on adults and children and develops our hypothesis. Section 3 presents our data. Section 4 outlines our research design, while Section 5 contains the main results. In Section 6 we show robustness tests. We summarize and conclude in Section 7.

2 Background: Ozone and health

There is substantial epidemiological evidence on the effects of ozone on the health of adults and children. Gryparis et al. (2004) use data from 24 different European urban agglomerations to conclude that an increase of 10 milligrams per cubic meter (mg/m^3) in the levels of 1-hour maximum daily ozone concentrations raise total mortality rates by 0.31%. Holgate et al. (2003) finds similar results by studying a 10 mg/m^3 increase in the average daily value of ozone. In a meta-analysis of different contributions relating ozone and mortality, Bell et al. (2005) suggests that the impact of ozone on death rates may be even more severe than those found by Holgate et al. (2003). Regarding morbidity, Devlin et al. (1991) conclude that even at ambient levels as low as eight particles per billion (ppb), ozone exposure has negative impacts on the respiratory system. Koken et al. (2003) find that ozone correlates with hospitalizations of elderly adults due to cardiovascular ailments, and Friedman et al. (2001) uses the variation in environmental policies during the Atlanta summer games to infer that the associated drops in peak daily ozone levels (81.3 to 58.6ppb) led to fewer asthma-related emergency room admissions. **?** use instrumental variable techniques to estimate the financial costs of ozone on hospital admissions. They determine that ozone exposure causes annual costs of $55 million U.S. dollars from respiratory hospitalizations and avoidance behavior.

Studies focusing of the effect of ozone on children's health have also produced substantial evidence regarding the damaging impact of ozone on respiratory health, lung capacity, long-term inadequacy of lung growth, increases in hospitalizations, mortality, and use of asthma medicine (Bates, 1995). Lleras-Muney (2010) studies the effect of pollution on children's hospitalization rates by using the relocation of military personnel as a source of exogenous variation in exposure. She finds that an increase in ozone exposure by one standard deviation increases the hospitalization rates of military children between 8 and 23 %. Burnett et al. (2001) analyze the effects of ozone on the hospitalization rates of children under two years of age. They find that increasing average concentration of ozone to one-hour maximum values typically found in summertime (45 ppb) would increase daily hospitalizations due to respiratory ailments by 35%. Thurston et al. (1997) find significant correlations between lower lung capacity and high levels of atmospheric ozone when studying the effect of ozone in children between seven and thirteen years old. Ostro et al. (2001) find that asthmatic children between the ages of eight and thirteen years increase medicine use during higher ozone episodes. Lee et al. (2002) observe that, for South Korean children under the age of fifteen, the risk of asthma-related hospitalization increases between 7% to 13% when atmospheric ozone rises by 21 ppb. Tolbert et al. (2000) find that increasing the 8-hour maximum ozone level by 20 ppb increases pediatric emergency room visits due to asthma by 4%. Finally, regarding the long term consequences of exposure to ozone on lung capacity, Galizia and Kinney (1999) conclude that exposure to high levels of ozone during childhood affect the lung capacity of university students several years after exposure to high ozone values.

Based on the epidemiological evidence and under the reasonable assumption that the utility of children enters the utility function of adults sharing the same household, we hypothesize that there are two channels for ozone to affect welfare outcomes of adult individuals: The first channel captures the direct effect of ozone through their health, which is the channel investigated in the existing literature. The second channel is through family effects: Adults' outcomes are affected by the welfare of their children. Our hypothesis is that in the case of ozone, the second channel is important because children are a sensitive group to the effects of atmospheric ozone.

3 Data

3.1 Data sources

We obtain household and personal data from the German Socio-economic Panel Study (SOEP) over the period 2005 to 2015. The SOEP is a representative longitudinal panel study that started in West Germany in 1984. Between 2005 and 2015, SOEP surveyed 30,051 different households and 80,339 unique individuals. On average, individuals spend around five years as members of the panel.

Our main outcome variables are responses to questions asking individuals to rate their life and health satisfaction. The questions are as follows: "How satisfied are you with your life, all things considered?" and "How satisfied are you with your health, all things considered?" Respondents are asked to provide an answer on an 11 point scale from 0 (completely dissatisfied) to 10 (completely satisfied) (Richter et al., 2013). In addition to our outcome variables, the SOEP also provides a broad set of sociodemographic and economic information, such as marital status, age, gender, income, employment status, and tax payments.

SOEP also provides two critical pieces of information necessary for the causal identification of the effects of atmospheric ozone on life and health satisfaction: First, SOEP provides the geo-coordinates of surveyed households' dwellings on a strictly confidential basis. We use these geo-codes to match surveyed individuals to nearby pollution measuring stations, enabling a clean spatial matching of exposure and individuals. Second, SOEP also contains information on the exact day of the interview allowing for a precise temporal match of individuals and their ozone exposure at the time when they provide information on their well-being and health satisfaction.

Data on the daily concentration of ozone and other air pollutants come from the German Environmental Agency (*Umweltbundesamt*, henceforth UBA). UBA maintains an extensive network of monitoring stations measuring different types of pollutants. In total, UBA has 696 stations of which 378 measure the concentration of ozone in the environment.[5] Figure 1 shows the spatial distribution of ozone monitoring stations across Germany. Stations tend to be concentrated in urban clusters such as Berlin in the northeast, Hamburg in the north, and the Ruhr area in the west.

Figure 1: Ozone measuring stations in Germany.

Source: German Environmental Agency.

Additionally, the German meteorological service (*Deutscher Wetterdienst, DWD*) provides weather data from its network of monitoring stations. Weather station data are also geo-coded and can be matched to individual-level data from the SOEP. Finally, Eurostat provides county-level macroeconomic controls. The macroeconomic variables we use in this paper are unemployment rate, gross domestic product per capita, and population density.

3.2 Ground-level ozone in Germany

Our primary explanatory variable is ground-level ozone. In Germany, over the period 2005-2016, ozone had an average annual concentration of 47.7 micrograms per cubic meter ($\mu g/m^3$) with a standard deviation of 24.45 $\mu g/m^3$ and a maximum of 199.9

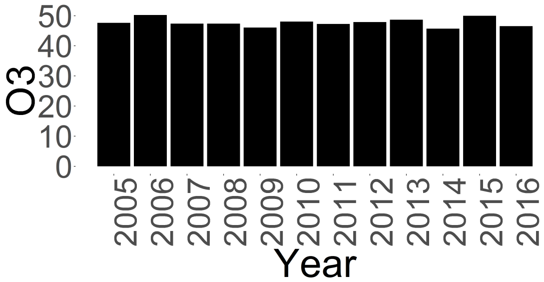
[5]Because of malfunction and routine maintenance, stations measuring ozone have missing values around 10% of the time.

($\mu g/m^3$). It is important to note that ozone is a secondary environmental pollutant created by the interaction of solar radiation with nitrous oxides and volatile organic compounds, both of which primarily occurs due to the burning of fossil fuels. There are two sides to the interaction of ozone with nitrous oxides (NO_x) and volatile organic compounds (VOC). On the one hand, the interaction of solar radiation with these contaminants is what forms ozone. On the other, it also degrades it back into oxygen. The relationship between these primary contaminants and ozone is non-linear and difficult to predict. For example, in areas with high levels of nitric oxide, such as urban centers and intense traffic regions, ozone degrades at faster rates. This phenomenon is referred to as the "ozone paradox." The ozone paradox explains why ozone levels are higher in German rural areas (57.4 $\mu g/m^3$ on average for 2006-2015) than in suburban (45.4 $\mu g/m^3$) and urban (42.1$\mu g/m^3$) districts.

Because of the contemporary implementation of public policies such as clean action plans and low emission zones, the concentration of all criteria pollutants except for ozone exhibit a downward trajectory. Even though the average level of ozone precursors such as PM_{10} and NO_2 have decreased over time, the average annual concentration of ozone remained stable between 2005 and 2016 due to the "ozone paradox" (Figure 2, panel (a)).

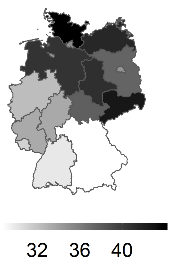
While annual averages are stable, ozone pollution varies significantly within the year (Figure 2, panel (b)). Given that the creation of ozone is triggered by the interaction of primary contaminants with solar radiation, its levels are higher during the summer months. Moreover, as the levels of primary pollutants and solar radiation vary across locations, the concentration of ozone also varies substantially across space. Figure 2, panels (c) and (d) show the spatial distribution of ozone across German states in winter and summer months. We observe lower ozone levels in densely populated states such as Northrhine Westphalia, Hamburg and Bremen, and higher levels in more rural areas, such as Schleswig-Holstein and Saxony Anhalt. Regional concentrations vary significantly by season. In the winter, the states with higher ozone levels are the more rural Eastern and Northern states, while in the summertime, due to the influence of solar radiation on ozone formation, southern states such as Baden Wuerttemberg and Hessen exhibit higher exposure levels. This

Figure 2: Ozone concentrations in Germany, 2005-2016

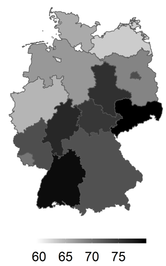


(a) Yearly averages

(b) Monthly averages



(c) Wintertime averages by region



(d) Summertime averages by region

Source: German Environmental Agency.

descriptive analysis shows that while average ozone levels in Germany are moderate compared to other countries, they exhibit substantial temporal and geographical variation.

We assign ozone exposure to individuals using inverse distance weighting (IDW) between ozone monitoring stations and individuals' dwellings.[6] IDW is a spatial interpolation technique that approximates the value of a point in space by weighting the values of comparable neighbors.[7] It assigns individual pollution measures to each person by providing more weight to stations located near the person's dwelling.[8]

[6]We assign the exposure to the other pollutants we use in our multi-pollutant specification analogously.

[7]Formally, IDW interpolation can be represented as follows

$$V_{jt} = \left\{ \begin{array}{c} \frac{\sum_i^N \omega(dist_{ij}) * pol_{it}}{\sum_i^N \omega(dist_{ij})} \\ pol_{it} \rightarrow dist_{ij} = 0 \end{array} \right\} \Longrightarrow \omega(dist_{ij}) = \frac{1}{distance(x_i, x_j)^p}$$

where pol_{it} is the value of pollution at station i at time t, and $dist_{ij}$ is the distance between pollution station i and household j. The power factor p modifies the weighting load; the higher p, the greater is the weight of closer stations. We use a weight of two, as recommended by De Mesnard (2013) for air pollution.

[8]To focus on local ozone concentration, we cut off stations located further away than 10 kilometres. We use the great circle distance formula (Shumaker and Sinnott, 1984) for maximum precision in calculating the distance between coordinate points.

3.3 Individual-level data

Table 1 presents basic descriptive statistics for the subsample of SOEP individuals residing within ten kilometers of ozone measuring stations. This subsample constitutes the primary sample for our empirical analysis.

Table 1: Full sample, descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
SOEP data:				
Life satisfaction	7.24	1.73	0	10
Health satisfaction	6.74	2.21	0	10
Income	43,554	35,374	0	1,507,150
Age	48.21	17.33	17	99
Unemployed	0.05	0.21	0	1
Married	0.59	0.49	0	1
Number of Children	0.88	1.19	0	12
Exposure to pollution and weather:				
O_3	14.32	13.01	0.12	147.53
PM_{10}	4.83	5.24	0.14	106.21
SO_2	1.28	1.40	-0.82	30.19
CO	0.17	0.14	0.00	1.97
NO_2	6.83	6.33	0.29	123.32
Sunshine duration	2.80	3.07	0.00	16.60
County-level data:				
GDP	37,478	41,545	985	121,783
Population density	1,692	1,428	57	4,630
Unemployment rate	7.48	3.29	1.14	19.40
Number of Observations: 46,677				
Number of individuals: 12,098				
Number of Households: 7,032				

Table notes: Unemployment and Marriage Dummies are a binary variables indicating if the person is employed (married) in each year or not. Post-government income is in thousand Euro. GDP in million Euro, Population density in persons per square kilometer, all pollutants are measured in μm^3. Additionally, negative values for sulfur dioxide occur due to the retrieval algorithm of UBA.

The mean of both life and health satisfaction is in the upper part of their categorical distribution, with a mean value of 7.24 for life satisfaction and 6.74 for health satisfaction. Health satsifaction has a standard deviation of 2.21, compared to 1.73 for life satisfaction. Further, 59% of surveyed individuals are married, have an average income of 43 thousand Euro, 0.88 children, are in their 40s, and are unemployed 5% of the time. Individuals in our regression sample are exposed to levels of ozone well below the German average, as they predominantly reside in urban areas.

Figure 3: Life satisfaction of SOEP individuals

(a) Distribution across individuals

(b) Evolution of averages over time

Source: SOEP.

Figure 3 shows the distribution of our two main outcome variables across individuals and the evolution of their average over time. For both variables, the highest frequency of responses is between seven and nine (Figure 3, panel (a)). On average, individuals were mostly satisfied with their life during the sample period. We observe that life and health satisfaction are correlated, although the correlation is not perfect. Scores for health satisfaction are spread across the scale more than for life satisfaction. We also observe similarities and differences in the evolution of the averages of the two variables over time (Figure 3, panel (b)). Both life and health satisfaction decrease during the years of the financial and economic crisis of 2008/2009, while in the ensuing years, life satisfaction increases in line with the positive development of the German business cycle and the concurrent increase in employment. In contrast, health satisfaction also rebounds after the crisis but remains stable after 2010.

4 Research Design

4.1 Identification

The econometric design identifies the effect of ozone on individuals from within-year variation in ozone levels, at daily, weekly, monthly, and quarterly frequencies, close to each person's household. Our identification strategy helps mitigate concerns about the endogeneity of pollution levels and is similar to the approach by Levinson (2012), except that the greater quality of our data allows us to exploit more variation in ozone concentrations across space and time (Figure 2). SOEP interviews take place at different times of the year all over Germany. Roughly half of of the interviews take place between September and March — months with low ozone concentrations — while the other half occurs during the period April and August when ozone levels are higher. This within-year variation in interview dates helps us identify the effect of ozone across several periods

The design controls for observable and unobservable heterogeneity with individual and time fixed effects in the form of year and weekday fixed effects. Additionally, we control for observable confounders at the individual and county levels plus for other pollutants and weather conditions that play a role in ozone generation.

One potential concern is self-selection through moving behavior. Some individuals may move to areas with less pollution. To avoid this issue from contaminating our results, we exclude individuals that moved from dwellings during the sample period. By eliminating movers, we estimate a lower bound of the effect of ozone, as people that relocate due to ozone exposure may be expected to react to ozone more strongly than those who remain in their prior location.

4.2 Empirical model

Our main analysis estimates the following equations:

$$LS_{it} = \alpha + \rho \; Ozone_{it} + \boldsymbol{X'_{it}\alpha} + \boldsymbol{Y'_{ct}\beta} + \gamma_t + \lambda_i + \epsilon_{it}, \tag{1}$$

$$HS_{it} = \alpha + \rho \; Ozone_{it} + \boldsymbol{X'_{it}\alpha} + \boldsymbol{Y'_{ct}\beta} + \gamma_t + \lambda_i + \epsilon_{it}, \tag{2}$$

LS_{it} and HS_{it} are subjective life amd health satisfaction values for each individual i at the interview date time t. ρ represents the coefficient of interest on pre-interview ozone exposure of different lengths. We estimate short-term effects by using the ozone exposure on the day of the interview as the main explanatory variable and capture longer-term effects by using rolling averages of ozone concentrations during the week, month, and quarter before the interview. $\boldsymbol{X'_{it}}$ is a matrix of time-varying individual level controls and $\boldsymbol{Y'_{ct}}$ contains county and weather controls. γ_t contains the matrix of time fixed effects, year fixed, and weekday fixed effects. λ_i are individual fixed effects and ϵ_{it} is the error term, clustered at the household level.

Furthermore, we analyze the mechanism behind our main results by estimating fixed effects Poisson models of workdays lost because a child was sick. The robustness section, besides spatial and temporal placebo tests, additionally includes probit models instead of OLS to robustify against the ordinal nature of the well-being data.

5 Results

5.1 Full Sample

We begin our main analysis by considering if variations in short-term exposure to ground-level ozone on the day of the SOEP interview affects either the life or health satisfaction of individuals in the full sample. For each outcome, we run six different specifications, building up from a model containing only the level of ozone and fixed effects (Tables 2 and 3, column (1)) to a full multi-pollutant design controlling for the level of ozone, socio-demographic, macroeconomic, sunshine duration in hours during the day of the interview, individual fixed effects, and time fixed effects (column (6)). The latter is our preferred specification.

Short-term exposure to ozone has negative effects on life satisfaction in the full sample (Table 2). The effects are weak statistically, with significance at the 10% level. The results for other covariates are as expected and in concordance with Frijters et al. (2004): Age, being unemployed, and the unemployment rate of the county in which the individual resides are all negatively related to life satisfaction. Income, on the other hand, is positively related to life satisfaction. As we are not only interested in the effect of ozone on subjective evaluations of people's lives but also on their subjective health, we run the same exercise with health satisfaction

Table 2: Short-term effect of ozone on life satisfaction, full sample

	Dependent variable: Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily Ozone	-0.002^{*}	-0.001^{+}	-0.002^{+}	-0.002^{+}	-0.001^{+}	-0.001^{+}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.013^{*}	-0.025^{***}	-0.025^{***}	-0.025^{***}	-0.025^{***}
		(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Income		0.001^{**}	0.001^{**}	0.001^{**}	0.001^{**}	0.001^{**}
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed		-0.398^{***}	-0.395^{***}	-0.395^{***}	-0.396^{***}	-0.396^{***}
		(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
GDP			−0.000	−0.000	−0.000	−0.000
			(0.002)	(0.002)	(0.002)	(0.002)
Unempl. rate			-0.033^{**}	-0.033^{**}	-0.033^{**}	-0.033^{**}
			(0.012)	(0.012)	(0.012)	(0.012)
Sunshine duration				0.000	0.000	−0.001
				(0.003)	(0.003)	(0.003)
Daily CO						0.111
						(0.088)
Daily PM_{10}						−0.001
						(0.002)
Daily NO_2						0.002
						(0.003)
Daily SO_2						0.001
						(0.006)
No. Observations	46,677	46,677	46,677	46,677	46,677	46,677

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction on ozone exposure on the day of the SOEP interview. All regressions contain individual and year fixed effects. Specification (1) contains ozone, individual fixed effects and year fixed effects. The other specifications add further controls while always keeping the covariates from the previous specification: (2) adds the sociodemographic covariates age, income, and unemployment status; (3) adds county-level macro covariates population density, gross domestic product, and unemployment rate; (4) adds sunshine duration; (5) adds day-of-the-week fixed effects; (6) adds additional pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Robust standard errors clustered at the household level in parentheses.

as the dependent variable (Table 3). In line with (Levinson, 2012), ozone has no short-term effect on individuals' life satisfaction. Of the remaining covariates, only age and employment status are significant across all specifications.

We next analyze the effect of different time aggregations of exposure to ozone on life and health satisfaction. Doing so is of interest as it may be that ozone levels on the day of the interview were low, even though the individual had been exposed to high ozone levels during the recent past. This is why we run additional estimations for average ozone concentrations during the week, month, and quarter before the interview, by computing the rolling mean over t days before the interview,

Table 3: Short-term effect of ozone on health satisfaction, full sample

	Dependent variable: Health satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily Ozone	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		-0.066^{***}	-0.060^{***}	-0.060^{***}	-0.060^{***}	-0.060^{***}
		(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Income		−0.000	−0.000	−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed		-0.129^{*}	-0.130^{*}	-0.130^{*}	-0.129^{*}	-0.129^{*}
		(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
GDP			0.002	0.002	0.002	0.002
			(0.002)	(0.002)	(0.002)	(0.002)
Unempl. rate			0.018	0.018	0.018	0.018
			(0.014)	(0.014)	(0.014)	(0.014)
Sunshine duration				−0.000	0.000	0.000
				(0.003)	(0.003)	(0.003)
Daily CO						0.015
						(0.110)
Daily PM_{10}						0.001
						(0.003)
Daily NO_2						−0.002
						(0.003)
Daily SO_2						0.006
						(0.008)
No. Observations	46,677	46,677	46,677	46,677	46,677	46,677

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of health satisfaction on ozone exposure on the day of the SOEP interview. All regressions contain individual and year fixed effects. Specification (1) contains ozone, individual fixed effects and year fixed effects. The other specifications add further controls while always keeping the covariates from the previous specification: (2) adds the sociodemographic covariates age, income, and unemployment status; (3) adds county-level macro covariates population density, gross domestic product, and unemployment rate; (4) adds sunshine duration; (5) adds day-of-the-week fixed effects; (6) adds additional pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Robust standard errors clustered at the household level in parentheses.

i.e., for weekly levels of exposure the value would be equal to $O_3^w = \sum_{t=-7}^{t} \frac{o_3^t}{7}$. The corresponding rolling means are also computed for the other pollutants included in the multi-pollutant specification. Table 4 shows the coefficients on ozone for four time aggregations and across all models. Again, there is weak evidence of a negative link between ozone and life satisfaction (10% significance). The results for health satisfaction are never significant.[9]

These initial results for the full sample show that levels of ozone are (weakly) negatively related to how individuals assess their life satisfaction and are not related

[9]For brevity, we do not show the results. They are available upon request.

Table 4: Effect of ozone on life satisfaction, full sample and different time aggregations of pollution

	Dependent variable: Life satisfaction					
	(1)	(2)	(3)	(4)	(5)	(6)
Daily ozone	-0.002^{*}	-0.001^{+}	-0.002^{+}	-0.001^{+}	-0.001^{+}	-0.002^{+}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weekly ozone	-0.002^{+}	-0.002^{+}	-0.002^{+}	-0.002^{*}	-0.002^{+}	-0.002^{+}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Monthly ozone	-0.002^{+}	-0.002^{+}	-0.002^{+}	-0.003^{*}	-0.002^{+}	-0.002^{+}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Quarterly ozone	-0.003^{*}	-0.003^{*}	-0.003^{*}	-0.003^{*}	-0.003^{*}	-0.003^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No. Observations	46,677	46,677	46,677	46,677	46,677	46,677

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction on ozone exposure. All regressions contain individual and year fixed effects. Specification (1) contains ozone, individual fixed effects and year fixed effects. The other specifications add further controls while always keeping the covariates from the previous specification: (2) adds the sociodemographic covariates age, income, and unemployment status; (3) adds county-level macro covariates population density, gross domestic product, and unemployment rate; (4) adds sunshine duration; (5) adds day-of-the-week fixed effects; (6) adds additional pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Estimations are performed using four different temporal aggregations of pollution exposure: daily, weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

to their health satisfaction. This finding corresponds to the result for ozone by Levinson (2012), who finds a surprising lack of significance of ozone on the life satisfaction of U.S. households but does not pursue this line of inquiry further. We next revisit our hypothesis by studying if ozone has a significant impact on individuals sharing their household with children. Further analysis focuses on our preferred specification.

5.2 Households with and without children

Recall that our central hypothesis is that in addition to the direct effects via people's health ozone may affect adults through a second channel: through the impact of ozone on their children.[10] If ozone affects the life satisfaction of adults through their children while not affecting their health satisfaction, we expect the point estimate

[10]By "individuals with children" we mean people sharing their households with children. By "individuals without children," we mean both; persons without children and those with children who no longer share the same family house. Our data do not allow us to distinguish between the latter two cases.

of ozone exposure on life satisfaction of adults sharing a household with children to be significant and negative in sign, while the same point estimate for persons without children should remain insignificant. With respect to health satisfaction, if the health satisfaction of adults with children is more affected by ozone than the health of childless adult, this would suggest differences in unobservables between adults with and without children that are relevant to the question of the impact of ozone.

Table 5 contains the coefficients of our preferred specification across all time aggregations of ozone levels and for the two subsamples, for both life and health satisfaction. The first insight is a lack of significance of ozone for either life or health satisfaction across the subsample of individuals without children. For individuals sharing a household with children, the results diverge. We find a statistically significant effect of ozone on the life satisfaction of adults with children across all time aggregations of ozone exposure. The effect is also economically significant: an increase in ozone is predicted to decrease life satisfaction between 0.004 and 0.007 points, depending on the level of aggregation. This coefficient corresponds up to about 12.5% of the estimated negative impact of becoming unemployed, one of the strongest shocks on life satisfaction found in the literature (Kassenboehmer and Haisken-DeNew, 2009). Additionally, the coefficient grows in size when extending the time interval for measuring ozone exposure prior to the interview, pointing to time accumulation of adverse outcomes due to ozone exposure. Concerning health satisfaction, we find no significance for adults with children, alleviating a potential concern about unobserved heterogeneity in the two subsamples. This result suggests that it is not differences in how the health of adults with and without children reacts to ozone that drive the consistent impact of ozone on health satisfaction, but that the effect is linked to their children. Implying that the effect of ozone on the well-being of adults works - at least partially - indirectly: Ozone exposure diminishes adults' well-being due to the negative impact of ozone on their children, a well-known high-risk group concerning ozone.

We next explore the heterogeneity of the effect of ozone on life satisfaction within the subsample of adults with children by analyzing the kids' ages for which

Table 5: Effect of ozone on life and health satisfaction, by child status

	Life satisfaction		***Health satisfaction***	
	No children	Children	No children	Children
Daily ozone	−0.001	−0.004*	0.001	−0.000
	(0.001)	(0.002)	(0.001)	(0.002)
Weekly ozone	−0.002	−0.005*	0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.002)
Monthly ozone	−0.001	−0.006**	0.000	0.000
	(0.001)	(0.002)	(0.002)	(0.002)
Quarterly ozone	−0.001	−0.007**	0.003	0.002
	(0.002)	(0.003)	(0.002)	(0.003)
No. Observations	30,591	16,086	30,591	16,086

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on ozone exposure in a multipollutant model controlling for individual fixed effects, year fixed effects, and day-of-the-week fixed effects; sociodemographic covariates age, income, and unemployment status; county-level macro covariates population density, gross domestic product, and unemployment rate; sunshine duration; air pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Estimations are performed using four different temporal aggregations of pollution exposure: daily, weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

the life satisfaction of adults is affected. To ensure large enough sample sizes we aggregate children ages into four-year bins and run the preferred specification for eight different group ages that steadily increase the lower and upper bounds of the bin in the sense $b_k = (age_{0+k} - age_{3+k})$ for $k \in (1, 2, 3, 4, 5, 6, 7)$.[11] Table 6 shows the results of this exercise. The point estimates for children of very young ages are never significant. We find statistical evidence for young kids in the age bins between 4 and 10 years old. Significance starts to occur after including four-year old children at the bottom of the age interval. The strongest results are for children of primary school age. In principle, we were expecting to find stronger effects for very young children. However, we believe this lack of significance for babies comes from a more noisy age group where ozone-triggered changes to life satisfaction conditions may not be relevant enough, given the many challenges facing adults having very young children.

[11]The SOEP only captures the age of the youngest child.

Table 6: Effect of ozone on life satisfaction for adults with children, different children's ages

	Dependent variable: Life satisfaction							
	(0-3)	(1-4)	(2-5)	(3-6)	(4-7)	(5-8)	(6-9)	(7-10)
Daily ozone	0.004	0.003	0.003	−0.001	−0.004	−0.008*	−0.010*	−0.015**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Weekly ozone	0.003	0.002	0.005+	−0.003	−0.008*	−0.010*	−0.017***	−0.018**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
Monthly ozone	0.003	0.002	0.002	−0.006	−0.012*	−0.011*	−0.019***	−0.022***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Quarterly ozone	0.005	0.005	0.004	−0.007	−0.015**	−0.016*	−0.030***	−0.030***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)
No. Observations	6,179	5,883	5,320	4,627	4,056	3,644	3,259	3,104

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction on ozone exposure in a multipollutant model controlling for individual fixed effects, year fixed effects, and day-of-the-week fixed effects; sociodemographic covariates age, income, and unemployment status; county-level macro covariates population density, gross domestic product, and unemployment rate; sunshine duration; air pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Estimations are performed using four different temporal aggregations of pollution exposure: daily, weekly, monthly, and quarterly. Numbers within parentheses refer to different intervals of children's ages. E.g., (0-3) is a regression for the subsample of individuals sharing the same household with one or more children, the youngest of which is between zero and three years old. Robust standard errors clustered at the household level in parentheses.

5.3 Mechanism

We have shown that adults with children suffer a decrease in life satisfaction due to ozone. We now consider the mechanism connecting ozone, the life satisfaction of adults, and their children's outcomes. An intuitive explanation is that ozone affects the health of children lowering the life satisfaction of adults sharing the same household with them. As shown in Section 2, there is a large stream of epidemiological literature demonstrating the negative consequences of ozone exposure for children's health. These range from increases in medication (Ostro et al., 2001) to pediatric hospitalizations (Burnett et al., 2001).

As data on the health status of children are not available to us, we cannot directly test whether ozone exposure affects children's health in our sample. However, the SOEP does provide relevant information to address this question. We use data on the number of workdays respondents lost because their child was sick.[12] If

[12] The variable stems from answers to the question: Over the last year, how many days did you miss work because your child was sick?

workdays lost due to child sickness are significantly affected by ozone, this provides evidence that ozone affects the health of children in our sample.

We estimate the effect of ozone on workdays lost by using a fixed-effects Poisson model. A Poisson model is appropriate due to the count nature of the dependent variable. Also, the Poisson approach allows for the incorporation of many zero values in the outcome variable, which is relevant in our case, as zero missed workdays are reported for 66% of the available observations.

Table 7 shows the results across five different specifications, corresponding to those in Section 5.1 and Section 5.2. Column (5) of Table 7 contains the multi-pollutant model, our preferred specification. The preferred specification finds statistically strong evidence of a positive relationship between monthly levels of ozone and workdays lost because a child was sick. The evidence is less strong for weekly ozone levels, and not significant for the daily and quarterly aggregation. In the multi-pollutant model, a marginal increase in the monthly concentrations of ozone increases the number of missed workdays of adults with children by 0.007 days. While strong statistically, quantitatively this is a rather moderate effect. We expect that the effect will be concentrated for young children, which may affect both the the statistical and the economic significance in the sample containing the parents of children of all ages.

Analogously to the results in section 5 we consider heterogeneity across children's age groups by dividing the sample into five-year age bins with respect to the age of the youngest child, from zero to ten years of age,[13] and run the preferred multi-pollutant specification for the different age bins and the different aggregations of ozone exposure. Table 8 shows the results. Ozone increases the number of workdays lost for all temporal aggregations, although the effects are much weaker - statistically and quantitatively - in the very short term. Weaker effects at the daily level are in line with our expectations, since a short-term episode of high ozone exposure is less likely to cause sickness due to which an adult may miss time at work than longer-term high ozone concentrations. The effect is concentrated on children

[13]Here we divide into five-year bins instead of four-year bins, as in Table 6, because of the smaller sample size for the missed workdays variable.

Table 7: Poisson regressions of missed work days due to child sickness

	Dependent variable: Missed worked days				
	(1)	(2)	(3)	(4)	(5)
Daily Ozone	−0.002	−0.002	-0.003^{+}	-0.003^{+}	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Weekly Ozone	0.003^{*}	0.003^{*}	0.003^{+}	0.003^{+}	0.003^{+}
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Monthly Ozone	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Quarterly Ozone	0.002	0.002	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Poisson regressions of workdays missed because a child was sick on ozone exposure. All regressions contain individual and year fixed effects. Specification (1) contains ozone, individual fixed effects, year fixed effects and the sociodemographic covariates age, income, and unemployment status. The other specifications add further controls while always keeping the covariates from the previous specification: (2) adds county-level macro covariates population density, gross domestic product, and unemployment rate; (3) adds sunshine duration; (4) adds day-of-the-week fixed effects; (5) adds additional pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Estimations are performed using four different temporal aggregations of pollution exposure: daily, weekly, monthly, and quarterly.

of up to nine years of age. It is not significant for older children and borderline reverses in the very short run for the age bin of 5-10 year-old children. Our results suggest stronger labor supply effects of ozone on adults sharing their household with very young kids. The point estimates increase in size, with a tripling of the point estimate to 0.017 workdays lost for a marginal increase in the ozone concentration for the age bin of 3-8 years and monthly ozone concentrations, compared to the result in Table 7.

This result is intuitive, as adults are more likely to miss work when they need to care for younger children. The results overlap with the results in Table 8 with respect to children's ages, suggesting that ozone leads to both losses in life satisfaction and workdays for adults sharing a household with young children. Our analysis of the effect of ozone on missed workdays suggests that at least some of the losses in adults' life satisfaction are due to the health effects of ozone on people's children. Moreover, we provide some evidence in favor of a labor supply effect of ozone exposure.

Table 8: Poisson regressions of missed work days due to child sickness, across children's ages

	Dependent variable: missed worked days					
	(0-5)	(1-6)	(2-7)	(3-8)	(4-9)	(5-10)
Daily ozone	0.004*	0.000	0.006**	0.007**	0.003	-0.005^{+}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Weekly ozone	0.007***	0.007**	0.012***	0.014***	0.012***	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Monthly ozone	0.013***	0.012***	0.015***	0.017***	0.013***	0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Quarterly ozone	0.012***	0.013***	0.014***	0.014***	0.009**	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
No. Observations	6,733	6,264	5,568	4,824	4,218	3,844

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Poisson regressions of workdays missed because a child was sick on ozone exposure in a multipollutant model controlling for individual fixed effects, year fixed effects, and day-of-the-week fixed effects; sociodemographic covariates age, income, and unemployment status; county-level macro covariates population density, gross domestic product, and unemployment rate; sunshine duration; air pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Estimations are performed using four different temporal aggregations of pollution exposure: daily, weekly, monthly, and quarterly. Numbers within parentheses refer to different intervals of children's ages. E.g., (0-5) is a regression for the subsample of individuals sharing the same household with one or more children, the youngest of which is between zero and three years old.

6 Robustness tests

6.1 Randomization of ozone exposure

This section runs two sets of placebo regressions to test whether our main results are an artifact of a defect in our research design. We randomize pollutants across space by randomizing exposure over individuals located in different parts of the country and across time by randomizing the exposure values of the same individual across the exposure values of all the years she was part of the panel. We then re-estimate our preferred specification. Table 9 contains the results of these additional estimations. Point estimates are always insignificant and very close to zero. Based on this exercise, we are confident that our main results are not driven by a flaw of our research design.

Table 9: Spatial and temporal randomization of pollutants, by child status

	Life satisfaction		***Health satisfaction***	
	No children	Children	No children	Children
Spatial randomization				
Daily ozone	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Weekly ozone	−0.000	−0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Monthly ozone	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Quarterly ozone	−0.000	−0.000	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Temporal randomization				
Daily ozone	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Weekly ozone	0.000	0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Monthly ozone	−0.000	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Quarterly ozone	−0.001	−0.001	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
No. Observations	30,591	16,086	30,591	16,086

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. OLS regressions of life satisfaction and health satisfaction on ozone exposure in a multipollutant model controlling for individual fixed effects, year fixed effects, and day-of-the-week fixed effects; sociodemographic covariates age, income, and unemployment status; county-level macro covariates population density, gross domestic product, and unemployment rate; sunshine duration; air pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Estimations are performed using four different temporal aggregations of pollution exposure: daily, weekly, monthly, and quarterly. Robust standard errors clustered at the household level in parentheses.

6.2 Cardinalization of well-being measures

One obvious caveat of this paper and others attempting to explain variation in subjective health and well-being is the cardinalization of ordinal data when running OLS type regressions (Levinson, 2012; Bond and Lang, 2018). The problem with cardinalizing ordinal scales is that we need to assume that the distance between values is the same: for example, the gap between zero and one is the same as between nine and ten. Changing the distance between them is a monotonic transformation of the ordinal scale. Such monotonic transformations may alter and even reverse regression results obtained by treating ordinal data as cardinal (Bond and Lang, 2018).

We run fixed-effects probit models to analyze if our results hold up when treating our subjective outcomes as ordinal.[14] We transform the health and life satisfaction scales into binary variables using a number of different cut-off points c_j for $j = (2, ..., 9)$. As an example, consider the cut-off point 2: If life satisfaction of an individual is smaller than or equal to 2, we assign a value of zero, i.e., the individual is deemed "unhappy." If life satisfaction is greater than 2, we assign a 1, i.e., the individual is considered "happy." Low cut-offs, therefore, place more people in the "happy" group, while the reverse is true for high cut-off points. Note that the location of the cut-off is arbitrary. Without information on the underlying distribution of happiness, it is difficult to make precise assessments of the suitability of a cut-off. We thus consider our results to be robust if they hold for multiple cut-off points used to create the binary happiness variable.

Table 10 contains the results of the probit estimations for the sample of adults with children in the preferred specification. Results show that for life satisfaction our point estimates are always negative and significant for multiple cut-off points. Almost irrespective of cut-off point, our results are significant for the longer-term aggregations, at monthly or quarterly frequency, while the results for daily ozone levels are only significant for very low and very high cut-offs. As in our baseline analysis, there are no significant results for health. Moreover, the corresponding analysis for the sample of childless people yields no significant results either for life satisfaction or health satisfaction, also confirming the results from the baseline regressions.[15]

7 Summary and conclusion

This article hypothesizes that pollution may – in addition to a direct effect through adults' health – decrease the well-being of adults through its effect on their children. The study tests this hypothesis for the case of ground-level ozone by analyzing

[14] We use the unconditional bias-corrected probit algorithm developed by Stammann et al. (2016). The algorithm uses the unconditional probit framework that corrects for the incidental parameters problem (Neyman and Scott, 1948) with the jackknife procedure developed in Hahn and Newey (2004).

[15] To limit the number of tables we do not report these results here. They are available upon request.

Table 10: Probit estimations of effect of ozone on life and health satisfaction, adults with children

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Dependent variable: Life satisfaction				
Daily Ozone	-0.015^{*}	-0.008^{+}	-0.005	-0.004	-0.004	-0.002	-0.005^{+}	0.004
	(0.007)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)
Weekly Ozone	-0.014^{+}	-0.011^{*}	-0.009^{*}	-0.005	-0.005	-0.002	-0.006^{*}	0.001
	(0.009)	(0.006)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Monthly Ozone	-0.021^{*}	-0.013^{*}	-0.010^{+}	-0.007^{+}	-0.006^{+}	-0.003	-0.007^{*}	0.000
	(0.010)	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.006)
Quarterly Ozone	-0.026^{*}	-0.017^{*}	-0.012^{+}	-0.009^{+}	-0.007^{+}	-0.006^{+}	-0.008^{*}	-0.002
	(0.012)	(0.008)	(0.006)	(0.005)	(0.004)	(0.003)	(0.004)	(0.007)
				Dependent variable: Health satisfaction				
Daily Ozone	-0.001	-0.000	0.001	-0.000	-0.003	-0.000	-0.003	-0.002
	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Weekly Ozone	0.003	0.002	0.004	-0.001	-0.003	-0.000	-0.002	-0.000
	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
Monthly Ozone	0.004	0.003	0.002	-0.001	-0.003	0.000	-0.003	-0.001
	(0.007)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Quarterly Ozone	0.001	0.005	0.005	-0.001	-0.003	0.003	-0.001	-0.001
	(0.009)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)
No. Observations	1,908	3,899	5,935	9,993	12,947	15,749	10,245	3,565

Table notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$. Fixed-effects probit regressions of life satisfaction and health satisfaction on ozone exposure in a multipollutant model controlling for individual fixed effects, year fixed effects, and day-of-the-week fixed effects; sociodemographic covariates age, income, and unemployment status; county-level macro covariates population density, gross domestic product, and unemployment rate; sunshine duration; air pollutants carbon monoxide, nitrous dioxide, sulfur dioxide, coarse particulate matter. Estimations are performed using four different temporal aggregations of pollution exposure: daily, weekly, monthly, and quarterly. Each columnt relates to a specific cut-off point between 2 and 9 used to transform the original 11-point scale into a happiness status of 0 or 1. The estimated specifications and cut-off points $c_j \in j = (2, ..., 9)$ are related as follows: $[(1) = c_2, ..., (8) = c_9]$. Robust standard errors clustered at the household level in parentheses.

whether ozone exposure affects individuals with and without children in different ways. We use a representative panel of German individuals, the German Socio-Economic Panel Study (SOEP), to study the effect of exposure to ground-level ozone on two measures of subjective well-being, health and life satisfaction. Furthermore, our analysis evaluates the children's health channel to adults' well-being outcomes by analyzing weather ozone exposure leads to losses in adults' labor supply when they need to care for their sick child.

We identify the effect of ozone on individuals from short-term variation in ozone levels by exploiting information on the precise date of the SOEP interview. To do so, we match pollution levels from measuring stations across Germany with geo-coded SOEP data between 2005 and 2015 and compute the individual level of exposure through inverse distance weighting techniques. The study estimates the effects of ozone on the health and life satisfaction of adults with and without children using multi-pollutant fixed-effects regressions, controlling for time and individual fixed effects, and include a battery of individual, county, and weather level covariates. Additional results correspond to the effect of ozone exposure on workdays lost because a child was sick using Poisson models.

This study finds statistically and economically significant adverse effects of ozone on the life satisfaction of adults sharing a household with children while finding no effects on children-less households. The economic significance increases with the length of exposure. However, and in contrast to life satisfaction, our analysis finds no evidence of a direct effect of ozone on adults' satisfaction with health. Examining the children's health mechanism to losses in adults' life satisfaction, we find that higher ozone exposure leads to a significant increase in workdays lost because a child was sick. Our results suggest that ozone concentrations in Germany are not high enough to negatively affect the subjective health of adults in general, but that they do have negative consequences for the health of children, which in turn diminishes the well-being of the adults they live with. We corroborate this hypothesis by showing that greater ozone exposure leads to significant losses in adults' workdays due to child sickness.

Based on our analysis, we recommend that the indirect influence of ozone on persons with children should be taken into account in further research and in policy debates regarding the costs and benefits of reducing air pollution. Our results suggest that stricter limits on ozone levels are required to account for the greater vulnerability of children to this pollutant and its secondary effect on the well-being and labor supply of the adults sharing the same household.

One limitation of our study is the lack of access to health data for children. Further research should attempt to shed further light on the children's health mechanism to losses in life satisfaction of adults identified in this paper by analyzing the impact of ozone on children using objective data on children's health status.

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