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Gray Skies and Blue Moms:
The Effect of Air Pollution on Parental Life Satisfaction[*]

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Abstract: We investigate the effects of air pollution on individuals' life satisfaction, uncovering important heterogeneity in the impact. Using self-reported life satisfaction data from South Korea, we show that individuals report, *ceteris paribus*, lower life satisfaction in response to worsening air quality if young children are present in the household. This observed impact is driven heavily by the subpopulation of mothers, and the impact on mothers attenuates as their children grow older. We conclude that mothers' disproportionate responsibility for child rearing and children's higher vulnerability to air pollution are the likely channels mediating the impact of air pollution on life satisfaction.

Keywords: Air pollution; Life satisfaction; Caregiving; Children; Social relations; Korea

JEL: I31; Q53

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1. Introduction

Air pollution has raised a lot of public concern and posed an important challenge for public policy in many countries. Researchers thus are paying increasing attention to estimating the socioeconomic consequences of worsening air pollution. Since the seminal work of Lave and Seskin (1970) raised an alarm of the adverse health effects of air pollution, subsequent studies have examined the impact on other human capital outcomes, such as labor market performance (e.g., Hanna and Oliva, 2015), school absenteeism (Currie et al., 2009; Hales et al., 2016), and students' cognitive performance (Zhang, Chen, and Zhang, 2018).[2]

Along with the growing interest in the studies of subjective well-being (SWB) in recent decades (see e.g. Easterlin, 1974 for earlier contributions, and Frey and Stutzer, 2002; Helliwell and Wang, 2012; van Praag and Ferrer-i-Carbonell, 2008 for recent overviews), another strand of literature on air pollution attempts to directly infer the monetary loss implied by air pollution, using people's SWB as a proxy for utility. Typically, researchers estimate the impact of household income and air quality on various SWB measures and evaluate the income-air quality tradeoff.[3] These studies have been conducted in various scopes. Some leverage the aggregate variation in air pollution and life satisfaction within specific blocks of countries, such as Ferreira et al. (2013) and Welsch (2006) in Europe, and Menz (2011) in Europe and South America. Other scholars utilize the within-country microdata, such as Ferreira and Moro (2010) in Ireland, Yuan, Shin, and Managi (2018) and Zhang, Zhang, and Chen (2017a; b) in China, Luechinger (2009) in Germany, and Levinson (2012) in the United States. Many studies further narrow down the scope to the cities or regions, such as Ambrey, Fleming, and Chan (2014) in Queensland, MacKerron and Mourato (2009) in London, Li, Folmer, and Xue (2014) in Jinchuan mining area of China.

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[2] See Graff-Zivin and Neidell (2013) for a detailed discussion.

[3] A detailed review on the life satisfaction approach to environmental good can be found in Frey, Luechinger, and Stutzer (2010).

Studying the link between air quality and SWB is important for multiple reasons. As it has been mentioned, the estimated slope of SWB in air pollution provides yet alternative approach to monetize air quality, a non-market good. While the approach is not entirely "assumptionless", it explicitly allows to overcome the primary challenges stemming from the existing alternatives - stated preferences and hedonic methods.[4] Besides, there is Easterlin Paradox (Easterlin, 1974): aggregate happiness does not always respond to positive changes in the national income. To the extent that air pollution varies substantially across counties with comparable income, scholars put forth the possibility that, among other things, the variation in air quality might provide one explanation to the Easterlin Paradox (Di Tella and MacCulloch, 2008).

Contributing to the existing literature, we propose a novel way to look at the relationship between air quality and SWB, which stems from the health effects of the most vulnerable group. There is abundant epidemiological literature that examines the air pollution effects on health (Braga et al. 2001; Brook et al. 2004; Brook et al. 2010; Currie and Neidell, 2005; He, Fan, and Zou, 2016; Chen, Guo, and Huang, 2018; Liu and Salvo, 2018; Gouveia and Junger, 2018). For example, He, Fan, and Zhou (2016) find a nonlinear effect of air pollution across age groups, with the largest effect observed in the group of children under 10 years old and the elderly. Air pollution tends to cause respiratory illness and then school absences among the young cohort (Chen, Guo, and Huang, 2018; Liu and Salvo, 2018). The absences may be either defensive behavior of parents or remedial response of adolescent students based on their own judgment about health conditions (Liu and Salvo, 2018).

Building on the evidence laid by the literature of air quality's effects on children health and parental responses, we hypothesize that air pollution has a significant impact on parental life satisfaction. The caregiving responsibilities of parents would rise either

[4] See Frey, Luechinger, and Stutzer (2010) for the detailed discussion of the differences between three approaches.

because the parents decide to keep their child at home as a protective measure or due to sickness of a child induced by the high levels of air pollution. For the youngest group of children under five, who are the most vulnerable to air pollution, the likelihood of getting sick in polluted days is higher than in other age groups (He, Fan, and Zhou, 2016). The ill-health of children, in turn, would affect the level of satisfaction of parents stemming from parental altruism and the burden of caregiving. The estimated well-being of parents seems to be significantly affected by their children's illness, and parents' preferences over relief from acute illness are stronger when the illness affects their children than their own health (Eiser and Morse, 2001; Dickie and Messman, 2004).[5] Longer hours of childcare also increase the stress levels of parents and decrease well-being (Rizzo, Schiffrin, and Liss, 2014; Roeters and Garcia, 2016).

We thus test the hypothesis by estimating the impact of air pollution on parental life satisfaction using the data from South Korea (Korea henceforth), which provides us two methodological gains. First, there exists a substantial variation of air pollution across geographic locations within the country while the overall country-level air quality often falls far below established standards. This partly addresses the concern related to the potential failure to detect the impact either due to the absence of a sufficiently high level of air pollution and/or low variation of this variable across units of observation. Second, we utilize the geography of Korea to leverage a plausibly exogenous variation in wind directions to identify the slope of life satisfaction in air quality in the two-stage least squares framework. If wind direction *per se* does not affect respondents' life satisfaction via any channel other than air quality, then the revealed impact can be interpreted as the causal impact of air pollution on individuals' evaluative well-being.

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[5] See Eiser and Morse (2001) for a summary of the relationship between the children's health-related quality of life of parents and children.

Our findings show that there is no significant impact of air quality on overall life satisfaction. However, further analysis paints a different picture. We show that individuals tend to report a lower level of life satisfaction in response to worsening air quality if young children are present in the family, possibly due to parental altruism and longer hours of child care as discussed above. Moreover, we find that the observed impact is heavily driven by the subpopulation of mothers. This is consistent with the fact that the main caregivers are mostly women in many countries, including Korea (Kim, 2000; Offer, 2014). We thus posit that mothers' disproportionate responsibility for child-rearing and children's high vulnerability to air pollution are the likely channels mediating the impact of air pollution on life satisfaction. We further show that the estimated impact on mothers diminishes as their children grow older, which is consistent with the age pattern of children's vulnerability to air pollution.

If a mother needs to stay home with her child due to air pollution, she tends to temporarily lose her social interactions with her peers, which may affect the level of satisfaction with social relations. Mothers of young children in Korea often mutually support each other in child-rearing, for example through hanging out together (Chung, 2010). Our empirical results support this hypothesis, suggesting that mothers of young children report lower satisfaction with social relations in response to heightening air pollution.

Finally, we assess the robustness of our estimation in numerous ways. The findings show numerical stability between the least and the most saturated model's specifications. Additionally, in the spirit of placebo tests commonly employed in quasi-experimental studies, we show that the revealed link between air pollution and life satisfaction vanishes if we substitute "future" kids for the actual number of children in the family at the survey moment. The latter finding reinforces our belief that children's vulnerability to air pollution and mothers' role of the chief caregivers in the family are the underlying force that drive the pattern.

Our study contributes to the rare discussion on the potential channels through which worsening air quality deteriorates individuals' SWB. As Luechinger (2009) points out, the life satisfaction approach may capture the indirect effects through channels that individuals are unaware of. With an exception of Laffan (2018) who infers decreasing physical activities and outdoor visits as potential channels, and Powdthavee and Oswald (2020) who show that air pollutants negatively affect memory and possibly increases the risk of dementia in later life, however, little has been explored beyond some epidemiologic explanation of adverse health effects of air pollution.

Our study also adds to the divergent arguments in the body of research on air pollution's impact on individuals' life satisfaction. In the current literature, air pollution may or may not affect life satisfaction across the general population. These mixed results may arise from a lack of examination of a channel, in addition to the methodological challenges mentioned earlier. For example, Zhang, Zhang, and Chen (2017a; b) argue that evaluative happiness, such as life satisfaction, is less likely to respond to temporal changes in air quality. Earlier works by Deaton and Stone (2013) and Kahneman and Deaton (2010) seem to support this argument, as they show that life satisfaction is invariant by the day of the week. However, many other studies such as Luechinger (2009) provide evidence that life satisfaction is negatively affected by air pollution in Germany. The methodological challenge could partially explain this disagreement about the relationship between air quality and SWB. Because air quality and life satisfaction are jointly determined by local economic, meteorological, and geographic conditions, an inclusion of one of the conditions without controlling for others may yield mixed results. For example, Yuan, Shin, and Managi (2018) find that deteriorating air quality index (AQI) has a negative impact on life satisfaction in China using the web-based survey data collected in early 2016. However, Zhang, Zhang, and Chen (2017a) leverage the within-individual variation of air quality and life satisfaction utilizing the household data from China collected in a close period and find that the impact of AQI on life satisfaction is not significant.

The remainder of the paper is organized as follows. Section 2 describes data and identification strategy. Section 3 presents the main results and robustness checks. One channel of the impact is discussed in section 4. Section 5 concludes.

2. Data and Identification

This study uses data from the Korean Labor and Income Panel Study (KLIPS), which provides a rich set of demographic characteristics of individuals and households. KLIPS is a longitudinal survey of the labor market and income activities, based on interviews of 5,000 households and their members older than age 15 in urban areas since 1998. Our study uses the panel of 13,109 individuals who were observed on average 5.7 times between 2010 and 2016. We utilize individual-level life satisfaction data reported by the KLIPS respondents, along with the set of conventional socioeconomic characteristics such as gender, age, employment, marital status, and educational attainment. The life satisfaction question is "How satisfied are you with your life in general?" Responses are on an ordinal scale from one to five, where one signifies "very dissatisfied" and five means "very satisfied." From the household-level data, we obtain information on the number of children in the households and their ages, proxies for each family's financial status (i.e., household income, the existence of financial debts, and the number of cars), and geographic location of the family.

Our measure of air pollution is the district-level concentration of coarse particulate matter (PM10), which is obtained from Air Korea of the Korea Environment Corporation. The unit of measurement is 10 $\mu g/m^3$, as we normalize the variable by 10 to scale up our point estimates. We focus on PM10 as a proxy for air pollution, as it is easily transmissible due to its microscopic size and has a direct and potentially fatal impact on human health (Brook et al., 2004; Brook et al., 2010; Hicken et al., 2013; Jans, Johansson, and Nilsson, 2018; Lucas et al., 1994; Pope, Ezzati, and Dockery, 2009). The levels of PM10 concentration in Korea tend to be much higher than that considered acceptable by international air quality standards, thereby increasing the likelihood that pollution affects individual life satisfaction (see the distribution in Figure 1).

We also collect other district-level weather information such as wind patterns, wind flow velocity, precipitation, and atmospheric pressure from the Korea Meteorological Association. We match individual data with the air quality and weather measurements from the district in which an individual resides or the geographically closest district (if there is no such information in the region where the individual lives) at the time of the survey.

We employ the two-way panel fixed-effects model to estimate the life satisfaction's equation of the following form:

$$Y_{idt} = \beta_1 \overline{PM}_{dt} + \beta_2 k_{idt}^{j} + \beta_3 \overline{PM}_{dt} \times k_{idt}^{j} + X_{idt}^{I} \delta^{I} + X_{dt}^{D} \delta^{D} + \theta + v_{idt}, \qquad (1)$$

where Y_{idt} is the self-reported life satisfaction of respondent *i* living in district d at time *t*. Life satisfaction is an ordinal variable, however whether one assumes the ordinality or cardinality of life satisfaction scores usually makes little difference, as Ferreri-Carbonell and Frijters (2004) show. We report results based on cardinality for ease of interpretation.

$\overline{PM}$ is the monthly average district-level concentration of PM10, measured in 10 μg/m³. k^j is the number of children aged $j = \{1,2,3\}$ years or younger, who reside with individual i in period t.[6] β_1 thus indicates the general impact of air pollution. $\beta \times k_{idt_3}^{j}$ can be viewed as a deviation of the overall life satisfaction of those, with k children of age *j,* from the outcomes of the others, in response to a unit-change in $\overline{PM}$.

X^I is a vector of individual-level controls, which includes age, age squared, labor force status (being employed or being unemployed), marital status, educational attainment, number of children aged below 18, log of household income, home ownership, vehicle

[6] We extend our analysis to take older children into account in Section 6.

ownership, and the presence of any financial debts, consistent with previous literature (Ferrer-i-Carbonell, 2005; Frijters, Haisken-DeNew, and Shields, 2004; Layard, Mayraz, and Nickell, 2008; Luechinger, 2009)[7].

We also control for X^D, a vector of district-specific, time-variant weather indicators, namely monthly average wind speed, precipitation, and ground air pressure. Those characteristics may be associated with individual's life satisfaction through emotional reactions or their impact on physical health (Barrington-Leigh and Behzadnejad, 2017; Howarth and Hoffman, 1984;). θ is a set of fixed effects (individual intercepts, seasonal dummies, and province-specific year fixed effects), and v_{idt} is the error term.

Although we explicitly partial out many potential individual-specific and district-specific confounders of air quality in Equation (1), concerns about consistency of the fixed-effects estimation may still remain.

First, the air pollutants might be measured imprecisely. Moreover, assigning each district the pollutant measures recorded at the closest station introduces another source of the measurement error. Although the inclusion of panel fixed effects controls for the time-invariant determinants of individuals' life satisfaction, the implied panel fixed-effects' data transformation amplifies the bias that arises from the measurement error in $\overline{PM}_{dt}$.

Second, we might not observe all the district-specific characteristics that affect both air quality and individual outcomes. The province-specific year fixed effects allow us to dummy out all the province-level characteristics that evolve by years, however it might not account for the omitted temporal district-specific characteristics. For example, as shown by Baek (2016) and Li et al. (2019), subway expansion introduces sizeable improvements to local air quality, potentially by reducing the utilization of personal

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[7] Given the potential endogeneity of household income, we instrument it using the occupation- and industry-specific average income at the district level in the same year, following previous literature (e.g., Levinson, 2012; Luttmer, 2005 Zhang, Zhang, and Chen, 2017a).

vehicles. If this event affects individuals' well-being through any channel other than improving air quality (such as traffic noise reduction, or the reduction in traveling time), then the concern about OLS overstating the magnitude of the impact emerges.

We address the above concerns by employing wind direction as the instrument for air pollution, based on existing evidence of transboundary air pollution traveling from China to Korea (Bhardwaj et al., 2019; Jia and Ku, 2019; Lee et al., 2013; Oh et al., 2015). We also add the interaction term between wind direction and the distance to China as an additional instrument, as the districts located farther away from China are generally exposed to lower flows of pollutants.

For wind direction (and its interaction with distance to China) to be a valid instrument, it must affect air quality, while being excluded from the second-stage equation. Those studies that document air pollutants' spillover from China, justify our belief that the proposed instruments affect air pollution. We also argue that wind direction and its interactions with distance are plausibly exogenous to Equation (1), after controlling for the other weather conditions.

Among the various weather variables, wind direction is neither easily perceptible as other indicators, nor documented as a factor that affects psychological or physical health. In addition, we explicitly control for quarter dummies, which accounts for the potential seasonality of wind direction, and include province-year fixed-effects, which reduce our identification to the comparison of individuals within the province-year cell.

Based on this rationale, we retrieve district-level time series on the wind patterns from Korea Meteorological Association. The raw data contains information of the prevailing wind direction (measured on 360-degree scale) for every district-month cell. We exploit the frequency of occurrence of west and north winds as our instruments, as they are more likely to affect Korea's air quality in view of its location relative to China. We also interact these two wind directions with the log of the distance from the centroid of the d-th district to the nearest point on the Chinese border, $\ln D_d$, as we expect that settlements located farther away from China would be less affected by transboundary pollution spillovers. Finally, we interact our excluded IVs with the number of kids to instrument for the $\overline{PM}_{dt} \times k_{idt}^{j}$ from Equation (1). $\ln D_d$ is then incorporated into the second-stage regression as a separate term.

Next we turn to the discussion of the issues related to our statistical inference. Our air quality measures vary by districts over time. Hence, clustering standard errors by districts would account for potential correlation of the disturbance term in Equation (1) within districts. Unfortunately, this approach is not feasible in our case, as individuals naturally migrate over time. We then cluster the standard errors by individuals in the main regressions, but we implement two kinds of robustness checks to address the potential over-rejection. First, we restrict our sample to the individuals who did not migrate within the study period, so that we can cluster standard errors by districts. In our next exercise, we exclude panel fixed effects from our model and cluster standard errors by districts, treating the same person observed at different points in time as independent observations. Both exercises produce results consistent with the baseline findings.

3. Main Results

3.1. Basic results

Table 2 reports the life satisfaction regressions for all respondents and for each gender. Columns (1)–(3) focus on the interaction between PM10 and the number of infants (i.e., children aged one or less). Columns (4)–(6) and (7)–(9) are for children no older than age two and three, respectively. The coefficients of control variables are generally consistent with the literature. Married men and women have higher levels of life satisfaction than those who are separated, widowed, or divorced. Higher education and employment status are positively related to the reported life satisfaction. Variables indicating household income and wealth have expected signs.

The main variables of interest are PM10 and the interaction term between PM10 and the number of young children. Table 2 shows that the coefficients of PM10 are negative in all columns, yet not statistically significant at the conventional level. This implies that air quality has no direct impact on people's life satisfaction, which is consistent with the recent findings of Zhang, Zhang, and Chen (2017a). However, we find significant impact of pollution on parents of young children. Combining this information with the observation that adults' life satisfaction does not respond to an increase in pollution levels, we infer that air pollution affects parents through its impact on their children. As shown in columns (1), (4) and (7), the coefficients of the interaction between PM10 and the number of young children are significant at the 0.05 level for the total sample. The interaction coefficient in column (1) is –0.061, implying that for each 10 μg/m^3 increase in PM10, the level of life satisfaction for individuals who have an infant declines by 0.061 (on a scale from one to five) compared to other families. This translates to the reduction of 0.11 standard deviations in life satisfaction.[8]

The heterogeneous effects by gender are even more noticeable. The interaction term's coefficient is not statistically significant for fathers, as shown in column (2), whereas it is significant at the 0.01 level for mothers, as indicated in column (3). Moreover, the coefficient is larger for mothers than for the total sample; for each 10 μg/m^3 increase in PM10, mothers' level of life satisfaction decreases by 0.113, which is about 0.2 standard deviations. Combining these observations, we find a significant impact of air pollution on the level of life satisfaction of mothers with infants, but not fathers. This highlights the gender inequality in parenting, supporting evidence that mothers typically bear the caregiving responsibility for young children in Korea (Choe and Retherford, 2009; Kim and Cheung, 2005; Koh, 2008; Tsuya, Bumpass, and Choe, 2000).

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[8] Table 1 reports the sample standard deviation of life satisfaction, 0.579. Thus, a 10 μg/m^3 increase in PM10 decreases the life satisfaction of parents with one infant by 0.11 standard deviations (–0.061/0.579 ≈ –0.11).

The same pattern is observed for parents with older children. The interactions' coefficients for fathers with children no older than age two or three are all close to zero and not statistically significant, as shown in columns (5) and (7) of Table 2, respectively. However, they are all significant for mothers, as shown in columns (6) and (9). The coefficient of the interaction term between PM10 and the number of children no older than two is –0.101 for mothers, as shown in column (6), and it attenuates further to –0.077 for mothers with children up to three years old, as reported in column (9). Comparing these figures with the coefficient in column (3), we observe that the impact attenuates as children grow older.

Following the literature, we calculate the willingness to pay (WTP) for air quality, which is a trade-off between the household income and air quality that keeps the life satisfaction being constant (e.g. Levinson, 2012; Luechinger, 2009; Zhang et al., 2017b). Column (1) of Table 2 suggest that a 10 μg/m3 increase in PM10 decreases the life satisfaction among parents with children younger than one year old by 0.0248 (=0.024+0.061×0.013) on a five-point scale, considering the share of parents with infants is only 1.3%. The log income's coefficient suggests that a 1% increase in the annual income increases life satisfaction by approximately 0.0062 (=0.062×0.01). The estimated WTP for a 1 $\mu g/m^3$ reduction in PM10 for parents with infants is thus 4% of the annual household income.[9] The implied monetary value evaluated at the average annual income is 1,100 $, which is a fairly significant amount.[10] The corresponding WTP for a 1 μg/m3 reduction for families with children younger than two years old and three years old are 4.07% and 4.03% of the annual income respectively.

Tables 3.1 and 3.2 report the two first-stage results for PM10 and for the interaction between PM10 and the number of children of specific age groups, respectively. In Table

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[9] The relative coefficient between 1 $\mu g/m^3$ of PM10 and income is (0.024+0.061×0.013)/0.062/10=4%.

[10] The exchange rate for US dollars and Korean won is set to be 1,200 KRW/US$. The annual average income is 33,018,640 Korean Won in the study period.

3.1, the coefficients of both north and west winds are positive, being significant at the 0.01 level. This observations confirms the existence of air pollution spillovers from China. In contrast, the interaction terms between wind and log of distance from China are negative and significant at the 0.01 level, implying that the farther away a district is from China, the less pollution spillover reaches that district. The *F* statistics of excluded instruments are at least 80 in all models, which are large enough to relieve concerns regarding weak instruments (Stock and Yogo, 2005). The *p*-value in the overidentification test is reasonably large in each column, which empirically supports the exclusion restriction of the instruments.

Table 3.2 reports the first stage for PM10 in interaction with the number of children of specific age groups. The interaction coefficient of the north wind and the number of children is significant in all columns, and a greater distance from China lowers the coefficient of the interaction term. However, the coefficient on the interaction between the west wind and the number of children is not significant, although the signs are as expected. The *F* statistics of excluded instruments are larger than 10 (except for columns (2) and (5), which correspond to the subsamples of males, for which we do not detect any effect), and the null hypothesis of the overidentification test is failed to be rejected in all columns.[11]

3.2. Age pattern of the impact

In this section, we further explore the impact of air quality on parents with older children. Our goal is to test whether parental life satisfaction indeed becomes less responsive to air pollution as children grow older. More specifically, we consider children aged one to ten and check if the negative impact of air quality fades as children age. Figure 2 plots the point estimates of the interaction term between PM10 and the

[11] The *F*-statistics of the excluded IVs for the interaction term are close to the weak instrument's threshold. One might view our point estimates as consistent, yet biased towards the center of the finite-sample's distribution of the OLS estimator.

number of children in the specific age group. A clear pattern is observed: the estimated coefficient attenuates as children grow older, and it loses its statistical significance from age six onward. The observed attenuating pattern closely matches the clinical observation that older children are less vulnerable to air pollution (e.g. Braga et al., 2001).

3.3. Robustness checks

We cluster standard errors by individuals in our mainline regressions with the individuals' fixed effects. As some individuals moved across districts during the study period, we are not able to account for the potential within-district correlation of the disturbance terms by clustering the standard errors by districts. To assess the validity of our main findings, we conduct two additional exercises related to the statistical inference.

We first restrict the sample to those who have never migrated during the study period. This naturally nests the panel units within districts and hence allows as to cluster standard errors accordingly (206 districts in our sample). Table 4 reports the second stage of the 2SLS regressions for non-movers, with the same structure as in Table 2. The total sample size is reduced from 74,554 to 59,925. We note that the coefficients of PM10 are (i) very similar to those in Table 2, and (ii) not statistically significant. The key coefficient of the interaction between PM10 and the number of children no older than one, two, and three are –0.116, –0.082, and –0.062. The magnitudes are comparable with the main results in Table 2. Besides, the key coefficients are statistically significant at the conventional levels.

For our second check, we utilize the full sample including both movers and non-movers, but now we omit the panel fixed effects. This also enables us to cluster standard errors by districts, as now the same individual observed at different points of time is viewed as distinct observations. If our instruments are truly exogenous, then excluding individual fixed effects should not alter our results. In Table 5, which shows the second-stage results of 2SLS regressions, the coefficients of PM10 are still not statistically significant in all models. The interaction coefficients in columns (3), (6), and (9) are qualitatively similar to the main results.

We now assess the stability of our point estimates to the alternative model specifications. One might concern that some weather conditions that correlate with our instruments also have impact on parental life satisfaction. We cannot rule out the possibility that certain wind direction might switch on jointly with other weather indicators. For example, north wind is likely to be associated with lower temperature. If temperature, which has not been considered in our analysis so far, affects parental life satisfaction, then its omission poses a threat to the validity of our analysis. To address this concern, we endow our model with a battery of additional weather indicators. The full list of weather indicators consists of average wind speed, maximum wind speed, average precipitation, average air pressure, average temperature, maximum temperature, and minimum temperature. All variables are averaged over one month preceding the survey date. Similarly, minima and maxima are chosen from the month preceding the survey date. To address the concern that above weather indicators might disproportionately affect families with young children, we also include the product of each weather indicator with the number of children of specific age group.

In addition, one may have a concern about the possibility that certain unobserved geographic characteristics of districts might also determine both life satisfaction and wind patterns. Elevation, proximity to the sea and terrain ruggedness are three probable candidates (out of many). The inclusion of district fixed effects relieves this concern.[12] Finally, we endow our models with district-specific cubic time trends to approximate the dynamics of those temporal district-level determinants of the individuals' life satisfaction.

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[12] In this case, district fixed-effects absorb the natural log of the distance from the district's centroid to China, which is included in the previous specification as a separate term.

Table A2 reports the results including all these additional controls. The coefficients of the interaction between PM10 and the number of children get amplified numerically, yet they preserve their cross-gender and age-specific pattern: air pollution affects mothers' life satisfaction, and the impact gets smaller as children age. Hence, we conclude that fluctuating weather conditions are unlikely to be the channel through which wind directions affect parental life satisfaction. This further reinforces our belief that air quality is likely to be the only link between wind direction and parental life satisfaction.[13]

3.4. Falsification test

There could be a concern that the unobserved determinants of life satisfaction among individuals with children might be substantially different from those without children. Although the panel fixed-effects transformation potentially addresses this possibility, the unobserved heterogeneity might contain time-variant components that drive our results. To further assess our findings, we run a falsification test using information on parents observed before having children. For each woman, whose oldest child is at age *j* in period *t* in our dataset, we assign a "pseudo-child" in the period *t-j-2*, as she was not pregnant at that time. In this case, the interaction between PM10 and the number of "pseudo-children" should not be significant for mothers, in contrast to the main results. The falsification test is reported in Table 6, which has the same structure as Table 2. We find no statistically significant interaction effect in all models, which supports our main findings that the impact of air pollution on mothers' life satisfaction is due to the presence of young children.

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[13] We have also experimented with standard errors in the setting with additional controls. As before, we have clustered them by districts after (i) excluding those who migrated across districts within the study period, (2) omitting the panel fixed effect, running the pooled regressions. The results do not change and hence we do not report them to preserve the space. The results are available upon request.

4. Refining the Link between Air Pollution and Parental Life Satisfaction

It is natural to think that the child's illness induced by air pollution affects the main caregiver's life satisfaction in multiple ways, such as through increased physical burden of caregiving and/or the implied psychological disturbance. Although we cannot test this channel due to the absence of the children's health information in our data, we instead explore parents' social relations as another potential channel.

Many studies show that the frequency of social interaction is positively associated with happiness (Bartolini, Bilancini, and Pugno, 2013; Rodríguez-Pose and Berlepsch, 2014; Tsuruta et al., 2019). In the Korean context, where the main caregivers are mostly women, mothers of young children often bond with each other to provide mutual support in child-rearing (Kim, 2000; Chung, 2010). When a child becomes sick due to high levels of air pollution or the mother chooses to keep her home (because of the potential negative impact of air pollution - a phenomenon known as avoidance behavior), the mother would temporarily lose her usual social interactions with her peers. [14] It is also unlikely that the online social networking could substitute adequately for the in-person social interactions, as evidence shows (Arampatzi, Burger, and Novik, 2018; Helliwell and Huang, 2013; Vigil and Wu, 2015).

To test this channel, we run the same models using satisfaction with social relations as the outcome variable. Table 7 shows a similar pattern as our results for life satisfaction; specifically, there is a significant negative impact of air pollution on mothers with young children, but not on fathers. Moreover, as Figure 3 shows, the effect of air pollution on satisfaction with social relations attenuates as children grow older and becomes statistically insignificant from age six onward. These results are consistent with the pattern for life satisfaction described in the previous section.

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[14] For more discussions on avoidance behavior, see Graff-Zivin and Neidell (2009) and Moretti and Neidell (2011).

5. Conclusions

This paper estimates the impact of air quality on life satisfaction by matching individual-level life satisfaction data obtained from a nationally representative longitudinal survey with regional PM10 data from Korea during the period from 2010 to 2016. Wind direction and its interaction with the distance from the Chinese border are employed as instrumental variables for the identification, in addition to controlling for a rich set of fixed effects.

Our results imply that PM10 does not have a direct effect on the general population, but it does significantly lower the life satisfaction of mothers with young children, as mothers are the primary caregivers in Korea. We further show that the estimated impact on mother's life satisfaction diminishes as the children grow older, consistent with the fact that children grow to be less vulnerable to air pollution.

Our results corroborate previous findings that life satisfaction responses provide valuable information on people's subjective evaluation of public goods. In addition, we identify a new group of people who are highly vulnerable to the psychological impact of air pollution, namely - mothers who are the primary caregivers for their young children. To the best of our knowledge, this is the first paper that explicitly highlights caregiving as the channel that mediates the negative impact of air pollution on individuals' life satisfaction. In support of the results, we also show that mother's satisfaction with social relations were affected by air pollution, as they are less likely to hang out with other mothers in case of worse air pollution. This gender- and age-specific effect of air pollution calls for special attention, as it tends to be ignored in general academic and policy discussions.

This paper complements existing studies on air pollution's negative impact on physical and psychological health. Air quality is often unsatisfactorily low in many developing countries, and even in some developed countries such as Korea. Our results suggest that alleviating pollution levels will have a significant impact on social welfare.

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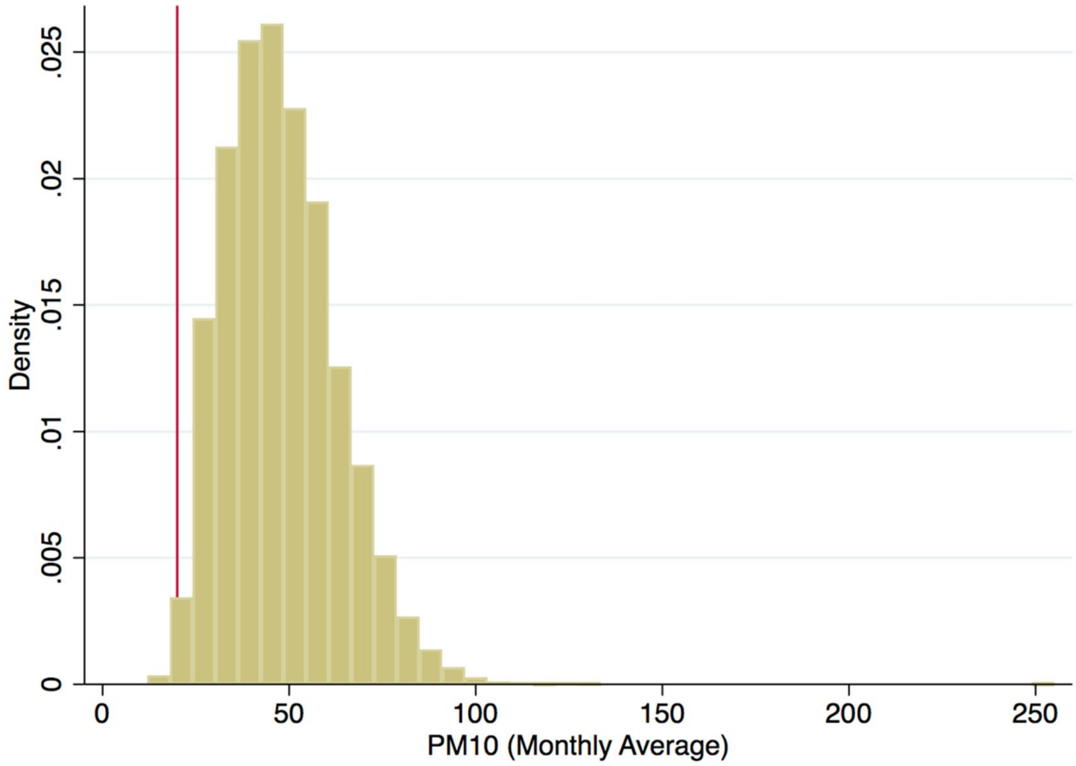
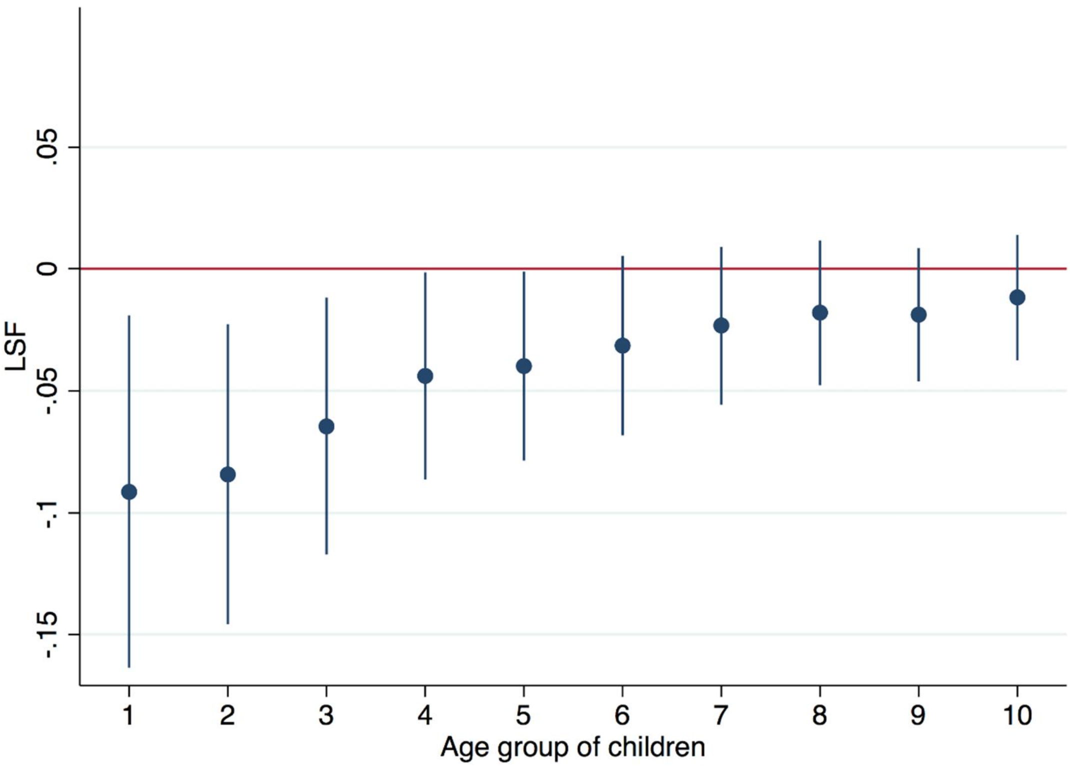
Figure 1: Distribution of Monthly Average PM10 (in μg/m^3), 2010–2016



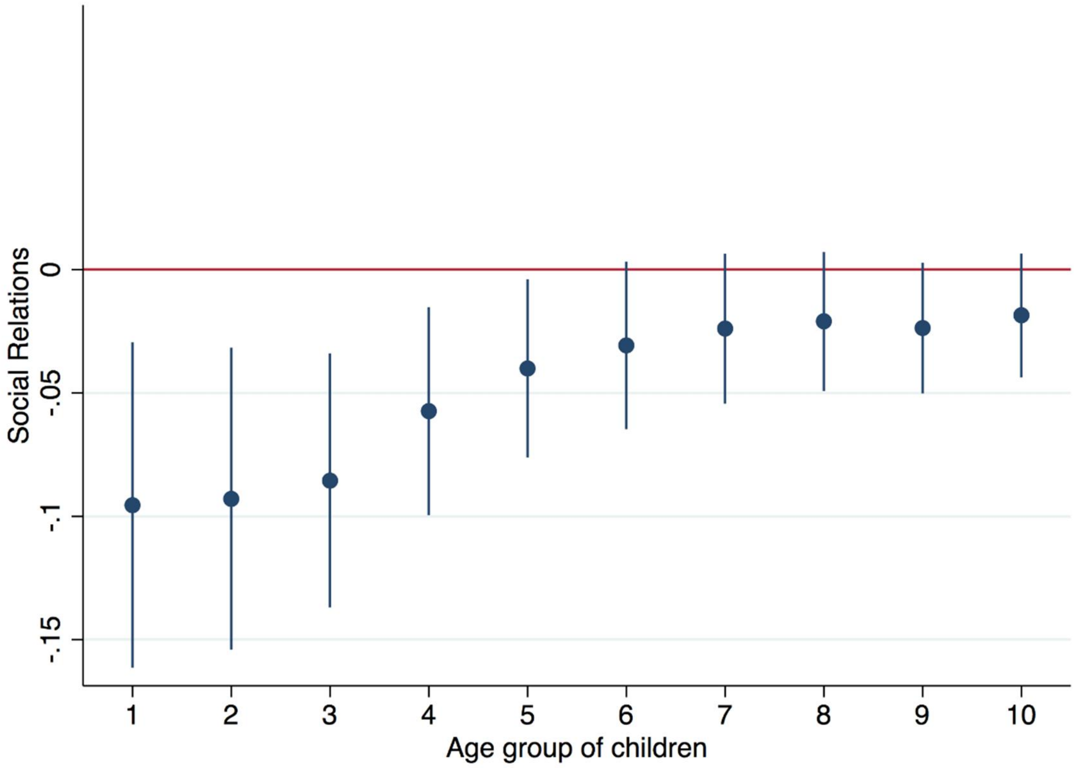
Notes: This figure illustrates the histogram of the monthly average PM10 during the study period. The vertical line at 20 μg/m^3 indicates the safety guideline recommended by WHO.

Figure 2: Heterogeneity Analysis for Life Satisfaction (by Age of Children)



Notes: The figure reports the coefficients (and 95% CIs) on the [PM10 $\times$ # Children $\leqslant j$ year old] terms. j is plotted on the x-axis and the slope estimators are shown on the y-axis. The outcome is the individuals' self-reported life satisfaction.

Figure 3: Heterogeneity Analysis for Satisfaction with Social Relations (by Age of Children)



Notes: The figure reports the coefficients (and 95% CIs) on the [PM10 × # Children ⩽ j year old] terms. j is plotted on the x-axis, and the slope estimators are shown on the y-axis. The outcome is the individuals' self-reported satisfaction with social relations.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Satisfaction with life	77,133	3.422	0.579	1	5
Satisfaction with social relations	77,105	3.497	0.571	1	5
PM10 (unit: 10μg/m^3)	77,475	4.115	1.325	0	11.1
Male	77,475	0.497	0.500	0	1
Age	77,475	44.386	17.796	14	101
Age squared/100	77,475	22.868	17.304	1.96	102.01
Married	77,474	0.583	0.493	0	1
Single	77,474	0.310	0.463	0	1
2-year college degree	77,462	0.142	0.349	0	1
4-year college degree	77,462	0.269	0.443	0	1
Master's degree or above	77,462	0.043	0.202	0	1
Employed	77,475	0.564	0.496	0	1
Unemployed	77,475	0.014	0.117	0	1
# children ≤ 1 year old	77,475	0.013	0.114	0	2
# children ≤ 2 years old	77,475	0.023	0.152	0	2
# children ≤ 3 years old	77,475	0.024	0.156	0	2
# children ≤ 18 years old	76713	0.647	0.910	0	5
Log of household income	77,475	5.333	1.551	0	9.287
House ownership	77,462	0.643	0.479	0	1
Car ownership	77,475	0.692	0.461	0	1
Having debt	77,473	0.486	0.500	0	1
Wind speed (unit: m/s)	75,982	2.229	0.650	0.6	5.1
Precipitation (unit: mm)	76,053	171.605	165.131	0	1,131
Ground pressure (unit: hPa)	75,982	1,003.427	7.721	927	1,026
Average temperature (unit: C°)	75,921	19.448	5.899	-3.6	27.333

Table 2: 2SLS with Individual Fixed Effects for Life Satisfaction: The Second Stage

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
PM10	-0.024	-0.029	-0.018	-0.024	-0.030	-0.019	-0.024	-0.029	-0.018
	(0.016)	(0.023)	(0.021)	(0.016)	(0.023)	(0.021)	(0.016)	(0.023)	(0.021)
PM10 × # Children ⩽ 1 year old	-0.061*	-0.003	-0.113**						
	(0.030)	(0.048)	(0.039)						
# Children ⩽ 1 year old	0.257*	0.037	0.447**						
	(0.123)	(0.194)	(0.160)						
PM10 × # Children ⩽ 2 years old				-0.054*	-0.006	-0.101**			
				(0.026)	(0.041)	(0.034)			
# Children ⩽ 2 years old				0.220*	0.015	0.408**			
				(0.105)	(0.164)	(0.134)			
PM10 × # Children ⩽ 3 years old							-0.040+	-0.004	-0.077**
							(0.021)	(0.031)	(0.028)
# Children ⩽ 3 years old							0.151+	0.011	0.290*
							(0.083)	(0.124)	(0.113)
Age	-0.055	-0.088	-0.031	-0.056	-0.090	-0.029	-0.056	-0.090	-0.030
	(0.067)	(0.093)	(0.082)	(0.068)	(0.095)	(0.082)	(0.068)	(0.095)	(0.083)
Age squared/100	0.016**	0.025**	0.011*	0.016**	0.025**	0.009+	0.016**	0.025**	0.009
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)
Married	0.085**	0.108*	0.062+	0.086**	0.110*	0.063+	0.085**	0.110*	0.060
	(0.029)	(0.046)	(0.038)	(0.030)	(0.046)	(0.038)	(0.029)	(0.046)	(0.038)
Single	-0.056	-0.040	-0.067	-0.058	-0.051	-0.056	-0.062	-0.049	-0.066
	(0.041)	(0.060)	(0.056)	(0.041)	(0.060)	(0.056)	(0.041)	(0.060)	(0.056)
Two-year college degree	0.082**	0.092*	0.080+	0.084**	0.096*	0.079+	0.085**	0.095*	0.082+
	(0.032)	(0.041)	(0.048)	(0.032)	(0.041)	(0.048)	(0.032)	(0.041)	(0.048)
Four-year college degree	0.087**	0.124**	0.054	0.088**	0.128**	0.053	0.089**	0.128**	0.055

	(0.024)	(0.034)	(0.034)	(0.024)	(0.034)	(0.034)	(0.024)	(0.034)	(0.034)
Master's degree or above	0.176**	0.228*	0.136+	0.175**	0.233*	0.129+	0.177**	0.233*	0.130+
	(0.061)	(0.091)	(0.075)	(0.061)	(0.091)	(0.075)	(0.061)	(0.091)	(0.075)
Employed	0.022+	0.078**	-0.013	0.022+	0.080**	-0.013	0.022+	0.080**	-0.014
	(0.013)	(0.024)	(0.015)	(0.013)	(0.024)	(0.014)	(0.013)	(0.024)	(0.015)
Unemployed	-0.071**	-0.053+	-0.088*	-0.071**	-0.054+	-0.089*	-0.072**	-0.054+	-0.089*
	(0.025)	(0.032)	(0.040)	(0.025)	(0.032)	(0.040)	(0.025)	(0.032)	(0.040)
Log of household income	0.062**	0.047**	0.077**	0.062**	0.045*	0.076**	0.062**	0.045*	0.076**
	(0.012)	(0.018)	(0.015)	(0.012)	(0.018)	(0.015)	(0.012)	(0.018)	(0.015)
House ownership	0.057**	0.051**	0.066**	0.057**	0.051**	0.066**	0.057**	0.051**	0.068**
	(0.011)	(0.016)	(0.016)	(0.011)	(0.016)	(0.016)	(0.011)	(0.016)	(0.016)
Car ownership	0.031**	0.030*	0.034*	0.031**	0.031*	0.033*	0.031**	0.031*	0.033*
	(0.010)	(0.015)	(0.014)	(0.010)	(0.015)	(0.014)	(0.010)	(0.015)	(0.014)
Having debt	-0.023**	-0.022*	-0.025**	-0.023**	-0.021*	-0.024**	-0.022**	-0.021*	-0.024**
	(0.006)	(0.009)	(0.009)	(0.006)	(0.009)	(0.009)	(0.006)	(0.009)	(0.009)
Additional controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	74,554	35,625	38,925	74,554	35,625	38,925	74,554	35,625	38,925
Number of individuals	13,109	6,437	6,671	13,109	6,437	6,671	13,109	6,437	6,671

Notes: This table reports the second stage of 2SLS with individual fixed effects for air pollution's impact on life satisfaction. The set of additional controls includes weather indicators (wind speed, precipitation, and air pressure), log of distance to the Chinese border, number of children aged below 18, and quarter- and year-region dummies. Robust standard errors clustered by individual are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table 3.1: 2SLS with Individual Fixed Effects for Life Satisfaction: The First Stage for PM10

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
North wind	7.279**	6.887**	7.534**	7.122**	6.743**	7.366**	7.315**	7.006**	7.498**
	(0.702)	(1.016)	(0.964)	(0.706)	(1.021)	(0.971)	(0.711)	(1.029)	(0.977)
West wind	7.976**	7.064**	8.814**	7.863**	6.965**	8.683**	7.878**	7.029**	8.665**
	(0.599)	(0.888)	(0.806)	(0.602)	(0.892)	(0.807)	(0.606)	(0.898)	(0.814)
North wind × Log of distance to China	-0.551**	-0.521**	-0.570**	-0.539**	-0.511**	-0.557**	-0.554**	-0.531**	-0.568**
	(0.053)	(0.077)	(0.073)	(0.053)	(0.077)	(0.073)	(0.054)	(0.078)	(0.074)
West wind × Log of distance to China	-0.579**	-0.510**	-0.642**	-0.570**	-0.502**	-0.632**	-0.572**	-0.507**	-0.631**
	(0.045)	(0.067)	(0.061)	(0.045)	(0.068)	(0.061)	(0.046)	(0.068)	(0.061)
North wind × # Children ⩽ 1 year old	5.126+	2.530	6.979+						
	(2.752)	(3.503)	(3.894)						
West wind × # Children ⩽ 1 year old	0.979	1.693	0.113						
	(2.037)	(3.268)	(2.396)						
North wind× Log of distance to China × # Children ⩽ 1 year old	-0.381+	-0.187	-0.520+						
	(0.206)	(0.264)	(0.291)						
West wind× Log of distance to China × # Children ⩽ 1 year old	-0.069	-0.124	-0.003						
	(0.154)	(0.248)	(0.181)						
North wind × # Children ⩽ 2 years old				5.747**	3.855	7.093*			
				(2.126)	(2.715)	(3.058)			
West wind × # Children ⩽ 2 years old				2.377	2.639	2.022			
				(1.535)	(2.361)	(1.933)			
North wind× Log of distance to China × # Children ⩽ 2 years old				-0.425**	-0.284	-0.525*			
				(0.160)	(0.204)	(0.229)			
West wind× Log of distance to China × # Children ⩽ 2 years old				-0.174	-0.194	-0.148			
				(0.116)	(0.179)	(0.147)			
North wind × # Children ⩽ 3 years old							2.004	-0.136	3.701

							(1.714)	(2.211)	(2.493)
West wind × # Children ⩽ 3 years old							1.396	1.044	1.528
							(1.416)	(2.111)	(1.860)
North wind× Log of distance to China × # Children ⩽ 3 years old							-0.142	0.018	-0.269
							(0.129)	(0.166)	(0.187)
West wind× Log of distance to China × # Children ⩽ 3 years old							-0.101	-0.074	-0.111
							(0.107)	(0.160)	(0.141)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	74,554	35,625	38,925	74,554	35,625	38,925	74,554	35,625	38,925
Number of individuals	13,109	6,437	6,671	13,109	6,437	6,671	13,109	6,437	6,671
F statistics of excluded instruments	158.27	74.96	86.01	160.81	75.78	87.35	161.30	76.60	87.13
Overidentification test (*p* value)	0.619	0.76	0.771	0.629	0.639	0.689	0.671	0.776	0. 747

Notes: This table reports the first stage of 2SLS with individual fixed effects for air pollution's impact on life satisfaction. The dependent variable is the level of PM10. All models control for individual characteristics (age, age squared/100, marital status, number of children aged below 18, employment status, and education levels), household characteristics (log of household income, house ownership, car ownership, and debt status), weather indicators (wind speed, precipitation, and air pressure), log of distance to the Chinese border, and quarter- and year-region dummies. Robust standard errors clustered by individual are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table 3.2: 2SLS with Individual Fixed Effects for Life Satisfaction: The First Stage for PM10 × # Children

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
North wind	0.569**	0.437+	0.563+	0.238	0.097	0.257	0.095	-0.127	0.176
	(0.194)	(0.226)	(0.299)	(0.245)	(0.300)	(0.374)	(0.308)	(0.411)	(0.448)
West wind	0.793**	0.613**	0.904**	0.579**	0.252	0.848**	0.631*	0.336	0.870*
	(0.175)	(0.217)	(0.259)	(0.217)	(0.284)	(0.311)	(0.263)	(0.361)	(0.372)
North wind × Log of distance to China	-0.044**	-0.034*	-0.044+	-0.021	-0.010	-0.023	-0.010	0.007	-0.017
	(0.015)	(0.017)	(0.023)	(0.019)	(0.023)	(0.028)	(0.023)	(0.031)	(0.034)
West wind × Log of distance to China	-0.062**	-0.048**	-0.070**	-0.047**	-0.022	-0.067**	-0.051*	-0.029	-0.069*
	(0.013)	(0.016)	(0.020)	(0.016)	(0.021)	(0.023)	(0.020)	(0.027)	(0.028)
North wind × # Children ⩽ 1 year old	12.768**	12.897*	12.528*						
	(4.084)	(5.391)	(5.859)						
West wind × # Children ⩽ 1 year old	2.370	0.452	3.942						
	(3.385)	(4.945)	(4.379)						
North wind× Log of distance to China × # Children ⩽ 1 year old	-0.921**	-0.934*	-0.900*						
	(0.307)	(0.406)	(0.440)						
West wind× Log of distance to China × # Children ⩽ 1 year old	-0.118	0.021	-0.231						
	(0.256)	(0.376)	(0.330)						
North wind × # Children ⩽ 2 years old				12.117**	10.586*	13.141*			
				(3.921)	(5.143)	(5.631)			
West wind × # Children ⩽ 2 years old				2.572	2.427	2.437			
				(3.337)	(5.143)	(3.946)			
North wind× Log of distance to China × # Children ⩽ 2 years old				-0.877**	-0.767*	-0.949*			
				(0.295)	(0.387)	(0.423)			
West wind× Log of distance to China × # Children ⩽ 2 years old				-0.142	-0.133	-0.129			
				(0.254)	(0.393)	(0.299)			
North wind × # Children ⩽ 3 years old							9.396*	9.337+	9.305+

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							(3.676)	(5.246)	(5.089)
West wind × # Children ⩽ 3 years old							1.453	0.401	2.185
							(3.038)	(4.520)	(3.932)
North wind × Log of distance to China × # Children ⩽ 3 years old							-0.668*	-0.666+	-0.659+
							(0.276)	(0.394)	(0.382)
West wind× Log of distance to China × # Children ⩽ 3 years old							-0.056	0.023	-0.110
							(0.232)	(0.345)	(0.299)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	74,554	35,625	38,925	74,554	35,625	38,925	74,554	35,625	38,925
Number of individuals	13,109	6,437	6,671	13,109	6,437	6,671	13,109	6,437	6,671
F statistics of excluded instruments	14.10	6.53	10.66	17.83	9.60	11.26	25.62	13.78	13.87
Overidentification test (*p* value)	0.619	0.76	0.771	0.629	0.639	0.689	0.671	0.776	0.747

Notes: This table reports the first stage of 2SLS with individual fixed effects for air pollution's impact on life satisfaction. The dependent variable is level of PM10 × # Children ⩽ 1 year old in columns (1)-(3), PM10 × # Children ⩽ 2 years old in columns (4)-(6), and PM10 × # Children ⩽ 3 years old in columns (7)-(9). All models control for individual characteristics (age, age squared/100, marital status, number of children aged below 18, employment status, and education levels), household characteristics (log of household income, house ownership, car ownership, and debt status), weather indicators (wind speed, precipitation, and air pressure), log of distance to Chinese border, and quarter- and year-region dummies. Robust standard errors clustered by individual are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table 4: 2SLS with Individual Fixed Effects for Life Satisfaction, Restricting the Sample to Non-Movers: The Second Stage

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
PM10	-0.010	-0.009	-0.014	-0.011	-0.012	-0.014	-0.009	-0.010	-0.012
	(0.027)	(0.034)	(0.032)	(0.027)	(0.033)	(0.032)	(0.028)	(0.034)	(0.032)
PM10 × # Children ⩽ 1 year old	-0.081+	-0.058	-0.116*						
	(0.046)	(0.057)	(0.054)						
# Children ⩽ 1 year old	0.334+	0.266	0.445*						
	(0.185)	(0.237)	(0.216)						
PM10 × # Children ⩽ 2 years old				-0.043	0.003	-0.082*			
				(0.033)	(0.044)	(0.038)			
# Children ⩽ 2 years old				0.168	-0.022	0.321*			
				(0.134)	(0.180)	(0.150)			
PM10 × # Children ⩽ 3 years old							-0.033	-0.001	-0.062+
							(0.025)	(0.032)	(0.032)
# Children ⩽ 3 years old							0.117	0.004	0.214+
							(0.104)	(0.131)	(0.130)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	59,925	28,481	31,441	59,925	28,481	31,441	59,925	28,481	31,441
Number of cities/districts	189	187	186	189	187	186	189	187	186

Notes: This table reports the second stage of 2SLS with individual fixed effects for air pollution's impact on life satisfaction, using only those survey respondents who did not move between cities or regions during the study period. All models control for individual characteristics (age, age squared/100, marital status, number of children aged below 18, employment status, and education levels), household characteristics (log of household income, house ownership, car ownership, and debt status), weather indicators (wind speed, precipitation, and air pressure), log of distance to the Chinese border, and quarter- and year-region dummies. Robust standard errors clustered by city/district are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table 5: 2SLS without Individual Fixed Effects for Life Satisfaction: The Second Stage

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
PM10	0.016	0.019	0.014	0.016	0.018	0.015	0.015	0.018	0.015
	(0.032)	(0.036)	(0.034)	(0.032)	(0.036)	(0.034)	(0.032)	(0.037)	(0.034)
PM10 × # Children ⩽ 1 year old	-0.019	0.028	-0.066+						
	(0.027)	(0.038)	(0.040)						
# Children ⩽ 1 year old	0.117	-0.088	0.311*						
	(0.107)	(0.157)	(0.158)						
PM10 × # Children ⩽ 2 years old				-0.025	0.023	-0.070*			
				(0.023)	(0.032)	(0.033)			
# Children ⩽ 2 years old				0.125	-0.095	0.327*			
				(0.093)	(0.133)	(0.132)			
PM10 × # Children ⩽ 3 years old							-0.019	0.021	-0.059*
							(0.019)	(0.027)	(0.028)
# Children ⩽ 3 years old							0.092	-0.088	0.265*
							(0.077)	(0.112)	(0.108)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	75,626	36,188	39,438	75,626	36,188	39,438	75,626	36,188	39,438
Number of cities/districts	205	203	202	205	203	202	205	203	202

Notes: This table reports the second stage of 2SLS pooled regressions for air pollution's impact on life satisfaction. All models control for individual characteristics (age, age squared/100, marital status, number of children aged below 18, employment status, and education levels), household characteristics (log of household income, house ownership, car ownership, and debt status), weather indicators (wind speed, precipitation, and air pressure), log of distance to the Chinese border, and quarter- and year-region dummies. In addition, the gender dummy is controlled for in models (1), (4) and (7). Individual fixed effects are not controlled for. Robust standard errors clustered by city or district are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table 6: Falsification Test for Life Satisfaction by Using Pseudo-Children: The Second Stage

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
PM10	0.005	-0.041	0.063	-0.056	-0.141	0.028	-0.032	0.027	-0.055
	(0.032)	(0.046)	(0.043)	(0.058)	(0.086)	(0.079)	(0.059)	(0.087)	(0.080)
PM10 × # Children ⩽ 1 year old	-0.039	0.006	-0.067						
	(0.047)	(0.078)	(0.056)						
# Children ⩽ 1 year old	0.198	-0.008	0.339						
	(0.178)	(0.298)	(0.211)						
PM10 × # Children ⩽ 2 years old				0.021	0.036	-0.010			
				(0.041)	(0.067)	(0.057)			
# Children ⩽ 2 years old				-0.104	-0.155	0.025			
				(0.158)	(0.255)	(0.223)			
PM10 × # Children ⩽ 3 years old							0.057	0.062	0.045
							(0.067)	(0.085)	(0.095)
# Children ⩽ 3 years old							-0.217	-0.279	-0.102
							(0.273)	(0.329)	(0.410)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	27,036	12,455	14,581	18,624	8,396	10,228	10,776	4,784	5,992
Number of individuals	7,599	3,570	4,029	6,668	3,025	3,643	5,388	2,392	2,996

Notes: This table reports the second stage of 2SLS with individual fixed effects for air pollution's impact on life satisfaction, whereas the pseudo-children are those to be born in the future. All models control for individual characteristics (age, age squared/100, marital status, number of children aged below 18, employment status, and education levels), household characteristics (log of household income, house ownership, car ownership, and debt status), weather indicators (wind speed, precipitation, and air pressure), log of distance to the Chinese border, and quarter- and year-region dummies. Robust standard errors clustered by individual are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table 7: 2SLS with Individual Fixed Effects for Satisfaction with Social Relations: The Second Stage

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
PM10	-0.006	0.000	-0.012	-0.005	0.001	-0.013	-0.004	0.003	-0.011
	(0.017)	(0.024)	(0.022)	(0.017)	(0.024)	(0.022)	(0.017)	(0.024)	(0.022)
PM10 × # Children ⩽ 1 year old	-0.081*	-0.051	-0.105*						
	(0.035)	(0.057)	(0.042)						
# Children ⩽ 1 year old	0.341*	0.231	0.420*						
	(0.137)	(0.226)	(0.167)						
PM10 × # Children ⩽ 2 years old				-0.087**	-0.068	-0.105**			
				(0.029)	(0.047)	(0.036)			
# Children ⩽ 2 years old				0.341**	0.260	0.408**			
				(0.117)	(0.185)	(0.144)			
PM10 × # Children ⩽ 3 years old							-0.069**	-0.051	-0.087**
							(0.024)	(0.037)	(0.030)
# Children ⩽ 3 years old							0.267**	0.195	0.333**
							(0.094)	(0.147)	(0.119)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	74,525	35,611	38,910	74,525	35,611	38,910	74,525	35,611	38,910
Number of individuals	13,107	6,438	6,668	13,107	6,438	6,668	13,107	6,438	6,668

Notes: This table reports the second stage of 2SLS with individual fixed effects for air pollution's impact on satisfaction with social relations. All models control for individual characteristics (age, age squared/100, marital status, number of children aged below 18, employment status, and education levels), household characteristics (log of household income, house ownership, car ownership, and debt status), weather indicators (wind speed, precipitation, and air pressure), log of distance to the Chinese border, and quarter- and year-region dummies. Robust standard errors clustered by individual are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Appendix

Table A1: Falsification Test for Social Relations by Using Pseudo-Children: The Second Stage

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
PM10	0.001	-0.018	0.063	-0.035	-0.083	0.028	-0.059	0.033	-0.055
	(0.031)	(0.044)	(0.043)	(0.060)	(0.077)	(0.079)	(0.066)	(0.079)	(0.080)
PM10 × # Children ⩽ 1 year old	0.034	0.056	-0.067						
	(0.047)	(0.078)	(0.056)						
# Children ⩽ 1 year old	-0.074	-0.194	0.339						
	(0.175)	(0.282)	(0.211)						
PM10 × # Children ⩽ 2 years old				-0.010	0.008	-0.010			
				(0.038)	(0.056)	(0.057)			
# Children ⩽ 2 years old				0.051	0.006	0.025			
				(0.144)	(0.208)	(0.223)			
PM10 × # Children ⩽ 3 years old							0.047	-0.052	0.045
							(0.057)	(0.070)	(0.095)
# Children ⩽ 3 years old							-0.102	0.243	-0.102
							(0.245)	(0.284)	(0.410)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	27,033	12,452	14,581	18,620	8,392	10,228	10,768	4,776	5,992
Number of individuals	7,599	3,570	4,029	6,666	3,024	3,643	5,384	2,388	2,996

Notes: This table reports the second stage of 2SLS with individual fixed effects for air pollution's impact on social relations, whereas the pseudo-children are those to be born in the future. All models control for individual characteristics (age, age squared/100, marital status, number of children aged below 18, employment status, and education levels), household characteristics (log of household income, house ownership, car ownership, and debt status), weather indicators (wind speed, precipitation, and air pressure), log of distance to the Chinese border, and quarter- and year-region dummies. Robust standard errors clustered by individual are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.

Table A2: 2SLS for Life Satisfaction with Additional Controls: The Second Stage

	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female	(7) Total	(8) Male	(9) Female
PM10	-0.023	-0.029	-0.023	-0.021	-0.026	-0.022	-0.020	-0.026	-0.021
	(0.021)	(0.031)	(0.028)	(0.021)	(0.031)	(0.029)	(0.021)	(0.031)	(0.029)
PM10 × # Children ⩽ 1 year old	-0.077	0.064	-0.171*						
	(0.072)	(0.127)	(0.081)						
# Children ⩽ 1 year old	-0.013	1.814	-2.387						
	(2.222)	(2.878)	(3.207)						
PM10 × # Children ⩽ 2 years old				-0.104+	-0.030	-0.167**			
				(0.057)	(0.104)	(0.061)			
# Children ⩽ 2 years old				0.375	1.534	-1.207			
				(1.956)	(2.268)	(3.283)			
PM10 × # Children ⩽ 3 years old							-0.083+	-0.017	-0.133*
							(0.048)	(0.087)	(0.055)
# Children ⩽ 3 years old							-0.051	0.889	-1.848
							(1.648)	(1.977)	(2.351)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of observations	74,489	35,594	38,891	74,489	35,594	38,891	74,489	35,594	38,891
Number of individuals	13,098	6,432	6,665	13,098	6,432	6,665	13,098	6,432	6,665

Notes: This table reports the second stage of 2SLS with individual fixed effects for air pollution's impact on life satisfaction. All models control for individual characteristics (age, age squared/100, marital status, number of children aged below 18, employment status, and education levels), household characteristics (log of household income, house ownership, car ownership, and debt status), weather indicators (mean wind speed, maximum wind speed, mean precipitation, mean air pressure, average temperature, maximum temperature and minimum temperature), their products with [# Children ⩽ J year old], a set of fixed effects (individual, quarter, district, region-year), and district-specific cubic trends. Robust standard errors clustered by individual are reported in parentheses.** $p < 0.01$, * $p < 0.05$, + $p < 0.1$.