The effect of air pollution on labor supply across gender: Evidence from South Korea

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HAN, Ahram

Thesis

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KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

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Committee in charge:

Professor KIM, Taejong, Supervisor ______________________

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ABSTRACT

THE EFFECT OF AIR POLLUTION ON LABOR SUPPLY ACROSS GENDER: EVIDENCE FROM SOUTH KOREA

By

Ahram Han

This paper investigates whether air pollution affects labor supply by exploiting a labor supply-air quality matched panel data on particulate matter (PM) and working hours in South Korea from 2010 to 2016. Using fixed effects panel regression, I find that working hours of individuals are not responsive to the level of PM concentration in general. However, the subgroup analysis reveals that women are responsive to a reduction in working hours if they have young children aged between 0 and 3. Given the epidemiological evidence of children's relative susceptibility to air pollution, caregiving of the vulnerable dependents is suggested as a channel through which air pollution affects labor supply.

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This paper benefits greatly from constructive comments by Professor Taejong Kim, Professor Shun Wang, and Gi Khan Ten. I truly appreciate the opportunity to co-author a more developed version of this paper, which was presented at the Western Economic Association International in March of 2019.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

Air pollution is the most significant environmental risk to human health worldwide, which contributes to one in every nine deaths annually (WHO, 2016a). The disease burden of air pollution comes to 84,934 disability-adjusted life years (DALYs), including 15,478 DALYs for children under five.[1] However, the effect of poor air quality may reach beyond adverse health outcomes and lead to school absenteeism, labor supply loss, and economic inactivity, which together dampen economic development. Despite the potentially broad impact of air pollution, literature pays little attention to its socioeconomic consequence, focusing instead on health outcomes.

In this paper, I examine one of the channels through which air pollution may affect labor supply. I investigate the causal effect of air quality on the working hours of individuals using panel data on labor merged with air pollutant measurements of coarse particulate matter (PM_{10}). In particular, I compare individuals living with and without a vulnerable demographic group to distinguish whether caregiving is a key contributing factor of the effect investigated. I hypothesize that in an environment with high exposure to harmful air pollution, the number of affected children may increase, which would decrease labor supply among working adults who have caregiving responsibilities for children.

Identifying a causal relationship between air pollution and labor outcomes is challenging due to some potentially endogenous confounders. For example, both the levels of air quality and labor supply may be affected by geographical proximity to manufacturing sites or seasonal trends. Also, household income may affect residential decision and fertility decision, creating a a

[1] The latest available data is from 2012, as reported in World Health Organization (WHO, 2016a). DALY calculates loss of healthy years as a sum of Years of Life Lost (YLL) due to premature death and the Years Lost due to Disability (YLD).

systematic difference between individuals living in different regions and the number of children they choose to have. It is also difficult to distinguish between labor supply loss and labor force loss.

To address these potential concerns, I adopt several strategies. First, I control for the unobservable characteristics of individuals and regions that are time-invariant by including panel fixed effects and province fixed effects. I also control for seasonality across regions with quarter and year fixed effects. Then, I turn to a heterogeneity analysis conducted by gender and the age of the children in their care to identify channels of causality. The interaction effect of the number of children within a certain age group and PM levels captures the effect of air pollution via caregiving. I find that the working hours of individuals are not responsive to the level of PM concentration, but the subgroup analysis reveals that only women are responsive to a reduction in working hours when they have young children aged between 0 and 3. This finding is in line with evidence that women's labor supply responds differently to that of men, and is consistent with epidemiological evidence that children are relatively more susceptible to the health impact of air pollution than adults. To find more direct evidence supporting the vulnerability of children, I also conduct an additional panel fixed effect regression on health outcomes with subgroup analysis by age. Moreover, to examine the strength of the endogeneity of fertility decision and to disentangle the combined effects of labor loss, I perform a falsification test and a Tobit regression, respectively.

This study aims to quantitatively measure the economic cost of deteriorating air quality. This aim acknowledges that environmental burden can be an essential part of meeting the Sustainable Development Goals (SDGs), which reflect the related concerns of "the mortality rate attributed to household and ambient air pollution (SDG 3.9.1)" and "annual mean levels of particulate matter in cities (SDG 11.6.2)(UN, n.d.)."

The rest of the paper proceeds as follows. Section 2 provides background and hypothetical framework. Section 3 describes the data and empirical strategy. Section 4 presents the results and provides analysis of potential channel through caregiving of the susceptible dependents due to adverse health outcomes. Section 5 discusses empirical challenges and further studies, and Section 6 concludes.

2. BACKGROUND

2.1. Air quality in South Korea

According to World Health Organization (WHO) Global Ambient Air Quality indicators, the coarse particulate matter (PM_{10}) and the fine particulate matter ($PM_{2.5}$) found in the air in South Korea exceeds the Air Quality Guideline values by more than 136 percent.[2] Among Organisation for Economic Coopeation and Development (OECD) countries, South Korea has the second highest $PM_{2.5}$ concentration, and a recent OECD report projects that the concentration of air pollution in South Korea is set to increase, leading to a higher incidence of related illness and premature death (OECD, 2016).

While both ambient (outdoor) and household (indoor) air pollution poses a major threat to human health and were responsible for 7 million deaths in 2016 (WHO, 2016b), ambient PM can easily penetrate indoors and thus increase the chance of exposure. In this study, I focus on PM over other types of pollutants as PM affects human health to a greater degree than any other single pollutants (WHO, 2016a). PM is more than five times smaller than a human hair, which is typically 50-70 microns (μm) in diameter. The diameters of PM_{10} and $PM_{2.5}$ are less than 10μm and 2.5μm, respectively (EPA, n.d.). This pollutant consists of a diverse range of chemical constituents that can be the source of various health problems, mostly induced by respiratory and cardiovascular diseases (Kim, Kabir, & Kabir, 2015). The adverse health outcomes of exposure to ambient air pollution are not only evident among those who engage in outdoor labor activities (Graff-Zivin & Neidell, 2012), but also impacts the productivity of indoor workers (Chang, Graff-Zivin, Gross, & Neidell, 2016). For some years, air pollution has been a growing concern in South Korea and thus in 2010 the government began to collect data on the levels of

[2] WHO Air Quality Guideline values for PM2.5 and PM10 are 10 and 20μg/m^3 annual mean, respectively; the annual means of Korea in 2016 were recorded at 25.4 and 47.3μg/m^3, respectively.

PM_{10} and levels of $PM_{2.5}$ in 2015 and consequently adjusted the air quality standards of the country so they were more in line with those of other developed nations (see Appendix A). The growing public awareness of this issue in South Korea is evidenced in a survey that asks respondents about their level of concern about PM on a five-point scale (not at all concerned; not particularly concerned, somewhat concerned; moderately concerned; extremely concerned). The number of respondents who answer "extremely concerned" has risen steadily from 29.3 percent in 2014 and 34.6 percent in 2016 to 45.3 percent in 2018.[3] This rising concern is also reflected in a sharp spike in the production growth of related goods, namely, indoor air purifiers, the production of which increased by 153 percent from 2010 to 2016 and reached a value of more than half a billion US dollars in 2016.[4]

2.2. Air quality and health outcomes

A vast amount of epidemiological evidence illustrates the link between air pollution and health (e.g., Brook et al., 2004; Currie & Neidell, 2005; Moretti & Neidell, 2011; Morales-Suárez-Varela, Peraita-Costa, & Llopis-González, 2017; Lee, Yoo, & Nam, 2018). Among all air pollutants, PM has the most severe health impact, causing both acute and chronic morbidity and inducing minor symptoms to mortality. Exposure to PM is associated with respiratory and cardiovascular disease and hospital admissions for these conditions, such as asthma, bronchitis, lung and heart dysfunction, and cancer, and increases the risks of mortality among infants and adults (Lucas et al., 1994; Brook et al., 2004; Pope et al., 2009; EPA, 2009; Brook et al., 2010; Hicken et al., 2013).[5] Beyond respiratory and cardiovascular disease, other health effects of PM exposure have been reported, such as diabetes (Pearson et al., 2010), autism spectrum disorders potentially

[3] Based on an environmental awareness survey reported by Statistics Korea. The survey investigates the attitudes of individuals over the age of 13.
[4] Calculation based on industry statistics produced by Statistics Korea (2010-2016).
[5] Kim et al. (2015) provide a survey of the epidemiological literature on the health effects of PM.

brought on by oxidative stress, neurological effects, and effects of neonatal immune systems (Morales-Suárez-Varela et al., 2017).

There is a strong body of evidence in the existing studies on the relative susceptibility of children to the negative health effects of air pollution worldwide (Currie & Niedell, 2005; Brooks et al. 2004; Brooks et al. 2010; Gouveia & Junger, 2018) and in South Korea specifically (Jia & Ku, 2019; Lee et al., 2018). In particular, Jia and Ku (2019) find evidence of cross-border pollution spillover from China that increases pollution-related mortality rates in South Korea, with a more significant effect seen in children under five and elderly people. Given the evidence, I hypothesize that adults, in general, are not responsive to moderate levels of PM but children are.

2.3. Labor outcomes

The association between health and labor has been explored extensively. For example, Parsons (1977) finds that a man with poor health works 1,300 hours less per year than a man in excellent health, with the reduction in working hours being less noticeable for married men as compared with single men. Hence, adverse health outcomes, regardless of their source, suggests a reduction in labor supply. However, despite the strong epidemiological evidence around air pollution, its socioeconomic impact has been largely neglected. Hausman, Ostro, and Wise (1984) find some of the first evidence of a positive association between the level of total suspended particles and workday loss. Since then, a growing body of literature has identified a link between air pollution and labor supply (Graff-Zivin & Neidell, 2012; Hanna & Oliva, 2015; Aragon, Miranda, & Oliva, 2016; Chang et al., 2016). Broadly speaking, there are two channels by which air pollution may affect labor, either through absenteeism or through "presenteeism" due to adverse health effects (Chang et al., 2016). That is, the working person may be either absent from work or they may be present in the workplace but lose productivity due to ill health. While presenteeism may arise from the direct effect of air pollution on the working person, absenteeism may arise either from the illness of the worker or from other affected household members who rely on the worker as their primary caregiver.

Hanna and Oliva (2015) examine the effect of pollution level on labor supply using the case of the closure of an oil refinery in Mexico City that reduced air pollution measured by SO_2. By comparing the changes in labor supply among those who lived nearby the refinery with those who lived far from the refinery, the authors find that the closure leads to working hour hikes among the first group. In their study, environmental regulations leading to the closure decision provide the basis for exogenous variations in the labor market, which disentangles the effect of pollution on reduced working hours through health impact from the direct effect of environmental regulations on businesses.

While Hanna and Oliva (2015) addresses the first channel of the employee absenteeism, Aragon et al. (2016) suggest evidence of the presenteeism. They find that a moderate level of air pollution does not affect overall work hours but does impact the work hours of those with susceptible dependents at home. Given the previous literature related to the association between ambient air pollution and elementary school absenteeism due to illness (Park et al., 2002; Currie et al., 2009; Hales et al., 2016), the evidence altogether point to a potential link between air pollution and the worker's absenteeism; specifically, if the worker is the primary caregiver of a dependent, the worker may be absent regardless of their health status. Hence, I hypothesize that the working hours of individuals who have children will vary according to PM levels. If acting as the caregiver of a dependent child who is susceptible to air pollution is the reason for employee absenteeism, I would expect to observe a declining trend in this absenteeism as the child matures and develops a more robust immune system.

2.4. Socioeconomic effect

Moreover, some studies find that bad air quality has different consequences for different groups based on socioeconomic and demographic factors such as gender, race, and income (Broschu et al., 2011; Yap et al., 2013; Liu et al., 2017; Mikati et al., 2018). This study does not intend to explore the broader topic of environmental justice. Still, I focus on different gender effects to find the channel of causality. Recently, some studies have reported different responses in labor supply by gender (Kim, Manley, & Radoias, 2017; Montt, 2018). In both studies, women's working hours were found to significantly decrease in response to bad air quality while men's working hours saw little or no reduction. In the context of South Korea, the traditional gender roles under ascribed by Confucian culture have persisted regardless of the changes in women's employment activities over the generations. Consequently, women in the country bear the primary burden for child-rearing, which induces behavior change (Kim & Cheung, 2015). Consistent with these findings, I expect women's labor supply will respond differently to men's in the context of this research.

3. EMPIRICAL STRATEGY

3.1. Data

This paper aims to find the potential channel of the effect of air pollution on labor supply by examining the presence of household members who are more vulenrable to the health conditions induced by air pollution. The outcome variable, labor supply, is measured by average hours of work per week based on the Korea Labor and Income Panel Study (KLIPS) survey data from 2010 to 2016. In this survey, respondents are asked how many hours per week they have typically worked since the last survey. Those who did not work for pay during that period report zero hours. The KLIPS is a longitudinal survey and the sample includes more than 6,700 households and their members older than age of 15, who are interviewed annually. The survey provides information about demographic and labor market characteristics including age, sex, educational attainment, employment, income, marital status, the number of children, and residence.

I use a monthly average concentration of PM_{10} as a proxy indicator of air quality. While there are other indicators (i.e., nitrogen dioxide, sulfur dioxide, carbon monoxide, and ozone), PM poses the most harmful threat to human health (WHO, 2016a) and it is capable of easily entering indoor spaces and the human body due to its microscopic size. This makes PM, particularly $PM_{2.5}$, an ideal candidate for this research in the sense that its effect on human health is expected to be larger than other pollutants. However, the amount of data collected in this regard thus far is insufficient, a shortcoming that future research can address. The measurements of PM_{10} concentration are collected from 264 measurement stations throughout the country, and the monthly statistics are obtained from Air Korea of the Korea Environment Corporation. Using the labor and pollution measures, I construct a panel dataset of labor supply matched with air quality with districts as the geographical unit applied.[6] The summary statistics show that 78 percent of the respondents are married, and 48 percent are male. The average working hours for all respondents, including those who reported zero hours, is approximately 25 hours per week (Table 1). The monthly average concentration of PM_{10} is approximately 48μg/m^3, which far exceeds WHO Air Quality Guideline limits (see Appendix A).

In addition, the health outcomes-air quality matched panel dataset at the province level is constructed to reinforce the relationship between health and air quality as the potential cause of a decrease in labor supply. I define "health outcome" as referring to the situation where an individual has visited an emergency room or an outpatient clinic or has been hospitalized for a diagnosis associated with PM_{10}, namely, respiratory and circulatory problems and headaches. The health outcome data is obtained from the Korea Health Panel Study (KHP) from the Korea Institute for Health and Social Affairs for the years 2010 and 2011.[7] The KHP is an annual survey and contains information about the use of medical services and medical expenses.

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[6] "District" is defined as the second-level administrative division including 262 local governments (Si/Gun/Gu) and "province" is defined as a group of 17 first-level administrative divisions including 9 provinces, 6 metropolitan cities, 1 special city, and 1 special autonomous city.

[7] In this study, only the years 2010 and 2011 are considered due to the noise in the dataset. The KHP codes for disease/diagnosis changed in 2012 when a standardized code system (KCD) was applied and thus the variable containing codes for disease/diagnosis is different for the years before 2012 and for the years from 2012. Due to the failure to change the codes entirely for each type of disease and diagnosis, the survey states that "the disease/diagnosis codes for 2008-2011 and after 2011 may not be compatible with each other," and the codes for the years immediately following 2011 also do not fully reflect the changes.

TABLE 1—DESCRIPTIVE STATISTICS

Variable	Mean (s.d.)
Hours/week (average hours worked per week)	25.43 (24.52)
PM (an average concentration of PM_{10} per month, μg/m^3)	48.09 (12.59)
Age	47.72 (18.06)
Graduated college (=1 if completed 4-yr college or above)	0.20 (0.40)
Married	0.78 (0.42)
Male	0.48 (0.50)
Children 1yr (number of children aged 0-1)	0.01 (0.12)
Children 2yr (number of children aged 0-2)	0.04 (0.22)
Children 3yr (number of children aged 0-3)	0.07 (0.29)
Number of observations	97,278

Standard deviations in parentheses.

3.2. Identification strategy

The ordinary least square (OLS) estimates of the effect of worsening air quality will be biased if unobservable characteristics of individual are correlated with labor supply. In this study, I use panel data and fixed effects to eliminate the unobservable covariates that are constant over time. The following regression model is used to find a relationship between labor supply and the number of children within a certain age group in response to PM levels.

$$y_{idpqt} = \gamma_1 \overline{PM10}_{dqt} + \gamma_2 \overline{PM10}_{dqt} children_{it}^{j} + \gamma_3 children_{it}^{j}$$
$$+X'_{it}\delta + \theta_i + \lambda_p + \pi_q + \mu_t + \varepsilon_{idpqt}, \qquad (1)$$

where y_{idpqt} is the average working hours per week, supplied by individual *i* in the district *d,* province *p*, quarter q, and year *t,* $\overline{PM10}_{dqt}$ is the average PM_{10} concentration over the last three months, and $children_{it}^{j}$ indicates the number of children within a certain age group in household *j*. A set of control variables X'_{it} includes individual characteristics (age, age^2, dummy for college education and marital status),[8] and ε_{idpqt} is an idiosyncratic error term.

The coefficient of interest in the equation (1) is γ_2, which captures the effect of air pollution via caregiving by estimating differences in labor supply responses to PM levels between individuals with the vulnerable group at home and those without. If the coefficient is negative, it would suggest that the first group of individuals has worked less than before in response to the levels of PM_{10} concentration.

One of the advantages of the main estimation strategy is that it allows controlling for unobserved time-invariant individual characteristics using the individual fixed effect, θ_i, and general trends of labor supply such as economic growth with year fixed effects, μ_t. The province fixed effects (λ_p) and quarter fixed effects (π_q) control for seasonality that can be potentially observed in the degree of pollution and labor. Nevertheless, my analysis heavily relies on an assumption that the individuals with and without children would have followed a similar trend in the absence of the children. Since fertility decision is likely to be endogenous, this concern is further addressed by falsification test in Section 4.

3.3. Vulnerability of children

One of the objectives of this paper is to test potential channels of the effect by reinforcing the evidence of the relative vulnerability of children's health to pollution hikes. To find a potential association between individual-level health outcomes and PM_{10} levels, I employ the following panel fixed effects model:

[8] Income of the household is omitted due to concern for simultaneity, but inclusion of income yielded similar results despite of a decrease in sample size.

$$y_{ipt} = \alpha_0 + \alpha_1[\frac{\sum_{m-13}^{m-1} PM10_{pmt-1}}{12}] + X'_{ipt}\beta + \theta_i + v_{ipt}, \quad (2)$$

where the outcome variable, y_{ipt}, is an indicator whether an individual *i* has visited an emergency room or an outpatient clinic or has been hospitalized for a diagnosis associated with PM_{10} in the province *p* and year *t*. The main regressor is the monthly average levels of PM_{10} concentration over 12 months preceding the survey month in province *p* of month *m* (e.g. a summation of PM_{10} level over the period of January 2010 to January 2011 divided by 12 months estimate the effect for an individual who was surveyed in February 2011.) The PM levels are normalized to capture an incubation period. The sign of the estimated effect of PM_{10} levels, α_1, captures the direction of likelihoods for individuals to use health services for PM-associated health issues. A negative association would serve as suggestive evidence of health damage due to poor air quality. The magnitude of the coefficient would be larger for the more affected group. A set of control variables, X'_{ipt}, controls for the individual-level characteristics including educational attainment, employment status, age, and age-squared. θ_i is the panel fixed effects that control for unobservable time-invariant characteristics across the individuals, and v_{ipt} is the error term.

3.4. Extrapolation

To take an incubation period of health effect into account, PM_{10} levels measured a year before the hospital visits are used in the equation (2). Due to incompatibility of health and air pollutant data, however, air pollutant measurements for year 2009 is extrapolated to retain the virtues of fixed effects panel regression. Given the province-specific seasonal variation in PM_{10} concentration, the predicted values of PM_{10} for 2009 for each of the 17 provinces are generated using the panel fixed effects estimates of the following equation:

$$PM10_{pmt} = \boldsymbol{\theta Month_m Province_p} + \delta \boldsymbol{Province_p\ Year\_trend_t} + \tau_p + w_{pmt}, \quad (3)$$

where the outcome variable is the value of PM_{10} levels in province p, month m, year t (for the years 2010-2016). The province-specific monthly fixed effects, $\boldsymbol{Month_m Province_p}$, control for seasonality by months within each province, and province-specific linear trends, $\boldsymbol{Province_p}$ $\boldsymbol{Year\_trend_t}$, partially control for general trend within the provinces. Each term controls for time-varying changes across the provinces and differences that may evolve differently across provinces, respectively. Lastly, the province fixed effects, τ_p, are added to control for time-invariant characteristics across provinces, such as geographical location and size.

Figure 1 shows the value of PM_{10} levels by province. The actual district-month-year PM_{10} concentration from 2010 to 2016 is presented on the right side of a vertical line, and the predicted value for 2009 is on the left. The extrapolated seasonal pattern resembles the trend of the rest of the years.

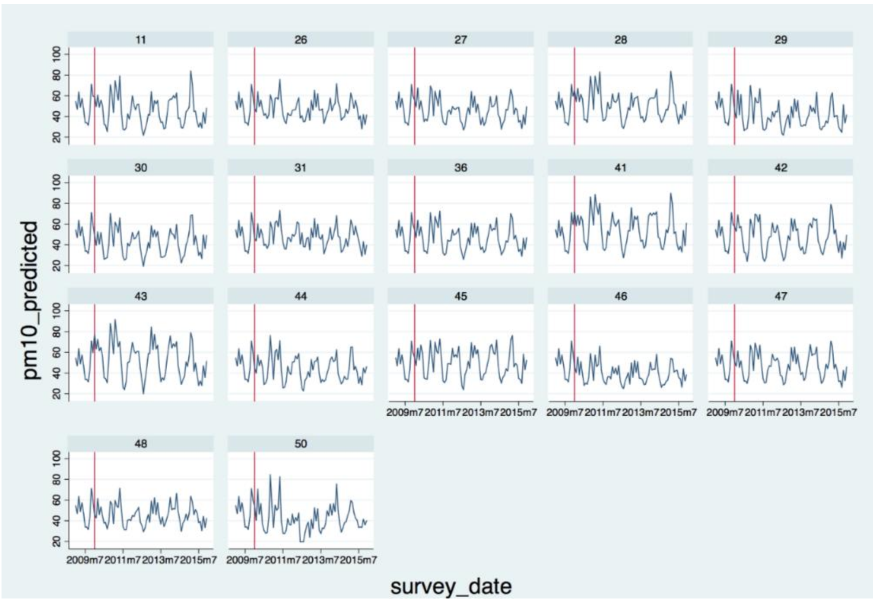

FIGURE 1—EXTRAPOLATED PM_{10} CONCENTRATION FOR 2009 (17 PROVINCES)

4. RESULTS

4.1. The effect of air pollution on health outcome

The estimates of the equation (2) in Table 2 reinforce the link between the levels of PM on health outcomes from the previous literature. The probability of using medical services for diagnoses associated with PM_{10} increases by 0.2 percent with a 1-unit (1 μg/m^3) increase in PM_{10} levels (column 1), and a larger coefficient is observed for children under 7 (column 2). Columns (3) and (4) report the estimates by OLS using cross-sectional data from year 2011 with no panel fixed effects. Still, the results show statistically similar results. Overall, the reported estimates support the adverse effect of PM_{10} levels on health outcomes, and the relative vulnerability of children.

TABLE 2—PANEL FIXED EFFECTS ESTIMATES OF PM ON HEALTH OUTCOMES USING KHP DATA

	Dependent variable (=1 if used emergency room/hospitalization/outpatient clinic due to the known symptoms of PM: respiratory or cardiac issues or headaches)			
	Total	Children	Total	Children
Variable	(1)	(2)	(3)	(4)
PM	0.002**	0.008**	0.001*	0.006**
	(0.001)	(0.004)	(0.000)	(0.002)
Employed	-0.016**		-0.050****	
	(0.008)		(0.006)	
Age	0.035****	0.105**	-0.001	-0.040
	(0.007)	(0.051)	(0.001)	(0.056)
Age²	0.000**	0.003	0.000***	0.004
	(0.000)	(0.007)	(0.000)	(0.009)
Panel FE	Y	Y	N	N
N	34,900	1,648	17,025	776
adj. R-sq	0.036	0.129	0.069	0.007

Robust standard errors in parentheses. "Children" is a sample restricted to age between 0 and 6 whearas "Total" includes the entire sample. "PM" is the average concentration of PM_{10} per month. Educational attainment is added as an additional control in "Total" sample.
* p<0.10 ** p<0.05 *** p<0.01 **** p<0.0001

4.2. The effect of air pollution on labor supply

The main findings of the study are reported in Table 3 and Table 4. In column (1) of Table 3, no statistically significant impact of PM on labor supply is observed, and the inclusion of individuals' covariates yields numerically similar estimates (column 2 and 3). However, the presence of children aged 2 or younger and 3 or younger seems to suggest a reduction of working hours. Standard errors are robust to heteroskedasticity.

The heterogeneity analysis by gender reveals more detail (Table 4). The overall impact of PM_{10} on labor supply is not statistically significant as observed in Table 3, but the presence of young children of different ages seems to affect differently in response to air pollution. Noticeably, the impact on the total sample is entirely driven by females. That is, the effect is significant only for females while it is statistically indistinguishable from zero for males when each children variable is interacted with PM levels. For women, a 1 $\mu g/m^3$ increase in the levels of PM_{10} concentration is associated with a reduction of working hours by 0.4 standard deviation, when they have one or more infant. This result is both statistically and economically significant; for females, one standard deviation increase in PM_{10} is associated with 60 minutes decrease in working hours per week, which implies 54 hours annually.[9] Applying the current minimum wage in South Korea, approximately 6.77 U.S. dollars, to the female sample in this study (48,543), yield loss of 17.7 million U.S. dollars per year. A consistent trend is observed for having 2-year-olds and below or 3-year-olds and below, with smaller coefficients in magnitudes. A gradual decrease of the effect is observed as children mature, which is in line with the epidemiological evidence of increasing immunity.

[9] Calculated using the standard deviation of PM and its coefficient

TABLE 3—PANEL FIXED EFFECTS ESTIMATES OF PM ON LABOR SUPPLY USING KLIPS DATA

	Dependent variable: Average working hours per week				
	Total	Total	Total	Male	Female
Variable	(1)	(2)	(3)	(4)	(5)
PM	0.005	-0.000	-0.000	0.004	-0.003
	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)
Age		1.899***	1.864***	1.978***	1.875***
		(0.094)	(0.094)	(0.135)	(0.134)
Age^2		-0.021***	-0.020***	-0.024***	-0.019***
		(0.001)	(0.001)	(0.001)	(0.001)
Married		-7.367***	-6.833***	1.543**	-16.596***
		(0.846)	(0.843)	(0.773)	(1.354)
Graduated college		13.899***	13.970***	14.250***	13.278***
		(0.852)	(0.852)	(1.184)	(1.213)
			-0.324	0.144	-0.728
Children 1yr			(0.460)	(0.584)	(0.688)
			-0.605**	-0.172	-0.970**
Children 2yr			(0.276)	(0.379)	(0.397)
			-0.907***	0.124	-1.849***
Children 3yr			(0.259)	(0.318)	(0.398)
Panel FE	Y	Y	Y	Y	Y
Yearly FE	Y	Y	Y	Y	Y
Quarterly FE	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y
N	93,227	93,216	93,216	44,673	48,543
Adj. R-squared	0.002	0.028	0.029	0.034	0.037

Robust standard errors in parentheses. "PM" is the average concentration of PM_{10} per month. "Children 1yr," "Children 2yr," and "Children 3yr" indicate the number of children aged between 0-1, 0-2, 0-3, respectively.
 * p<0.10 ** p<0.05 *** p<0.01

TABLE 4—PANEL FIXED EFFECTS ESTIMATES OF PM ON LABOR SUPPLY USING KLIPS DATA BY GENDER

	Dependent variable: Average working hours per week								
	Total	Male	Female	Total	Male	Female	Total	Male	Female
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Children 1yr × PM	-0.070**	-0.043	-0.082*						
	(0.028)	(0.029)	(0.045)						
Children 1yr	1.469	2.012	0.475						
	(1.293)	(1.384)	(2.102)						
PM	0.001	0.005	-0.002						
	(0.006)	(0.009)	(0.009)						
Children 2yr × PM				-0.036**	-0.018	-0.047**			
				(0.015)	(0.018)	(0.024)			
Children 2yr				0.221	0.836	-0.526			
				(0.752)	(0.874)	(1.176)			
PM				0.001	0.005	-0.001			
				(0.006)	(0.009)	(0.009)			
Children 3yr × PM							-0.034***	-0.016	-0.048***
							(0.012)	(0.015)	(0.018)
Children 3yr							0.255	0.790	-0.340
							(0.612)	(0.767)	(0.916)
PM							0.002	0.006	0.000
							(0.006)	(0.009)	(0.009)
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y
Panel FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yearly FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	93,216	44,673	48,543	93,216	44,673	48,543	93,216	44,673	48,543
adj. R-squared	0.028	0.034	0.036	0.029	0.034	0.037	0.029	0.034	0.037

Robust standard errors in parentheses. "PM" is the average concentration of PM_{10} per month. "Children 1yr," "Children 2yr," and "Children 3yr" indicate the number of children aged between 0-1, 0-2, 0-3, respectively.
* p<0.10 ** p<0.05 *** p<0.01

4.3. Falsification test

As mentioned in the Identification Strategy section, the potential endogeneity of fertility decision in the labor supply equation may arise from several channels. First, an individual's unobserved health condition jointly determines the labor supply and number of children (Angrist & Evans, 1998). Also, the higher hourly wage, both the willingness to work and affordability of more children may increase. While the likelihood of endogeneity remains as a potential concern, the strength of the confounding factors can be measured. For example, supposing that an *i*-th female has one baby aged between 1 and 2 in 2013, she is unlikely to have an infant or be pregnant in 2010. Assigning her a "pseudo-child" in 2010 may suggest a degree of the concern; if the individuals with and without children are systematically different, then the interaction term of PM_{10} with the pseudo-child would be significant. Table 5 reports the placebo estimates, which are not statistically significant at the conventional level. These estimates provide some evidence that the endogeneity of the number of children is not the primary concern. Other remaining concerns are discussed in the following section.

TABLE 5—FALSIFICATION TEST

	Dependent variable: Average working hours per week								
	Total	Male	Female	Total	Male	Female	Total	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Pseudo Infant 1yr x PM10	-0.067	-0.138*	-0.034						
	(0.073)	(0.082)	(0.113)						
Pseudo Infant 1yr	4.981	5.717	6.049						
	(3.388)	(3.818)	(5.375)						
Pseudo toddler 2yr x PM10				-0.035	-0.009	-0.075			
				(0.053)	(0.057)	(0.076)			
Pseudo toddler 2yr				1.122	0.582	2.093			
				(2.358)	(2.575)	(3.454)			
Pseudo toddler 3yr x PM10							-0.034	-0.003	-0.057
							(0.052)	(0.052)	(0.096)
Pseudo toddler 3yr							2.666	0.508	4.174
							(2.469)	(2.282)	(4.481)
PM 10 included	Y	Y	Y	Y	Y	Y	Y	Y	Y
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y
Panel FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yearly FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	50,648	23,841	26,807	38,110	17,745	20,365	26,441	12,134	14,307
adj. R-sq	0.020	0.024	0.029	0.016	0.018	0.025	0.013	0.013	0.025

Robust standard errors in parentheses. "PM" is the average concentration of PM_{10} per month. "Infant 1yr," "Toddler 2yr," and "Toddler 3yr" indicate the number of children aged between 0-1, 0-2, 0-3, respectively.
* p<0.10 ** p<0.05 *** p<0.01

5. DISCUSSION

5.1. The combined labor supply effect

The estimates of the probability of being in labor force suggest that both effects on labor supply, those who dropped out of the labor force and reduction of working hours, are in place. In Table 6, statistically significant estimates, $\frac{\partial E(L^S|\boldsymbol{X})}{\partial PM_{10}}$, suggest that PM_{10} drives women with children out of the labor force in response to the surging levels of PM. To precisely measure the labor supply loss (a reduction in working hours), it is important to clearly disentangle the combined effect.

TABLE 6—PANEL FIXED EFFECTS ESTIMATES OF PM ON LABOR FORCE PARTICIPATION

	Dependent variable: 1 if an i-th individual is in the labor force (employed/unemployed); 0 if an i-th individual is out of labor force (economically inactive/out of the labor force)								
	Total	Male	Female	Total	Male	Female	Total	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PM	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Children 1yr × PM	-0.002**	-0.001	-0.002**						
	(0.001)	(0.000)	(0.001)						
Children 1yr	0.011	0.030	-0.006						
	(0.028)	(0.024)	(0.050)						
Children 2yr × PM				-0.001	0.000	-0.001*			
				(0.000)	(0.000)	(0.001)			
Children 2yr				-0.018	0.003	-0.038			
				(0.017)	(0.015)	(0.029)			
Children 3yr × PM							-0.000	0.000	-0.001
							(0.000)	(0.000)	(0.000)
Children 3yr							-0.023*	0.005	-0.050**
							(0.013)	(0.013)	(0.022)
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y
Panel FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Yearly FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	93,227	44,676	48,551	93,227	44,676	48,551	93,227	44,676	48,551
R-squared	0.003	0.004	0.006	0.004	0.004	0.007	0.004	0.004	0.008

Robust standard errors in parentheses. "PM" is the average concentration of PM_{10} per month. "Children 1yr," "Children 2yr," and "Children 3yr" indicate the number of children aged between 0-1, 0-2, 0-3, respectively.
* p<0.10 ** p<0.05 *** p<0.01

A preliminary solution is to restrict the sample to the observation with a strictly positive labor supply and suffer from the sample selection problems in exchange.[10] Tobit is another alternative that permits the following estimation: $\frac{\partial E(L^S|L^S>0,\ \boldsymbol{X})}{\partial PM_{10}}$. Yet, the maximum likelihood estimate also suffers from sources of inconsistency. The OLS slope estimates are not sensitive to the presence of heteroskedasticity and autocorrelation, but standard errors need to be clustered given across regional variation of PM levels. Because clustering standard error and panel fixed effects are not applicable for Tobit, an alternative is to estimate using Tobit random effect. Appendix B displays the estimation of conditional marginal effects of PM levels on labor supply, conditional on $\mathrm{Ls} > 0$. The Tobit estimates show that 43 percent of individuals in the sample has the labor supply of zero (see Appendix B).

5.2. Endogeneity of air pollution

Another concern arises because of the endogeneity of PM_{10}, including omitted variable bias and measurement error. Omitted variable bias may arise from unobserved factors such as manufacturing intensity and traffic conditions; having the industrial parks nearby would increase both labor supply and exposure to air pollution. Also, white-collar indoor workers or those who can afford to minimize the exposure to air pollution at all cost is not distinguishable with the suggested model, so that such avoidance behavior is likely to attenuate the estimates. Also, the actual PM_{10} concentrations may have not been measured accurately. If the measurement error does not correlate with the true value of PM_{10}, it would lead to a bias toward zero, following classical errors-in-variables (CEV) assumption. These endogeneity problems may be addressed by using conventional instruments from literature, such as rainfall and wind direction (Jia & Ku, 2019).

[10] However, the results of this exercise are qualitatively similar and comparable in magnitude.

5.3. Future research

There are several reasons that the results might underestimate the effect of air pollution on labor supply. First, if the actual fraction of toddlers suffered from PM_{10} can be measured and the estimated impact can be divided by the fraction, it would result in larger impact because the fraction affected is lower than 1. As mentioned earlier, using $PM_{2.5}$ as a proxy indicator for the air quality is expected to yield consistent results with larger coefficients in magnitude, which is not used in this study due to the limited data availability of the $PM_{2.5}$ measurements.

Lastly, heterogeneity analysis by different subgroups might reveal further details of the effect. Some literature supports the claim that elderlies are more susceptible to PM (e.g., Simoni et al. 2015). Additional subgroup analysis, by household income and by a type of employment (wage or non-wage), might exhibit deviating impact for different socioeconomic groups. These limitations are left for future research.

6. CONCLUSION

This paper proposes that the need to provide care to child dependents impacted by worsening air quality explains the reduction in female labor supply in South Korea. Due to the relative susceptibility of children to air pollution, parents give up work hours to take care of their ill children and thus do not lose work hours due to any changes in their own health status. In the context of South Korea, where primary caregivers are usually mothers, only women's working hours are affected by increasing levels of PM concentration. The results of this paper present the estimates regarding the youngest dependent group, and the effect is more significant for those who have younger children. If the immunity of children develops over time, the caregiving effect on working hours may disappear after a worker's children reach a certain age, suggesting that the worker would be willing to restore the labor supply loss. Still, the economic cost of the temporary labor supply loss is significant, with the sample group of women with infants alone costing 17.7 million U.S. dollars per year, which implies the loss of approximately 2.5 billion U.S. dollars annually across the entire population.[11]

While this paper focuses on evidence from South Korea, the hypothesis can be applied to other countries. A similar result is expected in countries with poor air quality and gendered childrearing responsibilities (with women being the primary caregivers), while a reduction in labor supply among both parents may be observed in countries where air quality is poor but gender role is less narrowly defined. The conclusions of this study, therefore, provide implications for pediatric public health and childcare policy. An extended childcare policy for children in medical need due to air pollution should be considered, particularly to avoid placing a heavier burden on lower income households.

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[11] The preliminary calculation is based on the 2017 Census of women aged 20-39 (nearly 6.9 million individuals) and the minimum wage of 6.77 U.S. dollars per hour. The actual economic effect should consider macroeconomic factors in full demand and supply channel.

APPENDICES

Appendix A. Air quality standards

TABLE A.1—AIR QUALITY STANDARDS FOR PARTICULATE MATTER (PM)

	$PM_{2.5}$ (μg/m³)		PM_{10} (μg/m³)		Lastly updated dates and additional notes
	Annual	24-hr	Annual	24-hr	
WHO Air Quality Guidelines	10	25	20	50	WHO also sets three-level interim targets for both PM
E.U. Air Quality Standards	25[a]	-	40	50	1/1/2005 [a] limit value as of 1/1/2015
U.S. National Ambient Air Quality Standards	12[b]	35	-	150	3/18/2013 [b] 15 remains as a secondary target
South Korea's Air Quality Standards	15[c]	35[c]	50	100	3/27/2018 [c] changed from 25 & 50, respectively

Sources: WHO, European Commission, U.S. Environmental Protection Agency, and Air Korea

TABLE A.2—KOREA AIR QUALITY FORECAST ALERT

	Good	Moderate	Unhealthy	Very Unhealthy
PM_{10}	0~30	31~80	80~150	151
$PM_{2.5}$	0~15	16~35	36~75	76

Source: Air Korea

TABLE A.3—U.S. AIR QUALITY INDEX FOR PM

Good	0~50
Moderate	51~100
Unhealthy for the sensitive	101~150
Unhealthy	151~200
Very unhealthy	201~300
Hazardous	301-500

Source: U.S. EPA

Appendix B. Tobit random effects regression

TABLE A.4— TOBIT RANDOM EFFECTS ESTIMATES OF PM ON LABOR FORCE PARTICIPATION

	Dependent variable: Average working hours per week								
	Total	Male	Female	Total	Male	Female	Total	Male	Female
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PM	-0.0089	-0.0003	-0.0191	-0.0090	-0.0015	-0.0184	-0.0089	-0.0025	-0.0172
	(0.0084)	(0.0099)	(0.0148)	(0.0085)	(0.0100)	(0.0149)	(0.0086)	(0.0101)	(0.0150)
Children 1yr × PM	-0.0925*	-0.0182	-0.2603**						
	(0.0507)	(0.0557)	(0.1027)						
Children 1yr	0.6686	1.7350	-0.3166						
	(2.3282)	(2.5598)	(4.6801)						
Children 2yr × PM				-0.0237	0.0153	-0.0983*			
				(0.0279)	(0.0308)	(0.0553)			
Children 2yr				-1.4062	0.3760	-4.7306*			
				(1.3516)	(1.4928)	(2.6787)			
Children 3yr × PM							-0.0123	0.0183	-0.0682
							(0.0214)	(0.0237)	(0.0420)
Children 3yr							-1.4940	0.5463	-5.3113**
							(1.0521)	(1.1651)	(2.0646)
Covariates	Y	Y	Y	Y	Y	Y	Y	Y	Y
Panel FE	N	N	N	N	N	N	N	N	N
Yearly FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	93,227	44,676	48,551	93,227	44,676	48,551	93,227	44,676	48,551

Standard errors in parentheses. "PM" is the average concentration of PM_{10} per month. "Children 1yr," "Children 2yr," and "Children 3yr" indicate the number of children aged between 0-1, 0-2, 0-3, respectively.
* p<0.10 ** p<0.05 *** p<0.01

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