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Ahram Han
KDI School of Public Policy and Management

Taejong Kim
KDI School of Public Policy and Management

Gi Khan Ten
KDI School of Public Policy and Management

Shun Wang
KDI School of Public Policy and Management

April, 2020
Working Paper 20-15

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* We are grateful to the KDI School of Public Policy and Management for providing financial support.

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Ahram Han
KDI School of Public Policy and Management
263 Namsejong-ro, Sejong, South Korea 30149
Tel: +82 10 4665 1637; Email: arhan16@kdis.ac.kr

Taejong Kim
KDI School of Public Policy and Management
263 Namsejong-ro, Sejong, South Korea 30149
Tel: +82 44 550 1085; Email: tjkim@kdischool.ac.kr

Gi Khan Ten
KDI School of Public Policy and Management
263 Namsejong-ro, Sejong, Korea
Tel: +82 10 8985 7455; Email: ten.andrey@kdis.ac.kr

Shun Wang
KDI School of Public Policy and Management
263 Namsejong-ro, Sejong, Korea
Tel: +82 44 550 1109; Email: swang@kdis.ac.kr

Abstract: We investigate whether air pollution affects labor supply in South Korea. To address endogeneity in the level of local air pollution, we utilize plausibly exogenous changes in wind directions as instruments. This choice is based on the observation that air pollution in South Korea is affected by spillovers from the neighboring countries, mediated by wind directions. We find that mothers reduce working hours in response to the worsening air quality, and the impact attenuates, as children grow. Children's vulnerability to the air pollutants and mothers' role as the principal caregiver are the probable reason that drives the results.

Keywords: Air Pollution; Caregiving; Labor Supply; Particulate Matter; South Korea

JEL: J22; J16; Q53

1. Introduction

Extended exposure to ambient air pollution may cause respiratory and cardiovascular diseases (Kim, Kabir, and Kabir, 2015). The World Health Organization (WHO) claims that ambient air pollution is responsible for approximately 7 million annual deaths globally (WHO, 2016b). We thus hypothesize that labor supply of the working population might be affected by air pollution, as both working adults' and their children's health could be harmed by it. This paper aims to examine the impacts of ambient air pollution on labor supply in South Korea (Korea henceforth).

Korea provides an interesting setting to investigate the effects of ambient air pollution. First, its air pollution levels are very severe. For instance, Korean fine particulate matter (PM) sized less than 10 microns (μm) in diameter (PM_{10} henceforth) recorded 47.3 μg/m^3 in 2016 (Air Korea, 2017), which is way above the 20 μg/m^3 in annual average prescribed by the WHO safety standard. In addition, the variation of PM_{10} is large. Taken together, these facts constitute a good ground for investigating the effects of air quality on labor supply in the econometric framework. Second, Korean air pollution is sensitively affected by spillovers from neighboring countries, mediated by wind directions (Jia and Ku, 2019; Uno et al., 2009). The latter phenomenon provides a unique empirical setting, which allows us to isolate the impact of air pollution on labor supply from the other confounding factors.

The analysis relies upon the labor supply–air quality matched panel data set of Korean households over the period of 2010 through 2016. The key explanatory variable is the district-level measurement of PM_{10} concentration as the indicator of air pollution, which is likely to be correlated with the error term due to the residential choice, omitted variables, and measurement error (Hanna and Oliva, 2015). To address the potential endogeneity, we utilize 2SLS with individual fixed effects, taking changes in wind directions as a source of plausibly exogenous variation in local air quality. To the extent that wind directions are likely to be excluded from the individual-level labor supply equation, we interpret the resulting point estimates as causal impacts of air pollution on the working hours.

We find that mothers with young children substantially reduce their hours of work in response to heightened air pollution, with the negative impact attenuating as children grow older. However, our analysis shows that males' labor supply does not respond to local air quality. In addition, the findings reveal that the reduction in labor supply is more pronounced among low-income households. Taken together, these patterns are consistent with the still prevalent gender norms in Korea that expect mothers to be the principal caregiver for young children, and the possibility that the options for delegated caregiving will be more restricted for low-income households, in case children get sick. Overall, our preferred estimates suggest that a unit standard deviation increase in the district-level air pollution (measured as the quarterly average concentration of PM_{10}) reduces the weekly average working hours supplied by women with children aged 3 or younger by 0.13 standard deviations.

Our findings are robust to various specifications, including those, that explicitly partial out the province-year fixed effects, a rich set of individual and district-specific covariates and district-specific seasonality. For our results to be driven by the unobserved idiosyncrasy, one would have to believe that our proposed instruments are systematically related to the very specific unobserved heterogeneity, that varies substantially within province-year cells, doesn't exhibit any district-specific seasonal pattern and "switches on" only at the time when wind blows from China to Korea, being uncaptured by the set of district-specific weather controls. We conclude that such shock is unlikely to exist, which suggests that wind directions allow to consistently identify the slope of hours supplied in local air quality.

While there is growing literature that investigates the linkage between air pollution and labor supply, we find few papers that investigate the mechanism, and even fewer that employ a credible identification strategy. Probably the closest paper to our own from the literature is the study by Hanna and Oliva (2015), which utilizes a shutdown of a major factory in Mexico City as a source of exogenous variation in air quality, and finds a significant response in labor supply. There is also overlap in findings with Aragón, Miranda, and Oliva (2017), which investigates the caregiving for sick members of the family as the chief mechanism in the air pollution–labor supply nexus. In this regard, we directly communicate to the above studies by rigorously assessing the magnitude of the impact, while explicitly investigating the underlying mechanism through which air quality affects the working hours supplied.

The paper is organized as follows. Section 2 discusses the relevant literature and our contribution. Section 3 describes the data and identification strategy. Section 4 presents the main results and robustness checks. Section 5 reports heterogeneity analysis. Section 6 assesses the monetary loss implied by heightening air pollution. Section 7 concludes the paper.

(Figure 1 Distribution of quarterly average PM_{10} here)

2. Literature Review

2.1 Air quality and health outcomes

A vast number of epidemiological evidence illustrates the link between air pollution and health (e.g., Brook et al., 2004; Currie and Neidell, 2005; Jia and Ku, 2019; Knittel, Miller, and Sanders, 2016; Lee, Yoo, and Nam, 2018; Morales-Suárez-Varela, Peraita-Costa, and Llopis-González, 2017; Moretti and Neidell, 2011). Among all pollutants, PM notoriously earns a title of the most harmful threat to human health that causes acute and chronic morbidity and mortality (WHO, 2016a). The exposure to PM is mainly associated with respiratory and cardiovascular diseases and hospital admissions thereof, such as asthma, bronchitis, dysfunction of lung and heart, and cancer, increasing risks of mortality among infants and adults (Arceo, Hanna, and Oliva, 2015; Brook et al., 2004; Brook et al., 2010; Environmental Protection Agency, 2009; Hicken et al., 2014; Jans, Johansson, and Nilsson, 2018; Knittel, Miller, and Sanders, 2016; Lucas et al., 1994; Pope, Ezzati, and Dockery, 2009). The health effects other than respiratory and cardiovascular diseases also have been reported, such as diabetes (Pearson et al., 2010), and autism spectrum disorders, which potentially emerge due to oxidative stress, neurological effects, and neonatal immune system (Morales-Suárez-Varela, Peraita-Costa, and Llopis-González, 2017).

The evidence of the relative susceptibility of children is strong in previous studies elsewhere (Arceo, Hanna, and Oliva, 2015; Brooks et al. 2004; Brooks et al. 2010; Currie and Niedell, 2005; Gouveia and Junger, 2018; Knittel, Miller, and Sanders, 2016), as well as in Korea (Yap et al., 2013; Lee, Yoo, and Nam, 2018). Particularly, Jia and Ku (2019) find evidence of cross-border pollution spillover from China to increase mortality in Korea, with a more significant effect on children under five and elderlies. We utilize the above findings to put forth our mainline hypothesis, which is as follows: If air pollution harms the working hours supplied, then one of the likely channels is the presence of young children in the working individuals' household.

2.2 Labor outcomes

The association between health and labor has been extensively explored. For example, Parsons (1977) finds that a man with poor health works 1,300 hours less per year than men with excellent health. Despite the strong epidemiological evidence of the harmfulness of air pollution, its socioeconomic impact is relatively less explored. Hausman, Ostro, and Wise (1984) find one of the early evidences of a positive association between the level of total suspended particles' concentration and workday loss. A growing body of literature finds a link between the air pollution and labor outcomes (Aragón, Miranda, and Oliva, 2017; Chang et al., 2016; Graff-Zivin and Neidell, 2012; Hanna and Oliva, 2015). Broadly, the literature puts forth two channels through which the air pollution may affect labor – either by absenteeism or by "presenteeism" (Chang et al., 2016). That is, a working individual may either be absent from the work, or face a loss of functionality due to ill-health conditions while being present in the workplace. While presenteeism may arise from the direct effect of air pollution on the worker, absenteeism may arise either due to the illness of the worker or due to other affected household members who are in a need of caregiving.

Hanna and Oliva (2015) investigate the effect of pollution level on labor supply utilizing the closure of a large oil refinery in Mexico City that reduced air pollution as a natural experiment. By comparing the changes in labor supply of individuals living in the neighborhood of the refinery with those who live further away, the authors find that the closure leads to an increase in working hours. Aragón, Miranda, and Oliva (2017) find that a moderate level of air pollution does not affect the overall hours worked, however they show that the presence of susceptible dependents at home is likely to drive working hours down when air quality worsens. This finding, along with the previous literature related to the association of air pollution and elementary school absenteeism due to illness (Currie et al., 2009; Hales et al. 2016; Park et al., 2002) suggests a potential channel through which air pollution affects the worker's absenteeism – the worker may be absent regardless of his own health condition if he has to provide caregiving for his dependent. Accordingly, we hypothesize that the working hours of the individuals who have children would respond to the level of PM.

Our study contributes to the above literature by uncovering multiple dimensions of heterogeneity of air quality's impact on labor supply using plausibly exogenous variation in air pollution. First, we confirm that the presence of children is the likely channel through which air pollution affects mothers' working hours supplied. Doing so, we extend the work of Aragón, Miranda, and Oliva (2017), showing that mothers' labor supply response attenuates as children age. The latter findings echo those epidemiological studies that document the relative susceptibility of children to air pollution (Brooks et al. 2004; Brooks et al. 2010; Currie and Niedell, 2005; Gouveia and Junger, 2018; Knittel, Miller, and Sanders, 2016; Lee, Yoo, and Nam, 2018). Second, our paper shows a gender-bias in labor supply responses, which is in line with the findings of the heavier caregiving burden on mothers in Korea (Choe and Retherford, 2009; Kim and Cheung, 2015; Koh, 2008; Tsuya, Bumpass and Choe, 2000). The latter results serve as one potential explanation to the proportion of hours spent on domestic unpaid work by Korean males being observed to be one of the lowest among OECD countries (OECD, 2012). Finally, we show that the estimates are mainly driven by low-income families, which is consistent with Jans, Johansson, and Nilsson (2018), who find a larger impact of bad air quality on children from the low-income group. We further suggest that the income heterogeneity may operate through the difference in the affordability of external caregiving services among households.

3. Data and Graphical Evidence

Our primary data set is the Korean Labor and Income Panel Study (*KLIPS*), a longitudinal survey conducted by the Korea Labor Institute on a yearly basis. We extract the data on the average working hours in a typical week as an indicator of labor supply and socio-demographic characteristics of all individuals aged between 25 and 60.

The empirical analysis focuses on the comparison of the working hours' responses of women with and without young children. Thus, we further restrict the scope of our analysis to the subsample of married individuals.

We utilize 2010–2016 waves of the *KLIPS* following the years for which series for our measure of the air quality is available. The district-month panel on our key measurement of air pollution (PM_{10}) is obtained from Air Korea of the Korea Environment Corporation. We obtain the meteorological data needed to construct our instruments from the Korea Meteorological Administration. The district-level air pollution data is matched with *KLIPS* based on the distance from the district's centroid to the closest monitoring station.

Table 1 shows descriptive statistics of our sample of the labor force. Two observations of the basic statistics are relevant to our analysis. First, the cross-gender differences in the working hours' schedules are traceable along both extensive and intensive margins: the labor force participation is lower among women, while within the labor force women work less.[1] Given the observed gendered difference in the number of individuals in the labor force, there emerges the need to test the possibility that women might leave the labor force in response to the heightening air pollution.

Second, the average of PM10 is high. Figure 1 further elaborates on this point, showing the density of the district-quarter average PM10 in our data. As the figure shows, the average concentration of pollutants is far above the safety standard (labeled as the vertical red line on

[1] The difference in the number of observations is not driven by the overrepresentation of males in the KLIPS dataset, as their proportion in the sample is arbitrarily close to 50%.

the figure) prescribed by the World Health Organization. This observation relieves the concern about the potential failure to detect any systematic relationship between air quality and the working hours supply because the level of air pollution is not "high enough"

To conduct a preliminary investigation of the gender-bias in the labor supply's effects of air pollution, we depart from the visual analysis of the pattern. Figure 2 plots the working hours among economically active individuals against our measure of air pollution separately by genders and the presence of young children (aged three years or below). The trend shown in panel (a) of the figure seemingly goes in favor of our core hypothesis, showing the negative relationship between the working hours and PM10 among women. Additionally, women with young children seem to be more sensitive to heightening air pollution.

However, it is harder to explain the positive response of the males' working hours observed in panel (b) of Figure 2. We hence infer the likely presence of factors that confound the relationship between two variables of interest from this graphical observation.

For example, heightening air pollution is indicative of growing production intensity, with the relevant changes in the aggregate labor demand. Additionally, changes in the traffic conditions might jointly determine the local air quality and the working hours supplied.[2] To the extent that the development of transportation infrastructure is likely to affect the working hours supplied, a failure to account for the local traffic conditions might invalidate the causal interpretation of the results akin those shown on Figure 2. Finally, the literature highlights the importance of the residential choice which might be affected by the workers' characteristics, correlated with the air quality and relevant to the choice of the labor supply's schedule. Hence, the relationship between air pollution and the working hours supplied is a subject of a more rigorous empirical investigation.

To conclude this subsection, we highlight several observations that will guide our econometric framework. First, the labor force participation is considerably lower among women. Thus, the exclusion of inactive women from the regression analysis in case if air quality affects the labor force participation's decision introduces the problem of the endogenous sample selection. Second, while numerous health studies might offer some explanations to the pattern revealed in the subsample of women even in the absence of young children, the revealed positive response of the men's labor supply to air quality is likely to point at the strong presence of the

[2] For example, some studies show that subway expansion improves air quality (Baek, 2016; Li et al., 2019).

confounding factors that drive the relationship. The next subsection presents our effort to deal with these empirical challenges.

4. Econometric Framework

4.1 The baseline specification

Our core goal is to test the heterogeneity of the working hours' response to the air quality based upon the presence of children of various age groups in the household. More precisely, in line with the epidemiological studies showing that children become less vulnerable to air pollution as age goes by, we expect the mothers' working hours to be less responsive to the worsening air quality. However, the likely presence of the methodological problems discussed in the previous section motivates a thorough choice of the identification strategy that we present below.

The following model serves as the departing point of our econometric framework:

$$h_{idt} = \theta + \gamma_1 PM_{dt} + \gamma_2 (PM_{dt} - \mu_{PM}) \times \#children_{idt}^{j} + \gamma_3 children_{idt}^{j} + \\ + X'_{idt}\phi + \varepsilon_{idt}, \quad (1)$$

where i, d and t index individual, district and year respectively. The outcome variable h_{idt} is the self-reported weekly working hours supplied in a typical week. PM is the concentration of PM10 during three months preceding the survey date, and $children_{idt}^{j}$ is the number of children aged j or below; X'_{idt} is a vector of controls, which includes the individual's and the spousal educational attainment, age, age squared, five dummies for the spousal's annual earning's percentiles and a set of weather controls (temperature, atmospheric pressure, precipitation, wind speed). To further account for the unobserved determinants of labor supply and air quality, we control for a set of fixed effects (θ). The set includes the individuals', the districts' and the province-quarters' fixed effects.[3] We reparametrize our model by demeaning our PM10 variable prior to interacting it with the number of children of the given age group. Thus, γ_3 has the interpretation of the labor supply's response to the additional child at given the mean value of PM10. Finally, ε_{idt} is the error term.

Thus far, our proposed identification rests upon the assumption that the right-hand side variables effectively address the endogeneity of PM10. The inclusion of the individual's, spousal characteristics and weather controls accounts for the differences in the human capital and climatic characteristics that covariate with the hours supplied and the exposure to the given

[3] Our baseline sample covers 188 districts and 17 provinces

level of air pollution. Individual's and district fixed effects control for the full sets of time-invariant individual-specific characteristics and geographic determinants of labor supply (e.g. unobserved preference for cleaner air that might correlate with the working schedule). Nevertheless, the concern about the existence of the unobserved confounders still persists.

One possibility is the existence of the relationship between PM10 and the (unobserved) wage rate. On the one hand, higher pollution might be indicative of the higher local productivity and hence higher wages. On the other hand, those areas that generate better labor market opportunities for the given stock of human capital might also sustain better air quality, especially when the existing industrial mix, the available production technologies and the prevailing market demand permit to do so. Given the ambiguity regarding the relationship between the wage rate and PM10, the resulting direction of bias is ambiguous. Additionally, unobserved traffic conditions discussed in the previous subsection of the current paper constitute another example of the potential omitted variable. As Aragon, Miranda and Oliva (2017) point, the unobserved traffic condition is likely to cause the bias that works in favor of our hypothesis. Finally, the PM10 variable may contain the measurement error, as the Meteorological Administration cautions that fluctuating climatic conditions and equipment failures may cause noise.

We address these concerns leveraging a plausibly exogenous variation in the wind patterns as an instrumental variable. The next section provides the relevant details.

4.2 South Korean air pollution and wind patterns

A valid instrumental variable (IV) allows to avoid the methodological problems implied by the endogeneity of the air quality if and only if the IV affects the endogenous causal variable of interest (PM10) while being in no systematic relationship with the second-stage's error term. In this subsection, we first argue that our IV satisfies those two assumptions. We then provide details of its construction.

First, numerous studies document the existence of the transboundary spillovers carried by wind. For example, geophysical evidence points that fine dust from China travels as far as to Greenland and the French Alps (Bory, Biscaye and Grousset, 2003; Grousset et al., 2003). More generally, Uno et al. (2009) investigate the process of the spatial diffusion of China dust generated by a storm in Taklimakan Dessert and conclude that it takes 13 days for the particles to make one full circuit around the globe. Consequently, Jia and Ku (2019) show that air pollution induced by the wind dispersal of fine particles from China increases the infant mortality in Korean districts. Thus, the evidence above justifies the existence of the first-stage relationship between PM10 and upwind from China.

We now argue that the upwind from China is unlikely to affect labor supply via any channel other than PM10 itself. Probably, the possibility that wind patterns change simultaneously with those climatic characteristics that affect the labor supply independently (for example, via children's illness) could be the most important caveat. However, a rich set of weather characteristics that we explicitly control for should alleviate this concern.

Apart from the climate, there exists an array of the location-specific characteristics that potentially determines both wind pattern and hours worked. For example, mountainous areas might physically suppress the likelihood of certain wind directions' to occur, while affecting the labor supply via the location-specific industrial mix and transportation cost. If this is the case, then the inclusion of the districts' fixed effects aids the problem.

It is also important to account for the possibility both wind directions and labor supply change within year by seasons. We address this possibility by including the province-specific quarters' fixed effects.

Finally, there exists the possibility that individuals self-select themselves into locations where their future children are less likely to be exposed to the harmful environment. This concern gets amplified in light of the growing awareness about the harmfulness of the fine dust in Korea, and the technological advancement that allows to predict weather changes that determine the air quality. We investigate this possibility running the falsification test via assigning the leading values of the number of children to the families in our sample. The results rule out the case of individuals exhibiting precautionary relocating behavior of this kind. Taken together, the above arguments substantiate our belief that upwind from China is a natural IV candidate in the Korean setting.

We leverage data on wind directions from the Korea Meteorological Administration, which provides the district-month's most frequent wind direction measured on a standard 360-degree scale. For example, a wind blowing strictly from the east has a direction of 90 degrees, while the one from the south has 180 degrees. The geographic location of South Korea implies that the western wind direction defines the upwind from the mainland of China. Hence, the IV must be constructed such that it clearly captures the frequency of the western wind, while closely matching our PM10 variable along its temporal dimension (recall: our PM10 is the average concentration of PM10 over the 3 months preceding the survey date).

We first assign every observed wind direction into one of the four mutually exclusive categories: $[45 - 135)$ degrees for east,$[135 - 225)$, degrees for south, $[225 \sim 315)$ degrees for west, and $[315 \sim 45)$ degrees for north. We then construct a binary variable for each category of the wind direction, assigning the predominantly blown wind to every district-month cell in our data. By construction, only one out of four wind directions can take on the value of 1 in the given district-calendar month's cell. Finally, we sum the resulting four dummies over a quarter (three months) preceding the survey date for each district to match our instruments with our PM10 variable. The resulting wind directions variables, taking west wind as an example, means the number of months in the given quarter during which west wind is the most prevalent direction. We choose western and northern wind directions as our IVs, while omitting the rest as the comparison group.

We have two endogenous variables (PM10 and its interaction with the number of kids of the given age group) and hence two first-stage regression equations. Western and northern wind directions serve as the excluded IVs for PM10. The products of each wind direction with the number of children of the given age allow us to instrument the interaction term of PM10 and children. The means and the standard deviations of our excluded IVs are given in Table 1.

5. Results

5.1 Baseline findings

Table 2 presents our baseline 2SLS results with the weekly working hours as the outcome. We highlight several findings. First, none of the columns of Table 2 shows statistically significant coefficient of PM10. This suggests that heightening air pollution does not affect the working hours supplied by the subpopulation of individuals without young children.

Second, the results show that mothers of younger children do work less in response to the worsening air quality. For example, according to column (1) of Table 2, a unit increase in PM10 induces mothers of 1 child aged one year (or less) to work 0.24 hours less. This implies that a standard deviation change in PM10 changes the working hours of the mothers with one infant by –0.2 standard deviations – a moderate loss.

Column (2) of the same table shows that mothers with children of the older age category (≤ 2 years) lose less hours. Column (3) shows that mothers with children no older than three years do not respond to the changes in the air quality.

Thus far, the findings show that air pollution induces mothers of young children to work less, and the impact attenuates, as kids grow. Probably, numerous epidemiologic studies that show children's vulnerability to air pollution at the earliest stages of their lives supply a plausible explanation to the revealed pattern.

The rest of the columns of Table 2 investigate the response of the fathers' working hours. Column (4) shows suggestive evidence of the "added worker" effect: fathers of infants slightly increase their working hours in response to heightening PM10, although the estimated impact is only marginally significant. The estimated effect vanishes once wider age groups of children are taken into consideration. Taken together, the results of columns (4) to (6) od Table 2 reveal no loss in the fathers' working hours in response to worsening air. These findings are consistent with the past studies showing fathers being the main breadwinners in the family and the mothers' disproportionate role of caregiving in South Korea.

Table 3 shows the results of estimating the first-stage regression models. We have two endogenous variables (PM10 and its interaction with the number of children of the given age group) and hence two first stages for every column. Panel A (B) of Table 3 reports the set of first-stage regression results for PM10 (PM10 interacted with the number of children of the given age group). In line with the past environmental studies, the results confirm that western wind does increase the concentration of PM10 in the atmosphere. The numerical values of *F*-statistics of the excluded IVs relieve the concern about the weak-instruments' problem.

5.2. Additional checks

5.2.1 Margins of response

Our proposed econometric framework is designed to analyze changes in the labor supply's schedules within the subsample of the labor force. However, it is important to recognize the possibility that individuals might alter their state of economic activity in response to the worsening air quality. The importance rests upon two reasons. First, the transition of individuals across the states of economic activity is relevant for the interpretation of our point estimates. For example, the estimated negative impact of PM10 on the working hours might be driven by workers changing their schedules and/or individuals leaving the labor force. Second, if PM10 does affect the labor force participation, then the decision to supply non-zero hours should be modeled along with changes in the working hours.

Table B1 presents the estimated core parameters of Equation (1) using 2SLS, where the outcome variable is the binary indicator of the labor force participation (1 if employed/unemployed and 0 if inactive).[4] The results suggest that neither women's nor men's labor force participation decision is affected by PM10, as none of the point estimates is statistically significant at the conventional level. This finding suggests that the exclusion of inactive individuals from the analysis does not introduce the problem of the endogenous sample selection.

Table B2 presents the results of estimating the linear probability model of employment. According to the findings, worsening air quality does not induce unemployment in the subpopulation of economically active individual. From this observation, we conclude that any observed impact on the working hours can be interpreted as changes that occur at the intensive margin of the labor supply.

5.2.2 Inference

Our baseline results rest upon the assumption that the disturbance terms from our regression models are not correlated across individuals. This assumption might not be true, if, for example, the estimated coefficients systematically overpredict working hours in some areas, in which case our standard errors are attenuated (Cameron and Miller, 2015). However, the conventional tools developed for the cluster-robust inference are not applicable in our case, as our individuals are not nested within clusters due to high frequency of migration in our data (and, more generally, in Korea overall).

To account for the possibility of over-rejection, we report the results with the standard errors corrected by the cluster bootstrap procedure proposed by Cameron and Miller (2015). Table A1 shows the results with the bootstrapped standard errors clustered by PM10 measurement stations (149 stations). The findings show that our inference is unlikely to be prone to the statistical over-rejection.[5]

5.2.3 Endogeneity of the number of children

The validity of our results relies upon the assumption that, in the absence of children, mothers would have followed the labor supply trend of those women who have never had children. We believe, that the inclusion of a rich set of controls and the focus on married women speak to the promise of the plausibility of this assumption.

[4] We postpone the discussion of the first stages' results till the next subsection.

[5] We have also experimented with the bootstrapped standard errors clustered by provinces (17 clusters) and came to the same results. Available upon request.

To further assess the validity of this assumption, we borrow an idea of the falsification exercise commonly applied in the "canonical" differences-in-differences settings. To illustrate the idea of this empirical exercise, consider a woman who has the oldest child of age *j* in the period *t*. Observing the same individual in the period (*t-j*), we would expect her to have no children, yet being pregnant. Having traced the same person back to the period of (*t-j-1*), we would expect to observe her being neither being pregnant nor having children. Thus, for each woman with the oldest child of age *j* in the period *t* in our data set, we assign what we call a "pseudo child" in the period (*t-j-1*). This approach allows us to contrast two groups: families that never had children in the observed period and families with "pseudo children." A failure to document a differential labor supply response to the air quality between these groups serves as evidence that the observed disparity in the working hours (when we use the number of actual children) is not driven by unobserved characteristics of workers that correlate with the number of children.

Table 4 reports the results of our falsification exercise. Our primary focus is the interaction of the PM_{10} variable with the number of children of the particular age group. In all columns, no coefficient is statistically significant. These results suggest that families with and without children show no preexisting disparities in the working hours' response to the air quality, in support of our claim that caregiving serves as the chief channel of the impact.

5.2.4 Older groups of children

Up until now, our analysis has been focusing on mothers with children up to three years old. In this subsection, we extend the scope of the analysis, tracing down the behavior of the estimated impact, as we gradually widen the age group of children.

We first run a set of 2SLS regressions (separately for women and men) interacting PM10 with the number of children aged no older than *j*, *j* = 1, 2, …, 9. We then plot the resulting coefficients of the interaction term against *j* to see the dynamics of the working hours' effects as children grow older (in other words, as *j* goes higher).

Figure 3 shows the results. Panel (a) of the figure shows that mothers indeed lose less hours as their children grow, though the impact gets estimated imprecisely as age group higher than two is taken into consideration. These results are well-aligned with those epidemiologic studies that show that children become less vulnerable to air pollution as their ages go by.

Panel (b) of Figure 3 shows the results for fathers. With the exception of the left-most point estimate (that corresponds to the fathers of children aged no more than one year), the overall pattern is stationary over the age group of children and statistically indistinguishable from zero given any value of j. These findings further confirm the disproportionality of the burden of caregiving in South Korea.

6. Robustness Checks

Our findings show that mothers of young children loose working hours in response to the worsening air quality, and the impact diminishes numerically, as children age. Besides, additional specification tests show that the impact is unlikely to be driven by the unobserved characteristics of mothers that correlate with the number of children.

To further access the credibility of our results, we explore the sensitivity of our estimates to the different assumptions regarding the core model's specification. Table 5 shows the results. Every panel (panels A, B and C) corresponds to the different age group of children specified in the heading of the panel. Within the given column, the set of controls and the sample included in the analysis do not vary across panels.

Column (1) of Table 5 shows the results obtained after controlling for a set of the district-specific linear trends. This is a common empirical tool designed to approximate for the changes of the outcome driven by dynamics of the unobserved district-specific characteristics. As the results in the column show, the core findings (reported in Table 2) hold.

Our 2SLS identification assumes that the response of PM10 to does not depend upon the distance between the given district and China. We believe, this is not a strong assumption, given the geophysical evidence on the travelling capability of fine dust. However, we relax this assumption by interacting our excluded instruments with the distance to the Chinese border and including the resulting terms as additional IVs. The results are shown in column (2) of Table 5, showing no big difference in the point estimates comparing to the baseline findings.

We have previously shown that PM10 does not affect the labor force participation significantly. This finding motivated our decision to focus the analysis on those individuals, who are economically active at the survey moment. Column (3) of Table 5 shows the results after adding inactive individuals to our analysis. As before, the resulting point estimates show little numerical difference with the baseline results.

We next note, that some individuals report "unusual" working hours, such as 168 hours worked in a typical week. This is visually reflected by the presence of the outlying observation in panel (a) of Figure 2. In order to access whether those outliers influence our results, we trim our sample by excluding those individuals, whose working hours fall into top 1% of the hours' distribution in the sample. This limits the maximum working hours per week to 84 hours in our sample. Column (4) of Table 5 shows the findings after implementing this correction. Given that the resulting coefficients do not change much numerically, we conclude that our core findings are not driven by the outliers.

Finally, column (5) of Table 5 reports the result obtained after we implement all the modifications described in this section simultaneously. The coefficient estimates stay within the acceptable range of deviation from the baseline results, which preserves our main findings. Having the findings from this section, we conclude, that our main results maintain their numerical stability across various model specifications, which suggests that mothers of young children do loose working hours when air pollution goes up.

7. Conclusion

Our study examines the labor supply effects of air pollution utilizing Korean data. We find that only mothers bear the burden of loss in working hours when children are young, while the effect gradually attenuates as children grow. The convergence of the estimated impact towards zero echoes the epidemiological evidence showing younger children's relative susceptibility to air pollution.

Our baseline findings imply that the labor supply's elasticity with respect to PM10 is –0.26 for mothers with one child aged one or below.[6] This number is very close to the married women's own-wage elasticity reported by Blau and Kahn (2007), which suggests that sound improvements in the air quality are capable to smooth the prevailing gender pay gap in South Korea. Our study thus calls attention to a relatively lesser-known impact of air pollution that has implications for both environmental policy and social welfare policy.

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[6] The coefficient of the interaction term for mothers with children aged no more than one year is –0.240 (reported in Table 2
, column (1)). The mean values of the working hours and PM10 are shown in Table 1.

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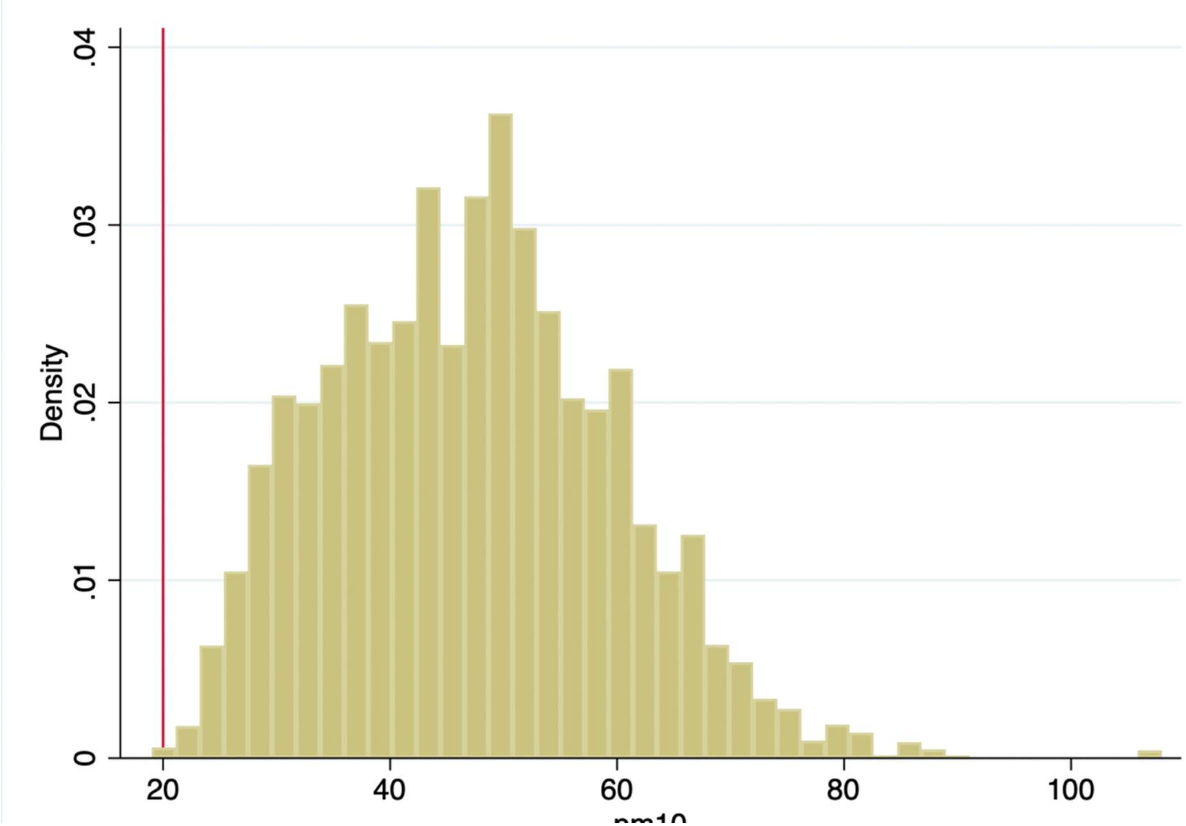
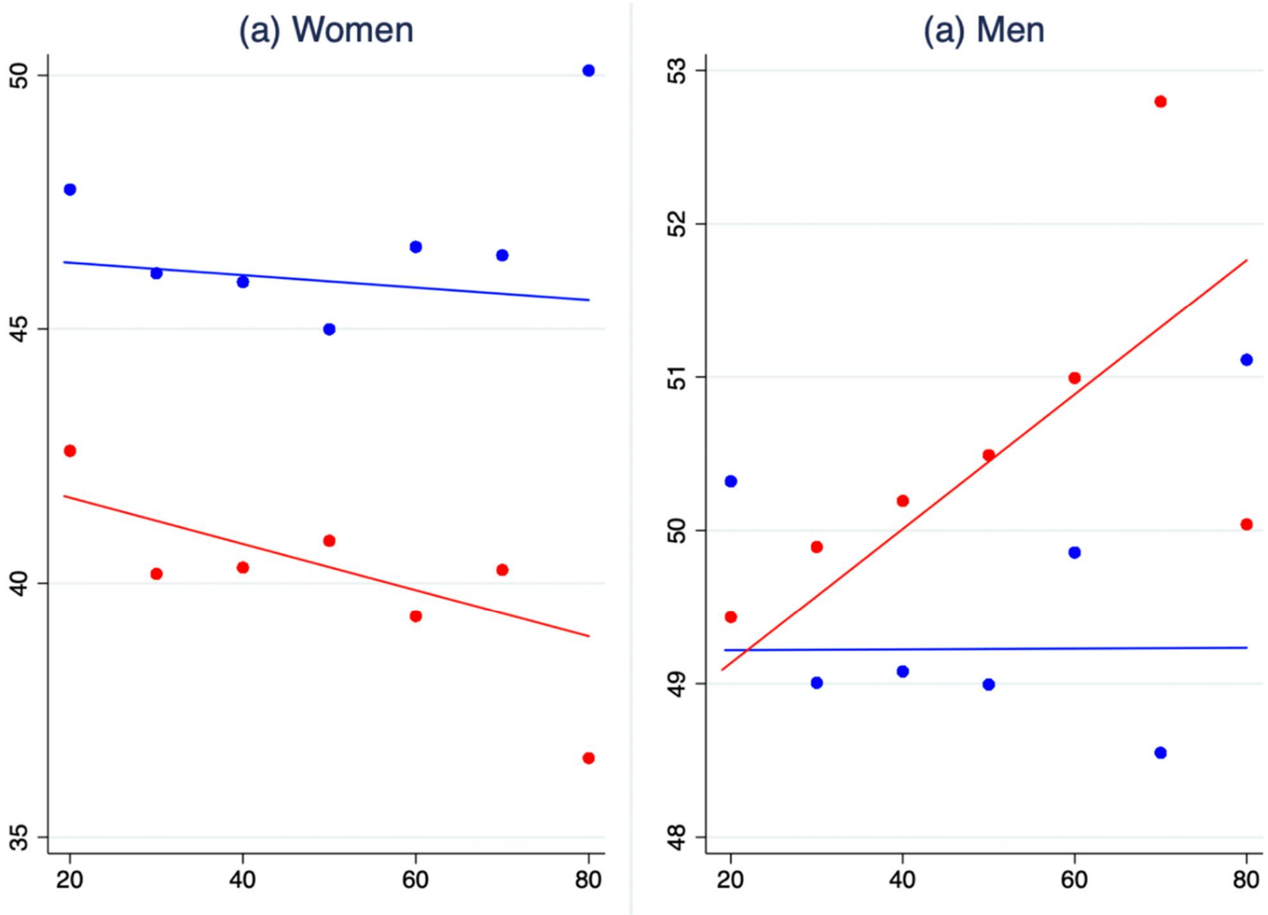
Figure 1 – Distribution of the district-quarter average PM10 (μg/m^3), years 2010-2016



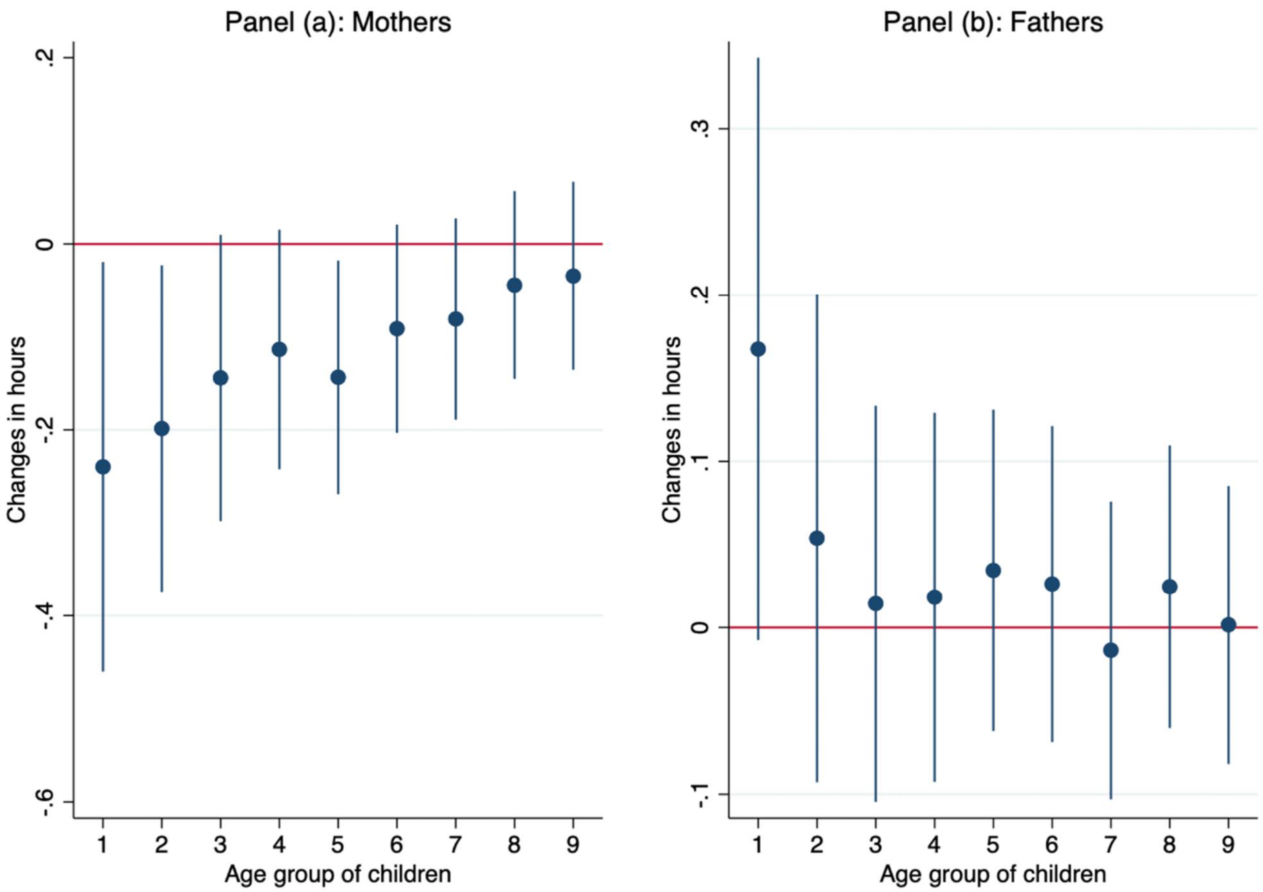
Notes: This figure illustrates the histogram of the district-quarter average PM10 in the study period. The vertical line at 20 μg/m3 indicates the safety guideline recommended by WHO.

Figure 2 – OLS relationship between PM10 and weekly average working hours by gender of respondents



Notes: The figure visualizes the relationship between PM10 and working hours by genders. Each marker displays the average of the outcome in a 10-units bin of PM10. Linear curves are fitted over the raw data points. Blue color marks individuals without children. Red color marks individuals with at least one child aged 3 or below.

Figure 3: Heterogeneity analysis (by age groups of children):



Notes: Both figures present estimated coefficients of the interaction term between PM10 and the number of children of the age group specified on the x-axes. The outcome variable is the weekly average working hours in a typical week. Vertical solid blue lines show the corresponding 95% confidence intervals. Standard errors are clustered by panel IDs.

Table 1 – Descriptive Statistics

	Wives	Husbands
Weekly average working hours	43.65	49.81
	(15.00)	(14.78)
Quarterly average PM10 (μg/m^3)	47.11	47.25
	(12.55)	(12.51)
North Wind	0.590	0.577
	(0.758)	(0.748)
West Wind	1.254	1.258
	(0.948)	(0.945)
#Kids aged≤1 yr.o.	0.0465	0.0875
	(0.214)	(0.292)
#Kids aged≤2 yr.o.	0.0825	0.149
	(0.292)	(0.387)
#Kids aged≤3 yr.o.	0.125	0.214
	(0.366)	(0.476)
Obs	8381	15140

Notes: The table reports means (standard deviations) of the key variables employed in the analysis. #Kids variables indicate the number of children of the given age group (1 year old or younger, 2 years old or younger, and 3 years old or younger). North and west wind variables denote the number of months during which the given wind direction was prevalent in the given quarter.

Table 2 – The impact of air pollution on labor supply

	(1)	(2)	(3)	(4)	(5)	(6)
		Wives			Husbands	
PM10	0.281	0.308	0.291	-0.074	-0.102	-0.094
	(0.203)	(0.206)	(0.207)	(0.169)	(0.172)	(0.172)
PM10 × #Kids≤1 yr.o.	-0.240*			0.168		
	(0.112)			(0.089)		
#Kids≤1 yr.o.	-0.805			0.163		
	(0.667)			(0.406)		
PM10 × #Kids≤2 yr.o.		-0.199*			0.054	
		(0.090)			(0.075)	
#Kids≤2 yr.o.		-1.291*			0.158	
		(0.592)			(0.372)	
PM10 × #Kids≤3 yr.o.			-0.144			0.014
			(0.079)			(0.061)
#Kids≤3 yr.o.			-1.471**			0.297
			(0.499)			(0.373)
Observations	8,381	8,381	8,381	15,140	15,140	15,140
Number of panel IDs	1,831	1,831	1,831	2,905	2,905	2,905
Controls	YES	YES	YES	YES	YES	YES
Panel FE	YES	YES	YES	YES	YES	YES
District, Year, Province-Quarter FEs	YES	YES	YES	YES	YES	YES

Notes: The table reports the second stage of the panel IV-FE estimation. The outcome variable is the weekly average working hours in a typical week. Controls include the respondent's and the spousal characteristics (age, age squared, college dummy), five dummies for the spousal earnings' percentiles and weather indicators (quarterly average, maximum, minimum temperature; quarterly average precipitation, wind speed and air pressure). Standard errors clustered by panel IDs are in parentheses. ** $p<0.01$, * $p<0.05$.

Table 3 – First stage results

	(1)	(2)	(3)	(4)	(5)	(6)
		Wives			Husbands	
Panel A: First stages for PM10						
Age group of children	≤1 yr.o.	≤ 2 yr.o.	≤ 3 yr.o.	≤1 yr.o.	≤ 2 yr.o.	≤ 3 yr.o.
West	0.563**	0.527**	0.529**	0.562**	0.549**	0.539**
	(0.125)	(0.126)	(0.127)	(0.091)	(0.093)	(0.094)
Other IVs included[a]	14.26	15.55	14.25	23.56	23.52	23.54
F-test of excluded IVs	Y	Y	Y	Y	Y	Y
Panel B: First stages for PM10 X #Kids aged J						
West × #Kids≤ 1 yr.o.	5.099**			4.747**		
	(0.659)			(0.366)		
West × #Kids≤ 2 yr.o.		5.193**			4.512**	
		(0.523)			(0.306)	
West × #Kids≤ 3 yr.o.			4.804**			4.419**
			(0.514)			(0.295)
Other IVs included[b]	24.14	30.96	30.74	53.74	69.23	66.61
F-test of excluded IVs	Y	Y	Y	Y	Y	Y
Observations	8,381	8,381	8,381	15,137	15,137	15,137
Number of panel IDs	1,831	1,831	1,831	2,905	2,905	2,905
Controls	YES	YES	YES	YES	YES	YES
Panel FE	YES	YES	YES	YES	YES	YES
District, Year, Province-Quarter FEs	YES	YES	YES	YES	YES	YES

Notes: The table reports the first stages' results of the panel IV-FE estimation. The outcome variables are reported in the heading of each panel. Controls include the respondent's and the spouse's characteristics (age, age squared, college dummy), five dummies for the spousal earnings' percentiles and weather indicators (quarterly average, maximum, minimum temperature; quarterly average precipitation, wind speed and air pressure). Standard errors clustered by panel IDs are in parentheses. ** p<0.01, * p<0.05.

[a] Other IVs: North Wind, West Wind × the number of kids of the given age group, North Wind × number of kids of the given age group. The age group is specified beneath the heading of the table.
[b] Other IVs: North Wind, West Wind, North Wind × the number of kids of the given age group. The age group is specified beneath the heading of the table.

Table 4 – Falsification Tests

	(1)	(2)	(3)	(4)	(5)	(6)
		Wives			Husbands	
PM10	0.046	-0.301	-0.781	0.001	-0.048	-0.405
	(0.319)	(0.422)	(0.709)	(0.268)	(0.368)	(1.299)
PM10 × #Pseudokids≤1 yr.o.	-0.067			-0.338		
	(0.284)			(0.314)		
#Pseudokids ≤1 yr.o.	0.595			-0.959		
	(1.636)			(1.384)		
PM10 × #Pseudokids ≤ 2 yr.o.		-0.030			-0.297	
		(0.215)			(0.213)	
#Pseudokids ≤ 2 yr.o.		0.832			-2.147	
		(1.739)			(1.425)	
PM10 × #Pseudokids ≤ 3 yr.o.			0.210			-0.538
			(0.399)			(0.348)
#Pseudokids ≤ 3 yr.o.			1.689			-2.969
			(2.765)			(2.403)
Observations	4,974	3,515	2,231	9,306	6,788	4,444
Number of panel IDs	1,358	1,114	861	2,311	2,022	1,660
Controls	YES	YES	YES	YES	YES	YES
Panel FE	YES	YES	YES	YES	YES	YES
District, Year, Province-Quarter FEs	YES	YES	YES	YES	YES	YES

Notes: The table reports the second stages' results of the panel IV-FE estimation. The outcome variable is the weekly average working hours in a typical week. The term “Pseudokids” refers to the children assigned to the families prior to their births. Controls include the respondent's and the spouse's characteristics (age, age squared, college dummy), five dummies for the spousal earnings' percentiles and weather indicators (quarterly average, maximum, minimum temperature; quarterly average precipitation, wind speed and air pressure). Standard errors clustered by panel IDs are in parentheses. ** p<0.01, * p<0.05.

Table 5 – Robustness checks

	(1)	(2)	(3)	(4)	(5)
			Wives		
	Panel A: #Kids ≤1 year old				
PM10 × #Kids≤1 yr.o.	-0.234*	-0.239*	-0.209*	-0.239*	-0.229*
	(0.111)	(0.107)	(0.106)	(0.112)	(0.105)
	Panel B: #Kids ≤2 years old				
PM10 × #Kids≤ 2 yr.o.	-0.188*	-0.192*	-0.200*	-0.220*	-0.244**
	(0.094)	(0.084)	(0.086)	(0.090)	(0.087)
	Panel C: #Kids ≤3 years old				
PM10 × #Kids≤ 3 yr.o.	-0.129	-0.146	-0.146*	-0.170*	-0.173*
	(0.081)	(0.075)	(0.071)	(0.079)	(0.070)
Obs	8,381	8,381	15,833	8,295	15,749
Controls	YES	YES	YES	YES	YES
Panel FE	YES	YES	YES	YES	YES
District, Year, Province-Quarter FEs	YES	YES	YES	YES	YES
District-Specific Linear Trends	YES	NO	NO	NO	YES
Additional IV	NO	YES	NO	NO	YES
Out of LF	NO	NO	YES	NO	YES
Outliers Excluded	NO	NO	NO	YES	YES

Notes: The table reports the second stages' results of the panel IV-FE estimation fitted separately for mothers with children no older than 1 year (Panel A), 2 years (Panel B) and 3 years (Panel C). The outcome variable is the weekly average working hours in a typical week. Controls include PM10, number of children of the age group specified in the heading of each panel, the respondent's and the spouse's characteristics (age, age squared, college dummy), five dummies for the spousal earnings' percentiles and weather indicators (quarterly average, maximum, minimum temperature; quarterly average precipitation, wind speed and air pressure). Standard errors clustered by panel IDs are in parentheses. ** p<0.01, * p<0.05.

Table A1 – The impact of air pollution on labor supply with cluster-bootstrapped standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
		Wives			Husbands	
PM10	0.281	0.308	0.291	-0.074	-0.102	-0.094
	(0.261)	(0.253)	(0.248)	(0.283)	(0.288)	(0.291)
PM10 × #Kids≤1 yr.o.	-0.240*			0.168		
	(0.116)			(0.093)		
#Kids≤1 yr.o.	-0.805			0.163		
	(0.690)			(0.402)		
PM10 × #Kids≤2 yr.o.		-0.199*			0.054	
		(0.088)			(0.085)	
#Kids≤2 yr.o.		-1.291*			0.158	
		(0.582)			(0.367)	
PM10 × #Kids≤3 yr.o.			-0.144			0.014
			(0.086)			(0.065)
#Kids≤3 yr.o.			-1.471**			0.297
			(0.514)			(0.428)
Observations	8,840	8,840	8,840	15,523	15,523	15,523
Number of panel IDs	1,831	1,831	1,831	2,905	2,905	2,905
Controls	YES	YES	YES	YES	YES	YES
Panel FE	YES	YES	YES	YES	YES	YES
District, Year, Province-Quarter FEs	YES	YES	YES	YES	YES	YES

Notes: The table reports the second stages of the panel IV-FE estimation. The outcome variable is the weekly average working hours in a typical week. Controls include the respondent's and the spouse's characteristics (age, age squared, college dummy), five dummies for the spousal earnings' percentiles and weather indicators (quarterly average, maximum, minimum temperature; quarterly average precipitation, wind speed and air pressure). Bootstrapped tandard errors clustered by station IDs (149 clusters) are in parentheses. ** p<0.01, * p<0.05.

Table B1 – The impact of air pollution on the labor force participation

	(1)	(2)	(3)	(4)	(5)	(6)
		Wives			Husbands	
mean (sd) of dep. var		0.545 (0.498)			0.957 (0.203)	
PM10	-0.004	-0.003	-0.003	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
PM10 × #Kids≤1 yr.o.	-0.003			-0.001		
	(0.002)			(0.001)		
#Kids≤1 yr.o.	-0.121**			0.004		
	(0.013)			(0.005)		
PM10 × #Kids≤2 yr.o.		-0.003			0.001	
		(0.002)			(0.001)	
#Kids≤2 yr.o.		-0.119**			0.003	
		(0.012)			(0.004)	
PM10 × #Kids≤3 yr.o.			-0.002			0.000
			(0.002)			(0.001)
#Kids≤3 yr.o.			-0.101**			0.003
			(0.010)			(0.003)
Observations	15,833	15,833	15,833	15,847	15,847	15,847
Number of panel IDs	2,991	2,991	2,991	2,993	2,993	2,993
Controls	YES	YES	YES	YES	YES	YES
Panel FE	YES	YES	YES	YES	YES	YES
District, Year, Province-Quarter FEs	YES	YES	YES	YES	YES	YES

Notes: The table reports the second stages' results of the panel IV-FE estimation. The outcome variable is the binary indicator of the labor force participation. Controls include the respondent's and the spouse's characteristics (age, age squared, college dummy), five dummies for the spousal earnings' percentiles and weather indicators (quarterly average, maximum, minimum temperature; quarterly average precipitation, wind speed and air pressure). Standard errors clustered by panel IDs are in parentheses. ** p<0.01, * p<0.05.

Table B2 – The impact of air pollution on the probability to be employed

	(1)	(2)	(3)	(4)	(5)	(6)
		Wives			Husbands	
mean (sd) of dep. var		0.986 (0.118)			0.989 (0.106)	
PM10	0.002	0.001	0.001	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PM10 × #Kids≤1 yr.o.	-0.000			0.002		
	(0.001)			(0.001)		
#Kids≤1 yr.o.	0.004			-0.004		
	(0.003)			(0.004)		
PM10 × #Kids≤2 yr.o.		-0.001			0.001	
		(0.001)			(0.001)	
#Kids≤2 yr.o.		0.001			-0.001	
		(0.005)			(0.003)	
PM10 × #Kids≤3 yr.o.			-0.001			0.000
			(0.001)			(0.001)
#Kids≤3 yr.o.			-0.002			0.000
			(0.005)			(0.003)
Observations	8,381	8,381	8,381	15,140	15,140	15,140
Number of panel IDs	2,991	2,991	2,991	2,993	2,993	2,993
Controls	YES	YES	YES	YES	YES	YES
Panel FE	YES	YES	YES	YES	YES	YES
District, Year, Province-Quarter FEs	YES	YES	YES	YES	YES	YES

Notes: The table reports the second stages' results of the panel IV-FE estimation. The outcome variable is the binary indicator of being employed. Controls include the respondent's and the spouse's characteristics (age, age squared, college dummy), five dummies for the spousal earnings' percentiles and weather indicators (quarterly average, maximum, minimum temperature; quarterly average precipitation, wind speed and air pressure). Standard errors clustered by panel IDs are in parentheses. ** p<0.01, * p<0.05.