Air Pollution and Fertility Outcomes in Thailand

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Abstract

The intertwining dynamics of air pollution and fertility have emerged as crucial facets of public health and demographic studies. This study examines the impact of air pollution from fires on fertility outcomes among women in Thailand. Using data from the 2019 Thai Multiple Indicator Cluster Survey (MICS) and high-resolution satellite data on fire incidents, we exploit fire proximity as an exogenous source of variation of air pollution exposure for women residing in downwind areas. By using wind direction as an instrumental variable for PM2.5 exposure, we isolate its causal effect on fertility. Our results show that a 1μg/m³ increase in PM2.5 leads to a 7-10% reduction in births the following year, with stronger effects in rural areas. This decline in fertility is intentional, driven by increased short-term contraceptive use. Additionally, we observe support for Becker's child quality-quantity tradeoff: early-life exposure to PM2.5 leads to greater parental investment in child quality, as seen in higher protein consumption and increased pre-school enrollment. These findings underscore the broad societal impacts of air pollution on fertility and demographic outcomes.

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Introduction

Air pollution has profound implications for human health and well-being. Elevated levels of air pollution have been linked to increased infant mortality rates (Arceo et al., 2016; Chay & Greenstone, 2003), compromised children's well-being (Janke, 2014; Neidell, 2004), decreased life expectancy and increased common chronic diseases (Qiu et al., 2023). Concurrently, fertility choices play a pivotal role in shaping demographic trends and societal structures. Therefore, in recent years, the intertwining dynamics of air pollution and fertility have emerged as crucial facets of public health and demographic studies (Frutos et al., 2015; Gao et al., 2024; Nieuwenhuijsen et al., 2014; Stump et al., 2023; Zhang & Yanni, 2023). However, there is limited available evidence regarding the effects of significant sources of pollution outside urban areas, such as forest fires, which are common in rural regions of developing countries. This study addresses a key gap in the literature by assessing the impact of air pollution on fertility using individual-level data from Thailand, while also identifying mechanisms such as heightened investments in child quality and increased contraceptive use.

Exposure to air pollution often correlates with unobserved socioeconomic factors, behavioral patterns, or other environmental influences that can also affect fertility outcomes. Failing to account for these unobserved factors can lead to biased estimates when assessing the impact of air pollution on fertility. In this study, we address these data and empirical challenges, providing robust evidence that quantifies the fertility consequences of short-term exposure to air pollution. To causally identify the effect of air quality on fertility and child health outcomes, we use upwind burning as an instrumental variable. We isolate exogenous fluctuations in PM2.5 levels resulting from neighborhood area fires and wind direction, which helps in disentangling air pollution from potentially confounding factors. The wind direction IV is considered exogenous to

local economic activities and therefore helps identify the causal effect of PM2.5 exposure on fertility (Freeman et al., 2019; Khanna et al., 2021). To carry out this analysis, we use the 17-province dataset in the Thai 2019 Multiple Indicator Cluster Survey (MICS) for women's fertility outcomes and socioeconomic variables. For our main fertility outcome analysis, we construct a woman-age panel dataset using information on marriage and birth timings from a cross-sectional survey of women aged between 15-49 years old. In addition, we utilize high-resolution remote-sensing data on PM2.5, fires, and wind, along with ground-based measurements of rainfall and air temperature. By integrating these data, we create a dataset that allows us to investigate how upwind burning affects PM2.5 and fertility outcomes in women downwind.

Our results show that an increase in the level of PM2.5 pollution concentration by 1 $\mu g/m^3$ would result in a drop of 7-10% births next year with respect to our sample mean.[3] These effects are in line with the effect of air pollution on fertility and fertility intentions in other parts of the developing world. Gao et al. (2024) document a 12-percentage point decline in births due to air pollution exposure in China. Zhang & Yanni (2023) show that air pollution significantly negatively affects fertility intentions in China. Similarly, Sellers & Gray (2019) show that higher temperatures in Indonesia were negatively associated with intention for another child suggesting that women may be deliberately reducing their fertility in the wake of environmental stress.

The impact of air pollution on fertility is particularly significant within Thailand's demographic context. While a 7-10% drop in births might seem modest historically, it is crucial to recognize that Thailand's fertility rate has already declined sharply. In 2022, the fertility rate was just 1.3 children per woman, one of the lowest in Asia. This decline carries profound implications

[3] The average number of births in our sample is 0.1 births per woman-year (see Appendix Table A1). Our results indicate a decline 0.007-0.01 births per woman next year due to pollution exposure.

for the country's demographic shifts, including an aging population, changes in gender and family structures, and broader economic and social consequences. To further contextualize this, the implementation of compulsory schooling laws in Thailand, which increased female enrollment in secondary and high school, led to a notable decline in birth rates—especially among 14- and 15-year-olds, where the drop was 4-5 percentage points (Chaijaroen & Panda, 2023). Therefore, the impact we observe is akin to other factors that may reduce fertility like increasing female education and family planning policies.

To assess if this decline in fertility is intentional, we use individual-level pooled cross-sectional data to analyze contraception use in these cohorts of women. This fertility decline is corroborated by an increase in short term contraceptive use by women. We find the effect to be higher for rural women, and most of the decline in fertility is concentrated in younger women under 25.

Furthermore, we evaluate the applicability of Becker's Quality-Quantity tradeoff model of fertility in the context of Thailand (Becker & Lewis, 1973). If parents value child quality, increased exposure to pollution can lead parents to make higher investment in children to compensate for probable adverse human capital effects. We show that, in Thailand, parents make investments to improve child quality if the child experiences PM2.5 exposure in their formative first year of life. With a first year of life exposure to PM2.5, we observe an increase in children's protein and milk consumption and an increase in pre-school enrollment. However, parents are not able to mitigate all the negative shocks of PM2.5 exposure. We show that first year increased PM2.5 exposure leads to a decrease in weight-for-age and weight-for-height z-scores of the affected cohort.

Forest fires and agricultural burning are major drivers of air pollution in rural Thailand, with far-reaching economic and public health consequences. The economic toll of fire-induced air

pollution includes increased healthcare costs, reduced productivity, disruptions to tourism, and damage to crops. Research has shown that agricultural fires contribute to serious health risks, including elevated hypertension and cardiovascular issues (Pullabhotla & Souza, 2022). Our study demonstrates that the air pollution resulting from these fires also influences microeconomic fertility decisions within households. The impact is particularly severe for vulnerable populations, such as pregnant women and children, exacerbating health disparities. By altering demographic structures, exposure to pollution has the potential to create long-term effects on economic development. Our findings contribute to the growing body of research by providing causal evidence of how poor air quality can profoundly affect women's fertility, child health, and household resource allocation in the context of a developing country.

Background

In Thailand, forest and agricultural fires have been a recurring environmental challenge with significant impacts on the country's ecosystems, air quality, public health, and economy. Air pollution in Thailand is seasonal, escalating after the rainy season ends in mid-October. Pollution levels peak during the burning season, typically from February to April, when farmers engage in slash-and-burn agriculture to clear land for cultivation (See Figure 4a). These fires often get out of control, leading to widespread forest fires and haze pollution. Additionally, forest and agricultural fires in neighboring countries, such as Laos, Myanmar and Cambodia, can also contribute to haze pollution in Thailand, particularly during the dry season when winds carry smoke across borders. Figure 1 shows a snapshot of Thailand, taken on March 15, 2019, showing the various fire hotspots within Thailand and neighboring countries of Laos, Myanmar, and Cambodia. Fires in these

neighboring countries are also of high intensity, potentially leading to a considerable impact on the health and well-being of Thai population, as shown in Figure 2.[4]

Forest and agricultural fires in Thailand result in elevated levels of air pollution, with high concentrations of particulate matter (PM2.5 and PM10) and harmful gases like carbon monoxide and nitrogen dioxide, leading to poor air quality and health risks for residents. As shown in Figure 3 and Appendix Table A1, the average annual PM2.5 for the 17 provinces in our dataset between 2013-2019 (calculated from monthly PM2.5) is 21.1 $\mu g/m^3$, which is much higher than the WHO's current recommended level at 5 $\mu g/m^3$ (Pai et al., 2022). While southern provinces experience lower levels of PM2.5, even the lowest provincial average is about 15 $\mu g/m^3$, suggesting substantial particulate matter exposure for residents in these 17 provinces. The persistently high levels of PM2.5, along with growing outliers over the last decade, have raised serious concerns for health policy (see Figure 4b).

At the same time, fertility patterns have been changing in Thailand. Per World Bank data, Thailand's Total Fertility Rate (TFR) has been sharply declining, with the TFR at 1.3 in 2022, much below the replacement rate.[5] An exposure to air pollution and resulting changes in fertility intentions could arguably exacerbate this trend. In our data, we observe the expected inverted U-shape patterns of fertility by age where women in 20-35 display peak fertility behavior and it decreases with age (see Figure 5 Panel A). Given that women in different age groups display

[4] Figure 2 plots the Fire Radiative Power (FRP) estimates from Fire Information for Resource Management System (FIRMS) platform. FRP is the rate of radiative energy emission per time unit from all fires within a pixel. FRP has been extensively used as a proxy of fire intensity to characterize fire types and is related to the rate of biomass combustion and rate of emissions.

[5] In 2022, Thailand's total fertility rate (TFR) was lower than that of many developed economies, such as New Zealand (1.7), the Netherlands (1.5), the United States (1.7), and the United Kingdom (1.6). It was also significantly lower than that of its developing economy counterparts, including Cambodia (2.3), Laos (2.4), Indonesia (2.2), and Vietnam (1.9).

heterogenous fertility patterns, it is important to take this into account as we evaluate the impact of air pollution on fertility decisions of women. Just evaluating the relationship between the number of births and PM2.5, we observe a negative correlation as shown in Figure 5 Panel B. Given the observed interrelationships between fires, PM2.5, and fertility patterns by age, we delve further into the impact of air pollution on fertility and the various mechanisms explaining those relationships.

Data

We combine data from multiple sources to conduct our empirical analysis. First, we tap on the 17-province dataset in the Thai 2019 Multiple Indicator Cluster Survey (MICS) for women's fertility outcomes and socioeconomic variables. The MICS surveys are conducted every few years and cover many aspects of children and women such as women's reproductive health, childhood development, and household socioeconomic status, among others. We first examine how air pollution affects household fertility decisions, specifically the number of children born. To this end, we construct a woman-age panel dataset for fertility using the 17-province cross-sectional survey in 2019. Here, we rely on birth timing information from the women module and household member information in the household rosters. Our main variable of interest in this part of the analysis is the number of births at each age. Due to sparse births before the age of 14, we bottom-code the age of births at 14. We also limit the maximum age for our fertility analysis at 40 years old. The average number of births per woman-year is approximately 0.1 as shown in Appendix Table A1. A limitation of this dataset is that the survey is not geocoded and therefore we must carry our analysis at the province level.

We also investigate how air pollution affects the quality of children through investments in children, such as young children's food consumption and enrollment in preschools, and how it

relates to children's anthropometric outcomes. Since the MICS surveys are not panel data, we need to create a pooled cross-sectional dataset. To do this, we combine data from two separate cross-sectional surveys together: the 2015 survey covering 14 provinces and the 2019 survey covering 17 provinces. Note here that the 14 provinces surveyed in 2015 are a subset of the provinces included in the 2019 survey. The food consumption data are available for children aged 2 and below. It indicates whether a child consumed a specific food group, such as protein or grains, in the day before the interview. The preschool enrollment variable is a dummy indicator for whether a child has ever attended preschool or kindergarten and is available for children aged between 3 and 4 years old.

We then combine the MICS data with air pollution and weather data from various sources. For air pollution exposure, we would use upwind burning as an instrument for PM2.5 exposure, so we require data on PM2.5, burning, and wind direction. We rely on remote sensing data sources from 2013 to 2019 to construct these variables. First, we use PM2.5 data from the Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) dataset. We create monthly average ground-level PM2.5 values by utilizing components of PM2.5 data from MERRA-2's assimilation aerosol diagnostics dataset. This dataset is available in a 0.5^{o} x 0.625^{o} grid format, so we construct our provincial PM2.5 variable as an area-weighted average of all grid point values that fall into a province's boundary. The average annual PM2.5 for our sample is approximately 21 $\mu g/m^3$ (see Appendix Table A1).

For the upwind burning instrument, we use remote sensing fire data from the Fire Information for Resource Management System (FIRMS) platform. Specifically, we use daily hotspots in Thailand and neighboring countries reported using the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra and Aqua satellites. Our wind direction data

comes from the National Centers for Environmental Prediction (NCEP) Reanalysis 1 dataset. We then locate fires within a specified distance that lie upwind, defined as being within the same octant as the prevailing wind direction, like that in Rangel & Vogl (2019). To alleviate the concerns over endogeneity, we focus only on hotspots outside of a province of interest. Given that Thai provinces are of different sizes, and we limit exposure to fires outside the province, our main specifications use 300 kms from the centroid of the province to locate fires that lie upwind.[6]

As weather conditions, such as rainfall and temperatures, can arguably influence both air pollution levels and many of the outcomes examined in this study, we control for both rainfall and temperature in all our regression models. The primary data source for these variables is the Global Historical Climatology Network (GHCN) daily database. This dataset is compiled from weather stations across Thailand and provides daily data. We observe approximately 19 annual upwind fire counts, average annual temperatures of 28C, and average daily rainfall of 4.4 millimeters in our dataset (see Appendix Table A1).

Empirical Specification

In the first step of our empirical analysis, we evaluate how air pollution affects fertility decision at the micro level. Let Y_{it} be the number of births given by woman *i* in year *t*. Then, our main estimating equation can be written as

$$Y_{it} = \theta + \beta_1 PM2.5_{pt-1} + \gamma_1 Weather_{pt-1} + \gamma_2 X_{it} + \mu_i + \epsilon_{ipt}, \qquad (1)$$

where $PM2.5_{pt-1}$ and $Weather_{pt-1}$ denote the woman's previous year exposures to PM2.5 and weather variations at the province, *p*, level, respectively. We control for average temperature and total rainfall as these weather conditions can affect both the air pollution levels

[6] We also check for robustness of results to upwind burning for various distances viz. 250 KM, 400 KM, and 500 KM.

and fertility decisions. X_{it} is a vector of control variables which includes a set of age fixed effects. The age fixed effects account for the heterogenous preferences over fertility by women in different age cohorts. By controlling for woman fixed effects, μ_i, we are effectively controlling for any mother or household specific time invariant unobservables that may affect birth patterns. This specification also accounts for differences in women in different provinces with spatially differentiated economic development. Standard errors are clustered at the province level to account for any error correlations within a province.

In the next step of our analysis, we evaluate how air pollution affects investment in children and their quality using the pooled cross-sectional data set. Let Q_{it} be an outcome of child *i* at time *t*. Then, our estimating equation of interest can be written as

$$Q_{it} = \alpha + \beta_1 PM2.5_{p,yr1} + \gamma_1 Weather_{p,yr1} + \gamma_2 X_{it} + \mu_p + \epsilon_{ipt}, \qquad (2)$$

where $PM2.5_{p,yr1}$ and $Weather_{p,yr1}$ denote the child's first-year-of-life exposures to PM2.5 and weather variations, respectively. X_{it} is a vector of control variables which includes the caretaker's education, the household's family size, the number of children below 5, the total number of bedrooms, the household head's ethnicity, whether the household resides in a rural area, and a set of interview month-region fixed effects. We also include province fixed effects, μ_p, to control for province-specific time-invariant unobservables that that might have confounded our estimation, such as topography and geographic location.

Estimating (1) and (2) using OLS may raise concerns over endogeneity. For example, slash and burn is one of the major causes of PM2.5, but it also helps generate income, which can affect fertility decisions or investment in children. To alleviate these concerns, we adopt an instrumental variable approach and use upwind burning as an instrument. The literature considers wind direction IV as exogenous to local economic activities for several reasons. First, as noted by

Freeman et al. (2019) and Khanna et al. (2021), wind direction is influenced by nature and is therefore less likely to impact local economic activities. We have also checked if the gross provincial products (GPP) are affected by our instrument and did not find any significant effects.[7] Second, wind directions, in combination with distant hotspots, are fast-changing (Rangel and Vogl, 2019) and hard to predict, so they are less likely to cause avoidance behaviors. Even though major seasonal wind patterns in Thailand are governed by the Indian monsoon and hence are predictable, we control for these prevailing wind patterns using the region-month fixed effects and still find significant effects of air pollution. In addition, in some parts of the country, such as the South and the West, local wind directions substantially deviate from the monsoon patterns.

Results

First, we present the results on the impact of PM2.5 exposure on fertility. Since our estimation methods include IV regressions, we first test if the instrument is weak, i.e., if its correlation with the endogenous regressors, conditional on any controls, is close to zero. We present these results in Table 1 Panel A. In all the specifications, the number of fires strongly predicts the PM2.5 levels, and we have an F-statistic far above the Stock and Yogo thresholds (Stock & Yogo, 2005).

Table 1 Panel B columns (1) and (2) present OLS estimates for the effect of PM2.5 on number of births. We note a significant decline in number of births. However, since OLS maybe biased, our preferred specifications are presented in Table 1 Panel B Columns (3)-(5). These present the IV estimation results of the effect of PM2.5 exposure in the previous year on the number of births using upwind burning as an instrumental variable. This is the resulting effect if

[7] Results are available upon request.

the fire is within 300 Kilometers and the woman is exposed to the pollution downwind.[8] Across the specifications, controlling for rain and average temperatures, we note a statistically significant fall of approximately 0.008 births in a year if the woman experiences increased PM2.5 exposure in the previous year. For reference, since the average number of births in our sample is 0.1 births per woman-year (see Appendix Table A1), this represents an 8 percent decline with respect to the mean. These results are in line with the existing literature showcasing a decline in fertility and fertility intentions due to exposure to air pollution in China (Gao et al., 2024; Zhang & Yanni, 2023) and climate shocks in Indonesia (Sellers & Gray, 2019).

<TABLE 1 HERE>

Given that we observe a decline in number of births, we next evaluate the heterogeneity in impact. Table 2 Panel A shows that the fall in births is concentrated among the rural, low education, and high asset women.[9] As depicted in Table 2 (2), (4), and (5), we document a decline in births of about 0.01 for rural, low education, and high asset women. Particularly, we see a statistically significant and a stronger decline in number of births for rural women.[10] This is anticipated as rural women have higher levels of fertility to begin with, leading to a more significant decline due to pollution exposure. It could also be argued that rural women may not have access to equipment to shield from the effect of air pollution, like access to HEPA air purifiers that are widely available in urban areas, leading to a change in their fertility intentions. Lastly, rural women do not have

[8] We also test for fires occurring farther or nearer to the woman at various radii like 250 KM, 400 KM, and 500 KM, and results are consistent across specification (see Table 5 Panel A).

[9] The MICS data does not have any information on income of the households. The survey collects data on possession of assets like radio, telephone, refrigerators, bicycle, etc. which leads us to categorize women into high asset vs. low asset groups.

[10] On the other hand, the magnitude of impact is very similar across the low educated and high educated women.

access to better quality healthcare that could help alleviate the impact of pollution (Panda & Chaijaroen, 2020). The fertility decline is also stronger in magnitude among the high asset women. Furthermore, we observe a significant heterogeneity by the age of women. As shown in Table 2 Panel B, we see a significant decline in fertility in younger women below 30 years.

<TABLE 2 HERE>

Since we observe a significant decline in births due to PM2.5 exposure, we ascertain that the impact is due to pollution and not due to other channels like increase in agricultural income. First, since we restrict our estimations to fires outside the province, that ensures that the changes are not due to local provincial economic activity. We also note that there is no effect on the gross provincial products (GPP) due to our instrument. Second, in Thailand, the agricultural season which consists of primarily rice cultivation, does not coincide with the peak fire season. Therefore, the increase in agricultural income is not contemporaneous with increase in PM2.5 levels. To further ease any concerns, we also limit our estimation to provinces which do not have large forest or crop field cover and get similar results (see Appendix Table A2 Panel b) corroborating that it is not an increase in agricultural incomes that is leading to these changes in fertility. Lastly, we check if the decline in births is limited to the burning season or if individuals postpone their fertility to non-burning season in the same year. These results are presented in Appendix Table A2 Panel A. We find the coefficients are similar in magnitude between the peak fire season and the agricultural season indicating no seasonal heterogeneity in fertility.

Mechanisms

We evaluate the various mechanisms that could explain a decline in fertility of women due to an increase in PM2.5 exposure. We show that the fertility decline is an intentional effect of the pollution exposure. With increased PM2.5 exposure three months before the survey date, in Table

3, we document an increase in contraception use by women. In this part of our analysis, we created a repeated cross-sectional dataset of women by pooling the MICS surveys in 2015 and 2019. We find that women increase their contraception use by about 8.8 percentage points after controlling for household assets, place of residence, woman's age and education, number of children in the household, province fixed effects, and region-month fixed effects (see Table 3 (1)).[11] Moreover, in Table 3 (2) and (3), we see the increase concentrated in short-term contraceptives like birth control pills rather than permanent contraceptives like sterilization. This elaborates on the mechanism by which we observe the decline in births. Due to pollution exposure, which they foresee to be a short-term shock, women take immediate measures to reduce the chance of pregnancy. This is in line with earlier work which shows that air pollution exposure can lead to an increase in online information gathering which leads to a decline in fertility in Thailand (Chaijaroen & Panda, 2025). On the other hand, we do not find any evidence of a biological mechanism i.e. an increase in miscarriages due to pollution exposure. In our survey, the question on miscarriage is asked only for the latest pregnancy without specifying the time dimension. Therefore, we tabulate failed pregnancy by province with high and low pollution exposure and find no correlation.

<TABLE 3 HERE>

Air quality can have an impact not only on the quantity of children, but also the quality of children. This is especially true if parents are substituting quantity for quality (Becker & Lewis, 1973). Adverse economic and climatic shocks like droughts or floods in the first year of a child's life has a significant impact on short- and long-term outcomes like child health, schooling, and

[11] The increase in contraception use is consistent across specifications when the fire is observed at 400 KM or 250 KM. Results available on request.

human capital formation (Abiona, 2017; Aguilar & Vicarelli, 2022; Ferreira & Schady, 2009). If there is an adverse shock, like increased air pollution exposure, parents may decide to spend more on existing children to alleviate the negative impact of exposure. Given limited household budget, we would see the substitution from quantity to quality, which would be another mechanism that explains the decrease in fertility due to air pollution. To evaluate this channel of impact and to assess the quality investments by parents, we document the impact of PM2.5 exposure during the first year of life of children on food consumption and pre-school enrollment.

Since protein calorie malnutrition in early childhood can lead to permanent impairment of central nervous system, parents can, in principle, make improvements in children's dietary intake to reverse any adverse effects (Fogel, 2004). In our context, we observe that parental investment in children increases as we document an increase in protein and milk consumption in the affected cohort of children. The results are presented in Table 4 Panel A. Controlling for household and province characteristics along with seasonality in food consumption, we show in Table 4 Panel A (2) and (4) that the protein consumption increases by approximately 0.1 percentage points and milk consumption increases by 2.5 percentage points. We do not see a statistically significant increase in either carbohydrate or fruits and vegetable intake. This is in line with less household spending on carbohydrates and foods that make up basic diets in developing countries (Colen et al., 2018; Salois et al., 2012).[12] The investments continue beyond food consumption and, in Table 4 Panel A (5) we find a 2.4 percentage point increase in pre-school enrollment for the child cohort affected by the increased PM2.5 levels in the first year of their life.

<TABLE 4 HERE>

[12] MICS does not collect data on income for us to be able to evaluate income elasticities for our sample or to decipher if there are income changes in the household due to exposure to air pollution.

Despite the increase in parental investment in children to avert the negative effect of air pollution exposure, we document a statistically significant fall in the Weight-for-Age z-scores (WAZ) and Weight-for-Height z-scores (WHZ) of children. However, we do not observe a statistically significant fall in the Height-for-Age z-scores (HAZ), perhaps as it is a more long-term indicator of child health. The results are presented in Table 4 Panel B. An increase in PM2.5 by 1 $\mu g/m^3$ leads to a fall of approximately 0.03 standard deviations in the WAZ and WHZ scores.

Robustness

We run various robustness checks to ensure that the baseline impact we observe is due to increased pollution exposure due to fires, and it is not dependent on our model specification. To alleviate the concern that our definition of treatment—fires within a range of 300 KM—is driving these effects, we also derive estimates of the effect of pollution exposure using various thresholds for the distance of upwind burning from the province centroid location. Specifically, we estimate the effects of upwind burning for various distances viz. 250 KM, 400 KM, and 500 KM as shown in Table 5 Panel A (1)-(3). The effect is robust across specifications and the effect ranges between 0.007 to 0.01 decline in births due to pollution exposure from the upwind burning and is consistent with our original specification. We also estimate the impact on births if we restrict the PM2.5 spike to the peak fire season only. These results are presented in Table 5 Panel A (4). As expected, the results are significant and greater in magnitude, with a decline of 0.01 births due to high PM2.5 exposure.

Next, we run a placebo test and show that the effects do not exist when fires are randomly generated. Specifically, we randomize the number of fires in the fire season overtime using a

uniform distribution and estimate the impact on PM2.5 levels.[13] These results are presented in Table 5 Panel B. As expected, we do not find any statistically significant impact of a placebo fire exposure on PM2.5 levels for different radii of exposure in Table 5 Panel B (1)-(4). With this falsification test, we validate the strength of our instrumental variable, and the causal impact of fires on PM2.5 levels downwind and correspondingly on women's fertility choices.

<TABLE 5 HERE>

We also show robustness of our results to alternate clustering of standard errors and alternate specifications. It may be argued that the level of clustering and the number of clusters derived at the province level can lead to false statistical significance. Therefore, we show that our results are robust to a more granular clustering by survey units. Table 6 Panel A (1)-(3) clusters standard errors at the survey unit level and we see that our results are statistically significant at this granular level of clustering as well. Moreover, we ensure that our results are not driven due to variable definitions. Therefore, in Table 6 Panel A (4)-(6), we estimate our IV specification with our dependent variable being any births to a woman in a year. We show that our results are effectively unchanged with alternate variable definition of our outcome.

To alleviate any remaining concerns about the exogeneity of fires as a source impacting PM2.5 levels in downwind areas, we show a statistically significant decline in fertility of women when the fires occur outside Thailand's border, specifically in the neighboring countries of Laos, Myanmar, and Cambodia. Fires in these neighboring countries are plausibly exogenous and are independent of Thailand's economic activity. Therefore, an increase in PM2.5 levels due to upwind burning in these countries will affect women's fertility and children's health outcomes in

[13] We also generate random fires using Chi Square distribution and results are similar. Results are available on request.

Thailand only due to an increase in pollution. Specifically, we analyze the impact of neighboring country fires within a 500 KM radius on women's fertility and children's outcomes in border provinces of Thailand. The results are presented in Table 6 Panel B. Table 6 B (1) shows a statistically significant fall of approximately 0.005 births in a year if the woman experiences increased PM2.5 exposure in the previous year. The magnitude of impact is a little bit lower than our main specifications, but it is to be expected as the fires are farther in neighboring countries. We see a similar decrease in WAZ and WHZ scores of children in Table 6 B (2) and (3), as our main specifications.[14]

<TABLE 6 HERE>

Lastly, migration could be a concern in this analysis. If women systematically migrate due to pollution exposure, then that could bias our results. To assess this, we check for migration patterns in our sample. Since pollution levels are similar within the same region, reducing exposure would require relocating to a different region. However, most migration in our data occurs in the Central and South regions, where air pollution is relatively low, and is largely intra-regional. This alleviates concerns that migration is driven by pollution. Moreover, since wind directions, in combination with distant hotspots, are fast-changing (Rangel & Vogl, 2019) and hard to predict, they are less likely to cause avoidance behaviors like migration. However, individuals can involve themselves in mitigation behavior, for example by using air purifiers or N95 masks, to reduce the impact of pollution exposure. Chaijaroen & Panda (2025) show that exposure to PM2.5 increases Google Searches on air purifiers in Thailand. Despite the increase in mitigation behavior, we still

[14] Though, it should be noted that the sample size is much lower due to the specification being restricted to border provinces.

find evidence on women's fertility outcomes illustrating that the effects are lower bound estimates that persist despite an increase in individual preventative measures to minimize pollution exposure.

Discussion

This paper reveals the causal impact of air pollution on women's fertility in Thailand, highlighting the negative and significant effects of pollution from fires and upwind burning. Our findings show that rural women are particularly affected, with rising PM2.5 levels prompting increased use of short-term contraceptives to avoid pregnancy. We also assess the relevance of Becker's Quantity-Quality fertility tradeoff in the Thai context. Our results support the theory, demonstrating that pollution exposure in a child's first year leads to greater parental investments in child quality—evidenced by increased protein and milk consumption and higher pre-school enrollment. This shift reflects a reduction in the quantity of children, as parents prioritize quality over quantity. However, despite these efforts, the long-term effects of early-life pollution exposure remain substantial. We observe a significant decline in children's WAZ and WHZ scores, indicating that parents cannot fully mitigate the detrimental effects of pollution on child health during the critical early years of life.

Air pollution in developing countries poses severe economic, social, and environmental challenges. Its costs are multifaceted, including increased healthcare expenses from respiratory illnesses, lost productivity due to sick days, crop damage leading to reduced agricultural yields, and broader environmental degradation. Despite these impacts, our understanding of how air pollution affects diverse global contexts and different sources of pollution remains limited (Pullabhotla & Souza, 2022). This study contributes evidence from a developing country context, highlighting an additional demographic impact channel that further amplifies the costs of air pollution. Given that declining fertility can reshape demographic structures and influence

economic development, these findings are crucial for policymakers. They enhance our understanding of the far-reaching societal impacts of air pollution and underscore the need for comprehensive strategies to address its effects.

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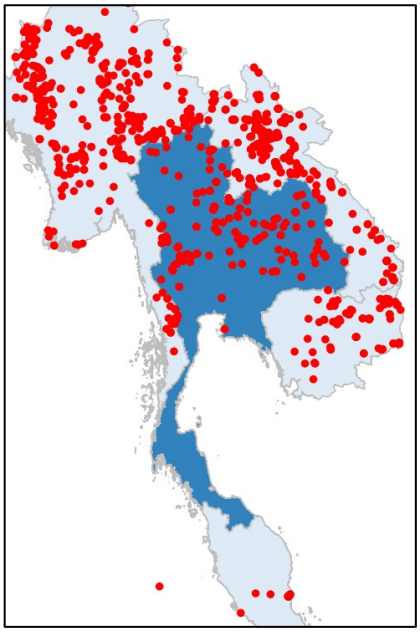
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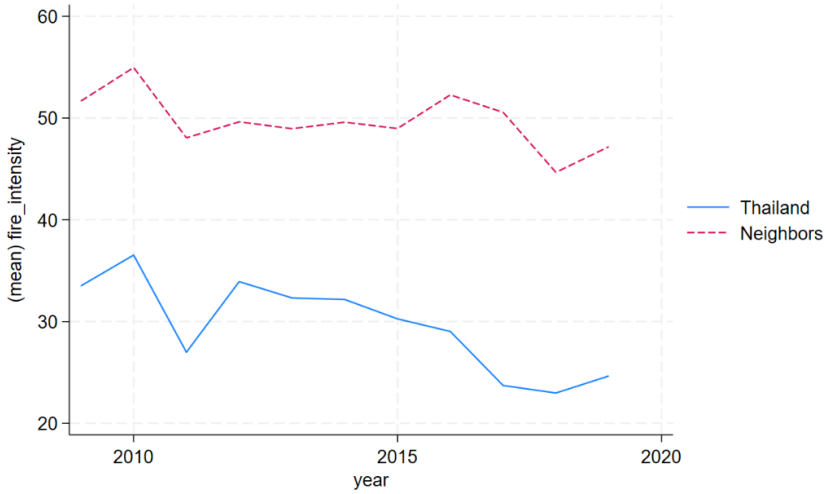
Figures

Figure 1: Fire Hotspots Map of Thailand



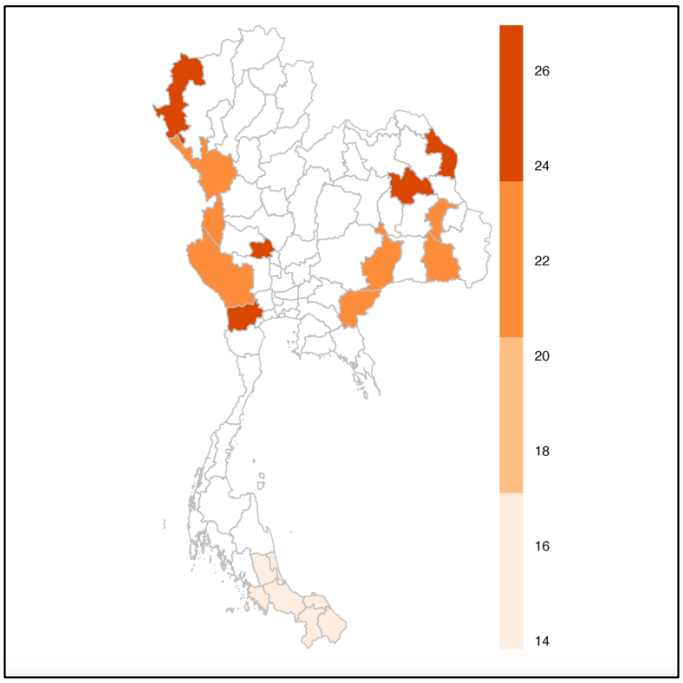
Note: This figure shows the fire hotspots (depicted by red dots) within Thailand and in neighboring countries of Laos, Cambodia, and Myanmar. The snapshot is taken on March 15, 2019.

Figure 2: Fire Intensity



Note: This figure shows the intensity of fires within Thailand and in neighboring countries of Laos, Cambodia, and Myanmar from 2009-2019. Fire Radiative Power (FRP) estimates are derived from Fire Information for Resource Management System (FIRMS) platform. It is the rate of radiative energy emission per time unit from all fires within a pixel. FRP has been extensively used as a proxy of fire intensity to characterize fire types and is related to the rate of biomass combustion and rate of emissions.

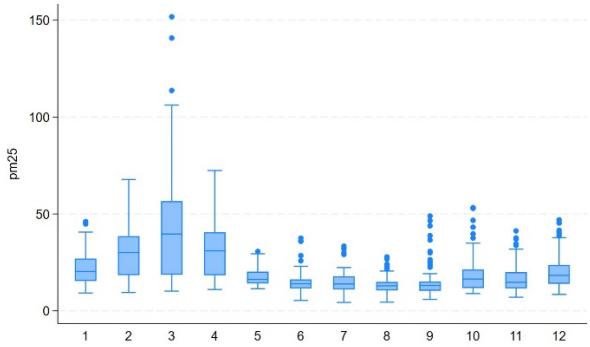
Figure 3: Average PM2.5 levels in Thailand



Note: This figure shows the average PM2.5 levels in our dataset for the 17-provinces within Thailand.

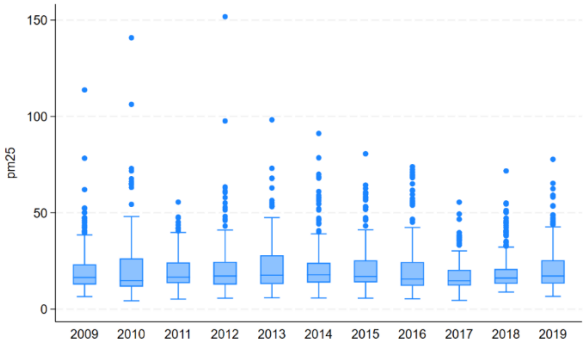
Figure 4: Trends of PM2.5 levels in Thailand

Panel A



Note: This panel shows the boxplot of the median monthly PM2.5 levels, using data from 2009-2019.

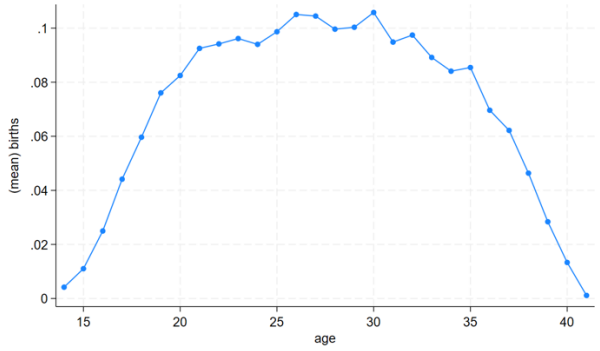
Panel B



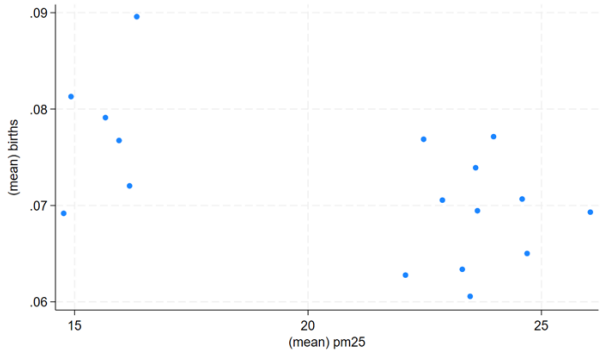
Note: This panel shows the boxplot of the median yearly PM2.5 levels from 2009-2019.

Figure 5: Fertility Patterns

Panel A



Panel B



Note: Panel A plots the average number of births by age of women. Panel B shows the negative correlation between a previous year exposure to PM2.5 and number of births.

Tables

Table 1: Impact on Fertility

Panel A: First Stage IV Results

	(1)	(2)	(3)
	PM2.5	**PM2.5**	**PM2.5**
Fire Count within	0.149***	0.113***	0.113***
300 KM	(0.000)	(0.000)	(0.000)
Rain		-1.019***	-1.023***
		(0.000)	(0.000)
Avg. Temp.		-0.711	-0.724
		(0.166)	(0.158)
Age at Birth			-0.436***
			(0.000)
Squared Age at Birth			0.000579*
			(0.052)
Kleibergen-Paap	64.5	20.02	20.11
Wald rk F-Stat	(0.000)	(0.0004)	(0.0004)
Age FE	YES	YES	NO
Observations	70077	70077	70077

Note: p-values in parentheses. These are first stage of IV estimation depicting a strong relationship between fires and PM2.5 levels. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Panel B: Impact of PM2.5 on Fertility

	(1)	(2)	(3)	(4)	(5)
Specification	**OLS**	**OLS**	**IV**	**IV**	**IV**
PM2.5	-0.00836***	-0.00712***	-0.00447**	-0.00850***	-0.00819***
	(0.000)	(0.000)	(0.012)	(0.008)	(0.008)
Rain		0.0105***		0.00896**	0.00883**
		(0.000)		(0.047)	(0.046)
Avg. Temp.		0.0439***		0.0444***	0.0431***
		(0.000)		(0.000)	(0.000)
Age at Birth					0.00936***
					(0.002)
(Age at Birth)^2					-0.000507***
					(0.000)
Age FE	YES	YES	YES	YES	NO
Observations	70129	70129	70077	70077	70077

Note: p-values in parentheses. All specifications estimate the effect of increased PM2.5 exposure on births because of fires occurring within 300 kms. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 2: Heterogeneity in Effect of PM2.5 Exposure

Panel A: By Place, Education, and Wealth

	(1)	(2)	(3)	(4)	(5)	(6)
	Urban	**Rural**	**High education**	**Low education**	**High assets**	**Low assets**
PM2.5	-0.00236	-0.0118**	-0.00541**	-0.00921**	-0.0131***	-0.00646*
	(0.499)	(0.018)	(0.037)	(0.016)	(0.004)	(0.076)
Rain	0.0166***	0.00495	0.00642	0.0106**	0.00525	0.0106**
	(0.003)	(0.363)	(0.310)	(0.029)	(0.476)	(0.016)
Avg. Temp.	0.0456***	0.0440***	0.0374***	0.0470***	0.0450***	0.0440***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	23469	46608	18384	51693	21224	48853

Note: p-values in parentheses. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Panel B: By Age

	(1)	(2)	(3)	(4)	(5)	(6)
	All	**Age <=20**	**Age 20-25**	**Age 25-30**	**Age 30-35**	**Age >35**
PM2.5	-0.00850***	-0.0131**	-0.00783	-0.0117*	-0.00150	-0.00236
	(0.008)	(0.014)	(0.249)	(0.068)	(0.710)	(0.590)
Rain	0.00896**	0.00243	0.0131	0.00937	0.00985	0.0108**
	(0.047)	(0.698)	(0.104)	(0.387)	(0.124)	(0.045)
Avg. Temp.	0.0444***	0.0490***	0.0316**	0.0738***	0.0265**	-0.00119
	(0.000)	(0.000)	(0.011)	(0.000)	(0.022)	(0.896)
Age FE	YES	YES	YES	YES	YES	YES
Observations	70077	13452	13138	14361	14998	10554

Note: p-values in parentheses. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 3: Contraceptive Use

	(1)	(2)	(3)
3-month before exposure	**Overall Contraceptive Use**	**Short-term Contraceptive Use**	**Permanent Contraceptive Use**
PM2.5	0.00882**	0.00954*	-0.000721
	(0.011)	(0.056)	(0.911)
Rain	0.00856*	0.0111	-0.00250
	(0.084)	(0.193)	(0.591)
Avg. Temp.	-0.0230	0.00241	-0.0255
	(0.361)	(0.947)	(0.164)
Province FE	YES	YES	YES
Observations	15036	15036	15036

Note: p-values in parentheses. All specifications control for household assets, rural area, women's education, woman's age (linear and quadratic), number of children, province fixed effects, and region-month fixed effects. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 4: Impact of First Year PM2.5 Exposure on Children

Panel A: Food Consumption and Pre-School Enrollment

	(1)	(2)	(3)	(4)	(5)
	Carbohydrate	Protein	Fruit and Vegetables	Milk	Pre-School Enrollment
PM2.5	0.00655	0.00987***	-0.00436	0.0247**	0.0234***
	(0.287)	(0.001)	(0.569)	(0.026)	(0.005)
Rain	0.0290*	0.000273	0.00106	0.0560***	-0.0182
	(0.067)	(0.963)	(0.928)	(0.000)	(0.127)
Avg. Temp.	-0.0111	-0.00338	-0.0486***	-0.192***	-0.133***
	(0.450)	(0.755)	(0.007)	(0.000)	(0.000)
Province FE	YES	YES	YES	YES	YES
Observations	5222	5222	5221	5220	7212

Note: p-values in parentheses. All specifications control for household assets, rural area, caretaker education, province fixed effects, and region-month fixed effects. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Panel B: Weight-for-Age Z-Scores (WAZ), Weight-for-Height Z-Scores (WHZ), and Height-for-Age Z-Scores (HAZ)

	(1)	(2)	(3)
	WAZ	WHZ	HAZ
PM2.5	-0.0288***	-0.0272**	-0.00522
	(0.007)	(0.021)	(0.764)
Rain	-0.0494*	-0.0467*	0.0077
	(0.097)	(0.087)	(0.728)
Avg. Temp.	-0.094**	-0.128***	0.0481
	(0.036)	(0.006)	(0.269)
Province FE	YES	YES	YES
Observations	13783	13568	13594

Note: p-values in parentheses. All specifications control for household assets, rural area, household size, household ethnicity, if the household has children under 5 years of age, caretaker education, province fixed effects, and region-month fixed effects. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 5: Robustness Checks – Fire exposure

Panel A: Proximity of Fires

	(1)	(2)	(3)	(4)
Specification	**Radius: 250 KM**	**Radius: 400 KM**	**Radius: 500 KM**	**Peak Season Only IV Specification**
PM2.5	-0.00659*	-0.00721	-0.00948***	-0.00953***
	(0.058)	(0.118)	(0.005)	(0.004)
Rain	0.0111**	0.0104*	0.00786*	0.00780*
	(0.024)	(0.078)	(0.052)	(0.087)
Avg. Temp.	0.0437***	0.0439***	0.0447***	0.0447***
	(0.000)	(0.000)	(0.000)	(0.000)
Province FE	YES	YES	YES	YES
Observations	70077	70077	70077	70077

Note: p-values in parentheses. Columns (1)-(3) estimate the effect of PM2.5 exposure on births with IV specification for alternate distance of neighborhood fires. Column (4) estimates the effect of PM2.5 exposure on births during peak burning season (February-April) with IV specification. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Panel B: Placebo Exposure

	(1)	(2)	(3)	(4)
Specification	**Radius: 300 KM**	**Radius: 250 KM**	**Radius: 400 KM**	**Radius: 500 KM**
Fire Counts	-0.0234	-0.0850	0.0223	-0.00693
	(0.737)	(0.479)	(0.499)	(0.680)
Rain	-1.112***	-1.130***	-1.110***	-1.128***
	(0.000)	(0.000)	(0.000)	(0.0000)
Avg. Temp.	0.369	0.269	0.269	0.370
	(0.391)	(0.546)	(0.583)	(0.402)
Province FE	YES	YES	YES	YES
Observations	70129	70129	70129	70129

Note: p-values in parentheses. All specifications randomize the number of fires in the fire season (December-May) for various distance of neighborhood fires using a uniform distribution and estimate the effect on PM2.5 for placebo fire exposure. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 6: Robustness Checks – Alternate Specifications

Panel A: Alternate clustering of standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
	Alternate Clustering			Alternate Dependent Variable		
Specification	**IV**	**IV**	**IV**	**IV**	**IV**	**IV**
PM2.5	-0.00447***	-0.00850***	-0.00819***	-0.00449**	-0.00842***	-0.00810***
	(0.001)	(0.000)	(0.000)	(0.011)	(0.008)	(0.009)
Rain		0.00896***	0.00883***		0.00884*	0.00872*
		(0.003)	(0.004)		(0.051)	(0.051)
Avg. Temp.		0.0444***	0.0431***		0.0435***	0.0422***
		(0.000)	(0.000)		(0.000)	(0.000)
Age at Birth			0.00936***			0.00967***
			(0.002)			(0.001)
(Age at Birth)^2			-0.000507***			-0.000507***
			(0.000)			(0.000)
Age FE	YES	YES	NO	YES	YES	NO
Observations	70077	70077	70077	70077	70077	70077

Note: p-values in parentheses. Columns (1)-(3) estimate the effect of increased PM2.5 exposure on number of births in a year due to fires within 300 kms in an IV specification. Standard errors are clustered at the survey unit level. Columns (4)-(6) estimate the effect of increased PM2.5 exposure on the probability of any birth during a year due to fires within 300 kms in an IV specification. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Panel B: Fire in Neighboring Countries

	(1)	(2)	(3)	(4)
Specification	**Fertility**	**WAZ**	**WHZ**	**HAZ**
PM2.5	-0.0576*	-0.0538**	-0.0747***	0.0196
	(0.056)	(0.032)	(0.000)	(0.732)
Rain	-0.0768	-0.0411	-0.0556	0.0306
	(0.202)	(0.408)	(0.187)	(0.536)
Avg. Temp.	0.0486***	-0.0470	-0.0193	0.0538
	(0.003)	(0.420)	(0.754)	(0.142)
Province FE	YES	YES	YES	YES
Observations	20802	3959	3911	3898

Note: p-values in parentheses. All specifications estimate the effect of exogenous fires in neighboring countries within 500km radius on fertility (column 1) and child outcomes (columns 2,3,4) in border provinces. All children outcomes specifications control for household assets, rural area, household size, household ethnicity, if the household has children under 5 years of age, caretaker education, province fixed effects, and region-month fixed effects. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Appendix

Table A1: Summary Statistics

	Mean	S.D.	Count	Min	Max
Woman-Age Panel Dataset					
No. births in a year	0.097	0.300	72093	0.000	2.000
Avg annual PM2.5	21.103	3.945	64664	12.420	27.814
Annual upwind fire counts	18.912	15.937	64664	0.090	55.940
Avg daily rainfall (in millimeters)	4.396	1.431	71963	1.896	9.297
Avg annual temperature (in Celsius)	28.074	0.718	71963	26.137	29.418
Pooled Cross-sectional Data for Women					
Ever given birth	0.674	0.469	11528	0.000	1.000
Age of woman	28.558	7.774	11544	15.000	46.000
Completed at least high school	0.615	0.487	11544	0.000	1.000
Rural	0.667	0.471	11544	0.000	1.000
Household never migrated	0.672	0.469	11544	0.000	1.000
Household speaks Thai	0.826	0.379	11544	0.000	1.000
Any household member owns agricultural land	0.522	0.500	11522	0.000	1.000
Number of rooms used for sleeping	2.204	0.938	11544	1.000	8.000
Children's Outcomes					
Weight for age	-0.362	1.339	15669	-5.842	5.837
Weight for height	0.005	1.525	15669	-5.924	5.996
Height for age	-0.662	1.449	15669	-5.989	5.965
Food consumption: grains and carbs	0.790	0.407	7002	0.000	1.000
Food consumption: fruits and vegetables	0.743	0.437	7005	0.000	1.000
Food consumption: Meat and other protein	0.834	0.372	7004	0.000	1.000
Food consumption: Milk and dairy	0.505	0.500	7003	0.000	1.000
Ever enrolled in pre-school or kindergarten	0.869	0.338	6702	0.000	1.000

Note: The summary statistics are calculated for our dataset and our analysis period between 2013-19.

Table A2: Effect of agricultural season on births

Panel A: Effect of Pollution exposure on births in agricultural vs. non-agricultural season

	Burning Season		Growing Season	
	(1)	(2)	(3)	(4)
Specification	**IV**	**IV**	**IV**	**IV**
PM2.5	-0.00440***	-0.00428***	-0.00412**	-0.00394*
	(0.000)	(0.000)	(0.049)	(0.055)
Rain	0.000595	0.000493	0.00747**	0.00744**
	(0.689)	(0.738)	(0.018)	(0.017)
Avg. Temp.	0.0144***	0.0139***	0.0277***	0.0270***
	(0.000)	(0.000)	(0.000)	(0.000)
Age at Birth		0.00627***		0.00516***
		(0.000)		(0.026)
(Age at Birth)^2		-0.000244***		-0.000277***
		(0.000)		(0.000)
Age FE	YES	NO	YES	NO
Observations	70077	70077	70077	70077

Note: p-values in parentheses. All specifications estimate the effect of increased PM2.5 exposure on births because of fires occurring within 300 kms. The first two columns note the effect of PM2.5 exposure on births in the fire/burning season. The last two columns note the effect of PM2.5 exposure on births in the agricultural/rice growing season. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Panel B: Omission of provinces with large shares of crop fields and forests

	(1)	(2)	(3)	(4)	(5)
Specification	**OLS**	**OLS**	**IV**	**IV**	**IV**
PM2.5	-0.00718***	-0.00539***	-0.00249	-0.00925**	-0.00902**
	(0.000)	(0.002)	(0.302)	(0.046)	(0.049)
Rain		0.0118***		0.00776	0.00759
		(0.001)		(0.152)	(0.157)
Avg. Temp.		0.0426***		0.0447***	0.0436***
		(0.000)		(0.000)	(0.000)
Age at Birth					0.0107**
					(0.012)
(Age at Birth)^2					-0.000531***
					(0.000)
Age FE	YES	YES	YES	YES	NO
Observations	48718	48718	48685	48685	48685

Note: p-values in parentheses. All specifications estimate the effect of increased PM2.5 exposure on births because of fires occurring within 300 kms. Standard errors are clustered at the province level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.