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 (Frutos et al., 2015). This study evaluates the impact of air pollution exposure due to fires on fertility outcomes of women in Thailand. We construct a woman-age panel using the Thai 2019 Multiple Indicator Cluster Survey (MICS) and high-resolution satellite data on incidence of fires in neighboring areas as an exogenous source of variation that impacts PM2.5 levels in downwind areas. Exploiting the exogenous fluctuations in PM2.5 levels using the wind direction IV, we identify the causal effect of PM2.5 exposure on fertility. Our results show that an increase in the levels of PM2.5 pollution concentration by1μg/m^3 causes a 7-10% drop in births next year with respect to our sample mean. The fertility decline is corroborated by an increase in short term contraceptive use by women. We find stronger effects for women residing in the rural areas. We use Google Search data to show that increased access to information has an impact on the fertility decisions of young women. We also find evidence of child quality-quantity tradeoff. With a first year of life exposure to PM2.5, we observe an increase in children's protein consumption and pre-school enrollment. Since declining fertility can change the demographic composition and affect economic development, these results add to our knowledge of the varied ways in which air pollution can affect society.

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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), life expectancy and 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 fills the gap in the literature by evaluating the impact of air pollution exposure on fertility by using individual-level data in Thailand and identifies mechanisms of impact such as increased information, increased investments in child quality, and increased use of contraception.

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 use a variety of sources to accurately measure air pollution and weather patterns. Specifically, 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 levels of PM2.5 pollution concentration by1$\mu g/m^3$ 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 points decline in births due to air pollution exposure in China. Similarly, Zhang & Yanni (2023) show that air pollution significantly negatively affects fertility intentions in China. Sellers & Gray (2019) show that higher temperatures were negatively associated with intention for another child suggesting that women may be deliberately reducing their fertility in the wake of environmental stress in Indonesia.

The magnitude of impact is also significant in Thailand's demographic context. In historical terms, a 7-10% drop in births might seem moderate, but it is important to understand that

[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.

Thailand’s fertility rate has already decreased significantly. In 2022, the fertility rate in Thailand was around 1.3 children per woman, one of the lowest in Asia. Therefore, this decline has profound implications on demographic shifts towards an aging population, changes in gender and family structures, as well as economic and social implications. To put this further in context, a compulsory schooling law in Thailand that increased female enrollment in secondary and high school lead to a decline in ever giving birth for females, with the largest drops around 4-5 percentage points at 14 and 15 years (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 below 25 years of age. We use Google Search data to show that increased access to information has an impact on the fertility decisions of young women.

We also 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 enrolment. However, parents are not able to mitigate all the negative shock 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 considered the main causes of air pollution outside of metro areas in Thailand. Air pollution from fires can result in economic losses due to healthcare expenses, decreased productivity, disruptions to tourism, and damage to agricultural crops. There is evidence of multiple adverse health effects from agricultural fires including increasing hypertension and cardiovascular risk (Pullabhotla & Souza, 2022). We show that the resulting ambient air pollution from fires can also affect microeconomic fertility decisions within a household. Our results emphasize that vulnerable populations like pregnant women and children could be adversely affected by the air pollution exacerbating health inequities. By altering the demographic structure, exposure to pollution can have long run effects on economic development. Therefore, we add to this growing literature and provide causal evidence of the varied ways in which poor air quality can affect women's fertility, child health, and household allocation of resources in a developing country context.

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

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.[4] 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 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.

[4] For comparison, the TFR is lower than many developed economies, e.g. New Zealand (1.7), Netherlands (1.5), United States (1.7), United Kingdom (1.6), etc. and much lower than its developing economy counterparts, e.g. Cambodia (2.3), Laos (2.4), Indonesia (2.2), Viet Nam (1.9), etc. in 2022.

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 two 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.[5]

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 annual rainfall of 4.4 millimeters in our dataset (see Appendix Table A1).

Finally, to investigate the potential role of public awareness in air pollution's impact on fertility decisions, we leverage Google Trends data. This data reflects the search frequency of specific terms on Google over time. In our analysis, we focus on searches for the term "PM2.5" between 2016 and 2019.[6] Over time, people have become more cognizant of the impact of climate change and air pollution on their lives. Correspondingly, we observe a big wave of public interest on PM2.5 that started in late 2018 to early 2019 and recurs every dry season when PM2.5 usually peaks (see Figure 6).

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

[6] There was an improvement in Google's data collection system at the beginning of 2016, so we restricted our data to 2016 onwards. This data was collected from trends.google.com in July 2023 in three steps. First, we collected monthly search volume data for all of Thailand for the years 2016 through 2019. This gives us a national baseline for search trends over time. Second, we obtained the monthly breakdown of search volume by province for the same time period. Finally, we calculated the estimated monthly search volume for each province. This was done by multiplying the national monthly search volume (from step 1) by the corresponding provincial search proportion (from step 2) for each month.

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

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

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 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

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

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 their 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, number of fires strongly predict

[7] Results are available upon request.

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 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

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[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.

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 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

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

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 Panel A, 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 Panel A (1)).[11] Moreover, in Table 3 Panel A (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. 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.

[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.

Furthermore, we evaluate the impact of information availability on births. To evaluate this mechanism, we use the Google Trends and Search data to see if an increase in search related to PM2.5 is correlated with future births. Table 3 Panel B documents the results. Table 3 Panel B (1) shows that, after controlling for woman's age and time trends, an increase in Google search related to PM2.5 leads to a decline of 0.33 births. Moreover, if younger women are more concerned about climate change and environmental impact, that group may see a stronger decline in fertility. There is suggestive evidence of this. We observe the decline to be strongest in women aged 20-25 years, though the decline lasts until 35 years (see Table 3 Panel B (3)-(5)).

<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 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 lower and diminishing income elasticities for 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>

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 of the fires within a range of 300 KM is

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[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.

leading to these effects, we also derive estimates of the effect of pollution exposure for various thresholds of the distance of upwind burning from the province centroid location. 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 clusters standard

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

errors at the survey unit level and we see that our results are statistically significant at this granular level of clustering as well.

To alleviate any remaining concern 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 the border of Thailand in neighboring countries of Laos, Myanmar, and Cambodia. Fires in 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 neighboring countries will affect women's fertility and children's health outcomes in Thailand only due to an increase in pollution. Specifically, we analyze the impact of neighboring country fires within 500 KM radii 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. We check for migration patterns in our sample. We note that migration occurs mostly in the Central and South region and most of the migration is within the same region therefore alleviating our concern of migration due to pollution.

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

Moreover, since 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.

Discussion

In this paper, we show that exposure to air pollution has a causal impact on fertility of women in Thailand. Our results demonstrate the negative and significant effect of air pollution arising from fires and upwind burning on women's fertility. We document stronger impact on rural, younger, and lower educated women. The rise in PM2.5 levels leads women to use more short-term contraceptives to avoid pregnancy. Moreover, we show that access to information changes fertility patterns. Using Google Trends data, we show that an increase in Google search related to PM2.5 leads to a decline in the number of births.

We also evaluate the applicability of Becker's Quantity-Quality fertility tradeoffs in Thailand's context. We provide evidence that, consistent with the theory, there is an increase in parental investment in children that are exposed to pollution in the first year of their life. Therefore, we observe an increase in quality and a decrease in quantity of children. We document a change in dietary patterns with an increase in protein and milk consumption as well as an increase in pre-school enrollment. However, parents are not able to overhaul all the adverse effect from the pollution exposure in the formative years of life of the child. The first-year exposure leads to a significant decrease in WAZ and WHZ scores for children.

Air pollution in developing countries can have significant economic, social, and environmental impacts. The costs of air pollution in these countries can include healthcare expenses due to increased respiratory illnesses, lost productivity from sick days, crop damage leading to lower agricultural yields, and environmental degradation. However, our knowledge is limited on the impact of air pollution globally across diverse contexts and different sources of pollution (Pullabhotla & Souza, 2022). We provide evidence, in a developing country context, on an additional channel of demographic impact which can further exacerbate the costs associated with air pollution. Moreover, since declining fertility can change the demographic composition and affect economic development, these results are of utmost importance to policymakers and add to our knowledge of the many ways in which air pollution can affect the society.

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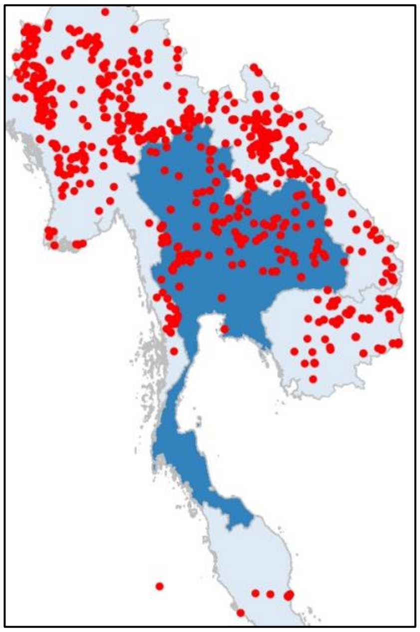
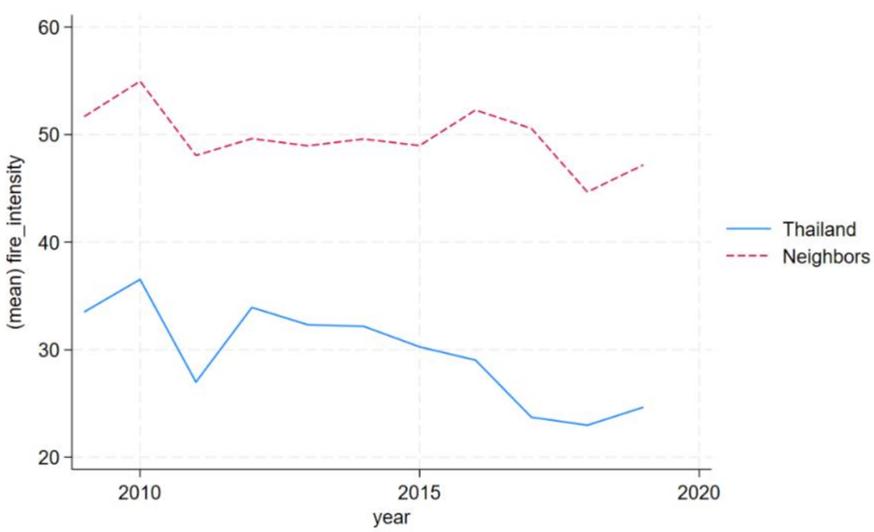
Figures

Figure 1: Fire Hotspots Map of Thailand



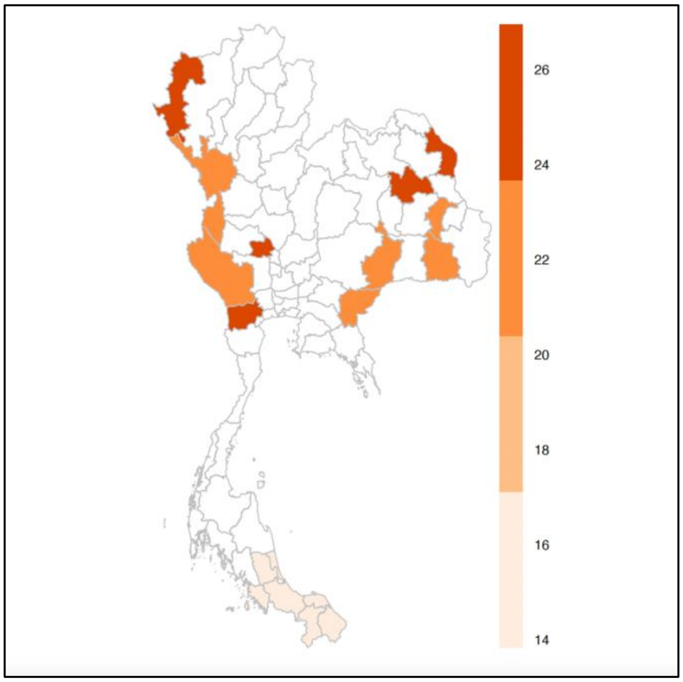
Note: This figure shows the fire hotspots (depicted by red dots) within Thailand and in neighboring countries of Laos, Cambodia, and Myanmar. The snapshot is taken on March 15, 2019.

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.

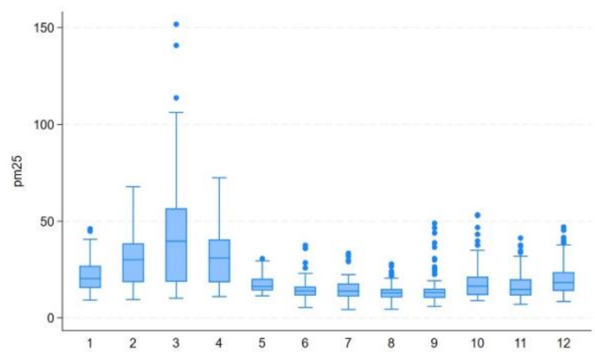
Figure 3: Average PM2.5 levels in Thailand



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

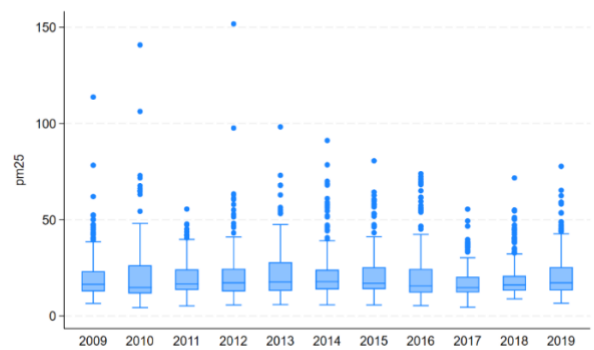
Figure 4: Trends of PM2.5 levels in Thailand

Panel A



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

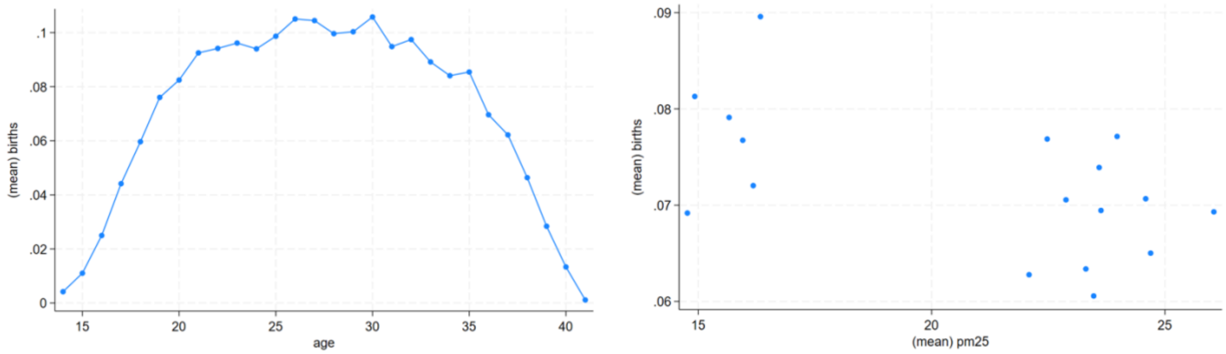
Panel B



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

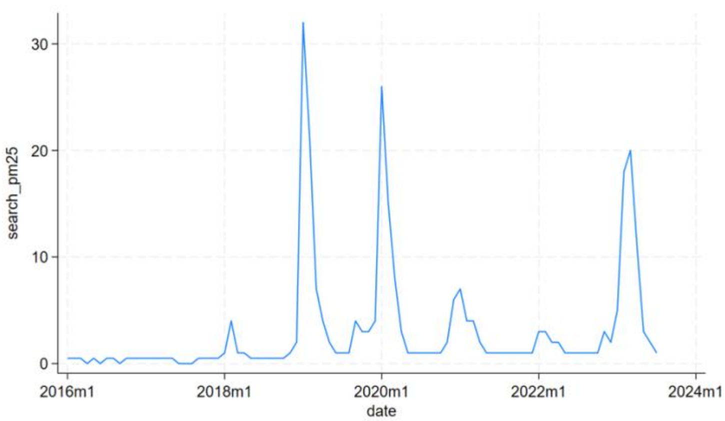
Figure 5: Fertility Patterns

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.

Figure 6: Information Seeking Behavior



Note: This graph plots the number of Google Searches of “PM2.5” overtime.

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: Fertility Decline Mechanisms

Panel A: 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, caretaker education, mother'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.

Panel B: Information Channel

	(1)	(2)	(3)	(4)	(5)	(6)
	All	**Age <=20**	**Age 20-25**	**Age 25-30**	**Age 30-35**	**Age >35**
Google Search	-0.331***	-0.0974	-0.777***	-0.493***	-0.447**	-0.237
PM2.5	(0.004)	(0.487)	(0.002)	(0.002)	(0.017)	(0.216)
Age FE	YES	YES	YES	YES	YES	YES
Time Trend	YES	YES	YES	YES	YES	YES
Observations	40260	7563	7283	8323	8519	8572

Note: p-values in parentheses. All specifications test for the impact of increased google search of pollution and PM2.5 levels on births for various age groups. 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)
Specification	**OLS**	**OLS**	**IV**	**IV**	**IV**
PM2.5	-0.00836***	-0.00712***	-0.00447***	-0.00850***	-0.00819***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Rain		0.0105***		0.00896***	0.00883***
		(0.000)		(0.003)	(0.004)
Avg. Temp.		0.0439***		0.0444***	0.0431***
		(0.000)		(0.000)	(0.000)
Age at Birth					0.00936***
					(0.002)
$(\text{Age at Birth})^2$					-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 survey unit 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 annual 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	0.439	0.496	2276	0.000	1.000
Age of woman	19.918	2.173	2282	17.000	41.000
Completed at least high school	0.654	0.476	2282	0.000	1.000
Rural	0.676	0.468	2282	0.000	1.000
Household never migrated	0.718	0.450	2282	0.000	1.000
Household speaks Thai	0.804	0.397	2282	0.000	1.000
Any household member owns agricultural land	0.494	0.500	2277	0.000	1.000
Number of rooms used for sleeping	2.285	0.899	2282	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 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 survey unit level.
*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.