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ABSTRACT

We incorporate pollution exposure into Becker's "Quantity-Quality" (Q-Q) model of fertility and quantify how air pollution distorts individuals' fertility behaviors in China. We document a robust pattern in which increased pollution over time negatively affects the fertility of ethnic Han people, who comprise approximately 92% of the Chinese population. These patterns are evident in both cross-sectional and panel data, when instrumenting for pollution using distant coal-fired plants upwind of cities or thermal inversions that trap pollution. Consistent with the stylized Q-Q model of fertility, we find that increased pollution drives up the parental expenditure per child, which increases the shadow price associated with the number of children and reduces fertility. Consistent with the model, we also find that the fertility choices of people who tend to have higher demand for child quality are significantly more sensitive to pollution changes. Pollution does not have a meaningful effect on the fertility of ethnic minorities, which can also be explained under the Q-Q framework.

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1. Introduction

A large body of literature has documented the negative effects of air pollution on health outcomes and human capital development of children. Severe air pollution raises the mortality rate among infants (Arceo et al., 2015; Chay and Greenstone, 2003), impairs children's health (Janke et al., 2014; Neidell, 2004; Bedi et al., 2020), and undermines their academic performance (Bedi et al., 2020; Bharadwaj et al., 2017).

In the Quantity-Quality (Q-Q) framework of human fertility (Becker and Lewis 1973; Becker and Tomes 1976), fertility choices depend on the shadow price of child quantity (i.e., the marginal costs associated with a new child). Driven by the adverse effects on children's health and education outcomes, air pollution is likely to change the parental expenditure on children's health and education inputs, altering the child quantity shadow price and consequently affecting fertility decisions. But so far, there has been little work analyzing the effects of air pollution on reproductive behaviors. In this paper, we employ individual-level data to empirically uncover how air pollution alters reproductive-age women's actual fertility decisions as well as their perceived ideal number of children in China and test whether the behavioral responses we observe are consistent with the predictions provided by the theoretical literature.

We incorporate air pollution into the standard Q-Q fertility model (Becker and Lewis 1973; Becker and Tomes 1976). In our framework, the shadow price of a new child depends on the costs of investment in child quality (e.g., education expenditures, health expenditures). Air pollution increases the health risks faced by children and can undermine their academic performance. Thus, parents are likely to increase their expenditures on their children's educational achievement and health status to mitigate the adverse effects of pollution exposure if they have a strong demand for child quality. Air pollution tends to increase those investments if parents have a strong demand for child quality but may not have a meaningful effect on it if parents' demand is not as strong. As a result, the overall effect of pollution on the shadow price of child number, and consequently the fertility choices of individuals, depends on the strength of parental preference for child quality.

China provides an important setting to test the predictions of the Quantity-Quality framework. First, the level of air pollution is hazardous in China and the amount by which pollution has increased over the years varies greatly across different cities (Khanna et al., 2021).[1] This allows

[1] Khanna et al. (2021) document that the mean concentration exceeds WHO air quality guidelines every year between 1998 and 2015, and the sharp increases in pollution in China in recent years were concentrated in a subset of cities.

us to look at behavioral responses to both the temporal change and the contemporaneous level of pollution. Second, the return to education also varies greatly across geographical locations (Liang et al., 2020). As parents tend to have stronger demand for child quality in places with a higher rate of return on human capital (Becker et al., 1990; Galor and Weil, 2000), the large spatial variation in the return to skill allows us to examine how the association between fertility and pollution depends upon the parents' preference for child quality. Third, China's One Child Policy (OCP) differentially affects two groups of people. Since 1979, the OCP has restricted the number of children for Han people (i.e., limiting them to have only one or two children in most cases), and this has increased the demand for child quality amongst this group.[2] This has, subsequently, increased the impact of pollution on the shadow price of child number. However, ethnic minorities in China have not been restricted by the OCP, and we may not therefore expect to see the same relationship between pollution and fertility for that group under the Q-Q model.

Although the OCP is unique to China, policies that aim to reduce fertility take other forms in many countries, such as the *Devi Rupak* program in India (Anukriti, 2018). Our analysis provides important insights on the fertility consequences associated with pollution in countries with policies or social norms that favor low fertility, and pollution is likely to exacerbate the implications of these policies based on the spirit of the Q-Q fertility model.

We use nationwide individual data drawn from the 2010 China Population Census to look at the impacts of air pollution on the fertility behavior of ethnic Han women in our baseline analysis. We quantify how the temporal change in pollution (within residential cities) and the contemporaneous level of pollution differentially affect individual fertility decisions—as defined by a binary variable of having a child born within the last 12 months (as in Avitabile et al., 2014). As the Han people are strongly restricted by the OCP, we use the sample of reproductive-age Han women whose stock of children was zero one year prior to the census in our baseline analysis.

Air pollution tends to be correlated with human economic activities. In order to disentangle it from potential confounding factors, we isolate exogenous fluctuations in pollution, leveraging a meteorological phenomenon called thermal inversion that traps pollution at the ground level (as in Arceo et al., 2016; Hicks et al., 2016) as well as variation in wind direction combined with the historical placement of distant thermal power plants (as in Freeman et al., 2019; Khanna et al.,

[2] The literature has documented that the OCP has increased affected people's demand for the education and health of children (Rosenzweig and Zhang, J., 2009; Liu 2014).

2021). We use the two instruments independently as they capture very different sources of variation in air quality and allow us to cross check the robustness of our empirical pattern.

Our results demonstrate a meaningful impact of pollution on fertility. Individuals' fertility decisions are more responsive to the change in pollution over time in comparison with the short-term exposure to pollution. If the PM2.5 concentration increases by 10 µg/m3 over three years, the probability of having a newborn child (within the 12 months) will decline by 12 percentage points, the effects of which corresponds to about 25% of a standard deviation of the dependent variable of experiencing a new birth and approximately 34% of mean of the dependent variable. We observe a similar empirical pattern when we use an individual-level longitudinal panel that tracks women's fertility outcomes from 1998 to 2010 regardless of their previous childbearing histories and additionally control for individual fixed effects.

Having shown that pollution distorts actual fertility choices, we next explore its effects on individuals' reported reproduction preferences. We employ the China Labor-Force Dynamic Survey (CLDS), which asks individuals for their ideal number of children were they not restricted by birth control policies or economic constraints. We find a pattern that is similar to the results of actual fertility outcomes—a temporal increase in the exposure to pollution significantly lowers the desired number of children, whereas the contemporaneous exposure to pollution does not systematically affect people's willingness to reproduce.

We next turn our attention to ethnic minorities who are not constrained by China's OCP. We replicate the specification in the baseline analysis (using women whose stock of children was zero one year prior to the census) and also employ a full sample of reproductive-age minority women irrespective of their previous childbearing histories. Our findings are robust across different samples and reveal no significant relationship between pollution and fertility for the minority group. The heterogeneous fertility response to pollution is in accordance with the spirit of the standard Q-Q framework. The ethnic Han people are likely to have higher demand for child quality due to the OCP under Becker's Q-Q model, and consequently their fertility choices are more sensitive to the adverse effects of pollution compared to their minority counterparts.

There is no shortage of explanations for why pollution may affect fertility. A priori, we view three mechanisms as particularly plausible: an increased shadow price associated with the number of children, increased infertility, and pollution-induced changes in income. Empirically, we find more consistency with the shadow price mechanism. Based on our Q-Q framework, the effects of pollution on the shadow price of child number is more pronounced among parents who have higher demand for child quality. As people who have higher education levels (Currie and Moretti, 2003), live in places with higher returns to human capital (Becker et al., 1990; Galor and Weil, 2000) or face strong restrictions under the OCP (Rosenzweig and Zhang, J., 2009; Liu 2014) are more likely to have higher preferences over child quality, we expect that the fertility choices of these three groups are more responsive to pollution. Indeed, our empirical evidence does verify these predictions. We also observe significant implications of pollution on the amount of parental expenditure per child, which can capture the shadow price of child number. However, the two competing mechanisms are not supported by the empirical evidence. In addition, the CLDS records individuals' ideal number of children had they been not restricted by their economic or health status, or by the OCP – with those recorded responses, we find a significant association between increased pollution and that ideal number, further demonstrating that the income and infertility mechanisms are not driving our results.

Our contributions to the literature are twofold. First, environmental economists document that pollution leads to economic losses by threatening health and lowering productivity and labor supply (Zivin and Neidell, 2012; Hanna and Oliva, 2015; Khanna et al., 2021). We are among the first to document how increased pollution lowers fertility. In the long run, declining fertility reduces the size of the working-age population and consequently undermines economic development (Bloom et al., 2009). In China, declining fertility has led to a shrinking labor supply, hurting the economy and creating an increasingly serious aging issue. In Europe, fertility is also falling and the population is similarly aging, raising labor costs and creating fiscal burdens. Thus, our analysis proposes a new "indirect" channel by which pollution adversely affects economic development and sheds light on additional economic benefits associated with environmental policies.

Second, we speak to the literature on the determinants of fertility (Becker, 1973; Becker et al., 1990; Galor, 2011). Our work is the first attempt to analyze the role of pollution in the standard Q-Q fertility framework. We document that pollution affects fertility choices by altering the shadow price of child number and identify a causal link between environmental quality and the incentives for having children.

2. A Quantity-Quality Fertility Model Incorporating Pollution

In this section, we incorporate air pollution into the standard "Quantity-Quality" (Q-Q) fertility model (Becker and Lewis 1973; Becker and Tomes 1976) and analyze the impacts of pollution on individuals' fertility decisions. At its heart is the impact of pollution on the shadow price of children with respect to their number (i.e., the cost of a new child or an additional child), which determines the reproductive decisions (the number of children) of people.

The utility of parents depends on the number of children n, the "quality" per child q (say, education attainment and health status of children), and the consumption of all other commodities c. We specify the following simple utility function with a budget constraint:

$$U = U(c, n, q) \tag{1}$$

$$s.t.\ I = c\pi_c + nq\pi_q + n\pi_n,$$

where I is full income, π_c is the price of the consumption good; π_n is the unitary cost of the number of children that is not dependent on quality (for instance, costs associated with basic nutrition); and π_q represents the costs of child quality that apply equally to each child.[3] We make no special assumptions about the elasticities of substitution among children n, q, and c in the utility function (as in Becker and Tomes, 1976). We expect that the marginal utility of child quality is higher for parents who have higher educational achievements and who are in regions with higher returns to human capital.

The first-order conditions for maximizing the utility function subject to the budget constraint are:

$$MU_n = \lambda\left(q\pi_q + \pi_n\right) = \lambda P_n,\ MU_q = \lambda n\pi_q = \lambda P_q, MU_c = \lambda\pi_c = \lambda P_c\ , \tag{2}$$

where $MU's$ are marginal utilities, $P's$ are marginal costs or shadow prices, and λ is the marginal utility of income. Thus, the shadow price of children with respect to number (holding their quality constant) is $P_n = q\pi_q + \pi_n$, and shadow price of children with respect to quality (holding their quantity constant) is $P_q = n\pi_q$.

An important feature of the model is that the shadow price of the quality of children is proportional to the quantity of children and the shadow price of quantity is increasing with the household's investment in quality.[4] Therefore, a change in the quantity or quality of children would

[3] Following Becker and Lewis (1973) and Becker and Tomes (1976), we assume parents invest in the same amount of resources in each of their children. Simplifying assumptions are introduced in order to generate testable implications.

[4] Quantity and quality interact in this way because an increase in the number of children drives up the cost of raising the quality of children, as the higher quality applies to more children; similarly, an increase in parental expenditure on quality raises the cost

result in further changes through this interaction. For example, an "exogenous" decrease in child number would drive down P_q, which would increase the demand for child quality. However, this would in turn increase the shadow price of child quantity, which would induce an additional decrease in child number, and so on (Becker and Tomes,1976).

Increased pollution negatively affects the health and academic performance of children. As a result, in order to produce a child with same quality q, parents need to increase their investments in quality (e.g., more health expenditure) as the amount of pollution exposure increases. Therefore, increased pollution would drive up the unit cost of child quality, π_q. Due to increased π_q, based on the demand theory in microeconomics, the effect of this increased cost on parental investments in child quality ($q\pi_q$) will depend on their preferences. If parents have a strong demand for child quality, they will increase investments to mitigate the adverse effects of increased pollution on the quality of their children. However, if they have a lower demand for child quality, an increase in pollution may not have a meaningful effect on (or may even decrease) parental expenditure on child quality.

Recall that the shadow price of child number $P_n = \pi_n + q\pi_q$, and we expect that pollution has non-negative effect on π_n. Consequently, increased pollution tends to lower fertility by increasing P_n for parents with higher preferences on child quality.

We next apply this framework in the context of China and take the effects of the One Child Policy (OCP) into account. Started in 1979, the OCP only authorizes Han people to have one or two children in most cases, and those who violate the OCP must pay financial penalties, the amount of which varies by provinces (Ebenstein, 2010).[5] Nevertheless, the OCP does not restrict the fertility of ethnic minorities. Thus, the utility maximization (regarding child number) for Han people can be rewritten as:

$$U = U(c, n, q) \tag{3}$$

$$s.t.\ I = \begin{cases} c\pi_c + nq\pi_q + n\pi_n, & if\ n < \bar{n} \\ c\pi_c + nq\pi_q + n\pi_n + (n - \bar{n})f, & if\ n > \bar{n} \end{cases},$$

Where $\bar{n}$ is the number of births authorized by the local OCP. The budget constraint of equation (3) takes into account the fact that Han people must pay a large fine if their child number exceeds

of an additional child, since children with higher quality would then be more "expensive" (Becker and Tomes,1976).

[5] Although there are other forms of non-financial penalties for violating the OCP, the financial fines are major forms of punishment for violating the OCP in China (Ebenstein, 2010).

that authorized by the OCP.[6]

The OCP has had long-lasting effects on Han people's preferences for child quantity and quality. In May 2021, China loosened its birth control policy to a three-child limit, and in July 2021 all limits on child number as well as penalties for exceeding them were removed. But the removal of the OCP did not meaningfully increase the fertility of Han people. Moreover, exposure to the OCP's fertility restrictions has also led to higher educational attainments for both men and women and a higher labor market participation rate for women (Huang et al., 2016; 2021), which may in turn increase their demand for their own children's quality and lower their preferences for child number. Therefore, we expect that the four decades of the implementation of the OCP has driven up Han people's marginal utility associated with child quality and driven down their marginal utility associated with child number. Indeed, the literature has also documented that the OCP has increased the Han people's demand for child quality. (Rosenzweig and Zhang, J., 2009; Liu, 2014).[7]

We therefore expect that Han people who are more stringently restricted by the OCP will be sensitive to increased pollution in their fertility choices. With a strong demand for child quality, pollution is likely to increase parental investments per child for this group (conditional upon they have children), making fertility more "expensive" and possibly lowering their fertility. Conversely, we would expect ethnic minorities, who are not restricted by the OCP, to be less sensitive to the effects of increased pollution in their fertility choices.

The literature has also demonstrated that people who live in cities with higher returns to human capital (Becker et al., 1990; Galor and Weil, 2000) and who have higher educational levels (Currie and Moretti, 2003) are likely to have higher demand for child quality (say, education achievement and health status). Thus, the fertility choices of these people may be more sensitive to pollution exposure.

We empirically examine the association between pollution and fertility in subsequent sections. We test whether parents with higher demand for child quality are more sensitive to air pollution regarding their fertility choices and evaluate the effects of pollution and parental expenditure per

[6] In some provinces, the amount of financial fines for an additional unauthorized birth increase with the number of excess births in a particular household. However, incorporating the non-linear relationship between financial penalties and the number of excess births in equation (3) does not affect the prediction of our model.

[7] The OCP can increase the demand for child quality for two reasons. First, the penalties for violating the OCP reduces the actual number of children for Han people, which – based on the spirit of the Q-Q framework – consequently decreases the shadow price of quality per child ($P_q = n\pi_q$), and in turn raises the demand for child quality. Second, the OCP alters the utility function of Han people, increases their preferences on child quality and lowers their preferences for child number.

child in Section 6.3. Based on equations (1)-(2), parental expenditure per child can be used as a proxy for the shadow price of child quantity.

3. Data

3.1 Air Quality Data

Following Freeman, Liang, Song and Timmins (2019) and Khanna et al. (2021), we use satellite PM2.5 data to measure air quality. PM2.5 has become the dominant air pollutant in China since 2000 (Barwick et al., 2019) and is viewed as the best indicator for health risks associated with atmospheric contamination by WHO.[8] We employ PM2.5 satellite data rather than official air quality data since it has the following advantages. First, satellite-based PM2.5 measures cover all cities since 1998, whereas official PM2.5 data are only available since 2012. Second, there is a concern that official air pollution data may be manipulated by the local government (Ghanem and Zhang, 2014; Greenstone et al., 2020). Satellite-based data appear to be more reliable – their correlation with monitor-based PM2.5 measurements conducted by U.S. Consulates in China is around 0.8. City-level yearly PM2.5 concentrations are measured using the Global Annual PM2.5 Grids constructed based on satellite data by Van Donkelaar et al. (2016).[9] This yields a comprehensive measure of air pollution for a wide array of Chinese cities, including all the prefecture, sub-provincial, and provincial cities.

3.2 Individual Fertility Data

We measure individual-level fertility decisions using the 2010 Population Census of China. China conducts its national population census every ten years,[10] and the 2010 Population Census is the most recent decennial census of which individual-level data are available to researchers. The census records a wide range of demographic and economic characteristics of individuals, including age, gender, education, employment, ethnic group, marital status, birth outcome, and residential city. Following recent work on individual fertility decisions (Avitabile et al., 2014), we define an indicator of fertility for whether a reproductive-age women gave birth within the last 12 months. As Han people account for approximately 92% of the Chinese population, we focus on the fertility

[8] For more background information see WHO report: http://www.who.int/mediacentre/news/releases/2014/air-quality/en/
[9] They estimate ground-level PM2.5 by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWiFS, which are subsequently calibrated to daily global ground-based observations of PM2.5 using Geographically Weighted Regressions (GWR) at high grid resolution
[10] China also conducts a mini population survey in the middle year between two censuses, with much smaller sample size than that of decennial censuses.

choices of ethnic Han women in the baseline analysis of section 6.1 and compare their behaviors with ethnic minorities in section 6.2.4.

We supplement the individual fertility data with a measure of the ideal number children, which come from the China Labor-force Dynamics Survey (CLDS). The CLDS is a national social survey, containing information covering about 21,700 reproductive-age women across 29 Chinese provinces.[11] In CLDS, there is a survey question for women: "What is your ideal number of children, had you not been restricted by the OCP and your current economic and health status?" Therefore, we are able to examine how pollution affects the desired number children of reproductive-age women. CLDS is conducted in three waves in 2012, 2014 and 2016. We combine three waves of the survey and construct individual-level pooled cross-sectional data for our analysis.

In addition, we also construct an individual longitudinal panel that tracks the fertility outcomes of women over time using information elicited from CLDS, as CLDS 2014 gathers very detailed information on histories of fertility and residential locations of each female respondent of reproductive age.

3.3 Inputs Into Instrumental Variables and Controls

We gather information on thermal inversions from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), which contains the 6-hour air temperature at different atmospheric layers. For each 6-hour period, we compute the change in temperature from the first to the second above-ground atmospheric layer. If a positive temperature change is observed, a thermal inversion occurs and the temperature difference between the first and second layers measures the strength of thermal inversions. We compute the yearly sum of thermal inversion strength based on the 6-hour data.

Information on large-scale (capacity>1 million KW) coal-fired power plants and their coal consumption comes from China's Electric Power Yearbooks and Energy Statistical Yearbooks. We manually collect information on the establishment year of plants, the distance of them to each city, and the angle between their locations and annual prevailing wind direction of each city.

We obtain data on city attributes, involving GDP per capita, wage and unemployment rate from the City Statistical Yearbooks. Weather condition data come from China Meteorological Data

[11] A probability-proportional-to-size sampling (PPS) procedure based on population size and administrative units is adopted to ensure that the survey is nationally representative. As a result, the distribution of sample size across cities in the CLDS is consistent with the geographic distribution of population in China.

Service Center. We gather housing price data from the Xitai Real Estate Big Data depository. Appendix Table A1 reports summary statistics and a description of the key variables used in the study.

4. Descriptive Patterns of Pollution and Fertility

In this section, we describe the empirical patterns of pollution and fertility in the raw data, which motivate more rigorous analysis in subsequent sections.

Figure 1 uses city-level data to relate the number of new births per reproductive-age woman with the annual mean of PM2.5 concentration as well as the three-year change in PM2.5. It is clear that the number of births is negatively associated with the change in PM2.5 over time (in Figure 1a), whereas the relationship between fertility outcomes and yearly mean PM2.5 is slightly positive but unclear (in Figure 1b). The pattern indicates that fertility decisions tend to be more responsive to the temporal change in pollution rather than the contemporaneous level of pollution.

Figure 2 examines the association between pollution and age-specific fertility rate for the cohorts aged 20-25 and 26-30, respectively. We find similar patterns—age-specific fertility rate is negatively correlated with the three-year change in PM2.5 but does not have any detectable relationship with the short term PM2.5 exposure, as measured by yearly PM2.5.

Figure 3 explores whether air pollution alters people's willingness to reproduce. There is a clear negative association in Figure 3a: the number of ideal children (perceived by women) is lower in cities that experience a higher increase in the amount of PM2.5. As illustrated in Figure 3b, the relationship between the number of desired children and yearly PM2.5 is also negative.

Figures 1-3 jointly document a robust pattern of how changes in pollution over time affect people's fertility choices and reproductive preferences. Nevertheless, the relationship between contemporaneous pollution and fertility is less robust and less clear.

5. Empirical Specification

As documented in Section 2, under the standard Quantity-Quality fertility framework, pollution affects the shadow price of child number and consequently alters people's fertility decisions. First, we follow Avitabile et al. (2014) and La Ferrara et al. (2012) to begin our empirical analysis with the actual reproductive outcomes of women. Our empirical specification is as follows:

$$Birth_{ij,t} = \beta_0 + \beta_1 PM2.5_{jt-1} + \beta_2 \Delta PM2.5_{j,t-1,t-3} + \beta_3 Z_{ij} + \eta_{Cohort} + \delta_{\ Tier} + \varepsilon_{ij,t} \quad (4)$$

where $Birth_{ij,t}$ is an indicator for whether a reproductive-age woman i in city j gave birth in year t. $PM2.5_{jt-1}$ and $\Delta PM2.5_{jt,t-2}$, respectively, are the annual mean of PM2.5 concentration in year t-1 and the three-year change in PM2.5 between year t-1 and t-3. As air pollution undermines children's health and human capital development, parents make reproductive decisions based on their expected future pollution exposure experienced by their prospective children. They make expectations based on available information on contemporaneous pollution $PM2.5_{jt-1}$ (when making fertility choices) and changes in pollution over the recent past $\Delta PM2.5_{j,t-1,t-3}$, which are our primary independent variables of interest. We include city tier fixed effects $\delta_{\ Tier}$ to account for differentiated environmental and economic policies by city tiers. As women of different ages may have heterogenous preferences over reproduction, we additionally add cohort fixed effects η_{Cohort} based on the age of women. Z_{ij} are controls, including weather conditions that may be correlated with pollution and distances to big cities and three large seaports that account for spatial differentiated economic development.

We use the 2010 Population Census of China to estimate equation (4), and thus the dependent variable $Birth_{ij,t}$ is defined based on whether woman i experienced a new birth within the last 12 months leading to the census. We use the sample of ethnic Han people in our baseline analysis for two reasons. First, ethnic Han people account for 92% of the Chinese population and they are more likely to settle in polluted areas compared to their ethnic minority counterparts. Second, the one child policy restricts the number of children of Han parents, raising their demand for child quality (as documented in the standard Q-Q model in Section 2). As pollution is negatively associated with children's health and human capital development, we expect that the implications of pollution on fertility will be stronger for Han parents.

We use the sample of married reproductive-age Han women who had not had children at any time prior to one-year before the census in the baseline estimation in Section 6.1.[12] In Section 6.23,

[12] We use married reproductive-age Han women who had not had children at any point prior to one-year before the census due to the following reasons. First, Han women are strongly restricted by the OCP, so the majority of them do not have a second child. Second, we only use married women because Chinese population census only records the birth outcomes of married women. Data in China Marriage and Family Report show that about 98.8% Chinese women have their first child after they get married. We do not apply the two restrictions when we employ CLDS data to look at women's actual fertility choices and their ideal number of children. Despite different specifications and data sources, the pattern of pollution and fertility estimated using CLDS data is quite similar to that estimated using the sample drawn from the population census.

we employ an individual longitudinal panel to re-estimate the association between pollution and fertility. The individual-level panel data track birth outcomes of reproductive-age women regardless of previous childbearing histories and enable us to control for individual-fixed effects. Different from our baseline estimation in Section 6.1, we include those who had and who had not had children when employing the individual longitudinal panel in Section 6.23.

We examine the behaviors of ethnic minorities separately in Section 6.24 in order to make comparisons with the fertility outcomes of Han people. We use two different specifications. First, we use married reproductive age minority women who had not had children one year prior to the census in order to replicate the specification of Han people analysis. Second, we use married reproductive age minority women regardless of their birth histories and control for the number of children they had one year prior to the census.

In Section 6.3, we test whether the fertility responses to pollution are stronger for people who are likely to have higher demand for child quality, and whether the pollution exposure drives up parental expenditure per child which capture the shadow price of child number.

A caveat with the specification with equation (4) is that individuals' fertility outcomes may not reflect their actual fertility preferences due to fertility policies or unobservables that affect reproductive outcomes. So as to get around these issues, we next use individual-level pooled cross-sectional data to uncover whether pollution affects people's willingness to reproduce. The empirical specification is given by:

$$Num_{ij,t} = \beta_0 + \beta_1 PM2.5_{jt-1} + \beta_2 \Delta PM2.5_{j,t-1,t-3} + \xi_i + \eta_{cohort} + \delta_{\ Tier,t} + \varepsilon_{ij,t} \qquad (5)$$

where $Num_{ij,t}$ is the ideal number of children for reproductive-age woman i in city j year t. We use pooled cross-sectional data by combining CLDS 2012, 2014 and 2016 to estimate equation (5), controlling for an individual fixed effect ξ_i , cohort fixed effect η_{cohort} and city tier-by-year fixed effects $\delta_{\ Tier,t}$. The two different fertility measures in equations (4) and (5) allow us to look at how air pollution distorts individuals' actual fertility decisions as well as their fertility preferences. We also present the estimation of equation (5) in our baseline results in section 6.1.

Pollution is likely to be associated with local economic activity, so potential confounding factors may bias the OLS estimates. To deal with the endogeneity concern, we use two different strategies to identify the ceteris paribus effects of pollution—an instrumental variable based on a meteorological phenomenon called thermal inversion that traps pollution at the ground level (as in Hicks et al., 2016 and Khanna et al., 2021), and an alternative instrument leveraging how wind direction interplays with the siting and coal consumption of distant coal-fired power plants (as in Freeman et al., 2019 and Khanna et al., 2021).

5.1 Instrument #1: Thermal Inversions

Our first plausible exogenous source of variation leverages the strength of thermal inversions, a meteorological phenomenon in which the above-ground temperature is abnormally higher than the ground temperature, trapping air pollutants at the ground level. This instrument has been used to isolate the exogenous fluctuation of air pollution in the U.S. (Hicks et al., 2016) , Mexico (Arceo et al., 2016; Molina, 2021), China (Khanna et al., 2021) and Sweden (Jans et al., 2018), among other countries. Our first-stage regression is:

$$PM2.5_{jt} = \gamma_0 + \gamma_1 Thermal\ Strength_{jt} + \mu_{jt} \tag{6}$$

where $Thermal\ Strength_{jt}$ represents the annual mean strength of thermal inversions in city j and year t. In the specification, we control for weather conditions that may be associated with the occurrence of thermal inversions, like temperature and sunshine.

In the atmospheric dispersion literature, pollution is a function of winds, settling and emissions; whereby inversions lower atmospheric ventilation and trap pollutants in the nearby atmosphere (Sharan and Gopalakrishnan, 2003). In addition, thermal inversions are a function of chemical potential and natural parameters, which are unlikely to be affected by regional economic activity (Ferrini, 1979; Antoine, 2019).

Since polluting potential increases over time in China, cities that experience higher strength of inversions are more likely to trap pollutants at the ground level. As illustrated in Figure 4, although we cannot observe detectable trend in the fluctuation of thermal inversions, as cities pollute more over the decade, those with more stronger inversions saw a substantial increase in air pollution over time. The right panel reveals a strong positive association between inversions and PM2.5. Panel A of Table A2 shows the results of the corresponding first-stage regression. Our thermal inversions instrument does a good job to predict city-level PM2.5, with F-statistics greater than 10.

5.1 Instrument #2: Wind Direction and Coal-Fired Power Plants

Our second instrumental variable is created on the basis of an insight from Freeman, Liang, Song, and Timmins (2019) and Khanna, Liang, Mobarak and Song (2021). We measure the extent to which distant large-scaled coal-fired power plants are located upwind of a particular city. The value of the instrument variable is penalized if the location of plants deviates from the upwind direction of the city and if it is further away, based on the following first-stage equation:

$$PM2.5_{jt} = \gamma_0 + \gamma_1 \sum_p^P \left(\frac{1}{\alpha_{pt}+1}\right)\left(\frac{1}{dist_{pj}}\right) C_{pt} + \mu_{jt} \quad (7)$$

where α_{pt} represent the angle between the plant p and the annual prevailing wind direction of city j and, $dist_{pj}$ is the distance between the plant p and city j, and C_{pt} is the coal consumption of plant p in year t. We employ large-scale coal-fired plants that are located more than 50 km but within a 450km distance of the city. The left panel of Figure 5 shows the intuition of the instrument. The underlying variation lies in how wind patterns blow air pollutants from distant thermal power plants to cities. The right panel of Figure 5 shows a clear positive relationship between the wind direction IV and air quality, and Table A2 Panel B reports the results of first-stage estimation for the wind direction IV.

The wind direction IV is considered to be exogenous to local economic activities by the literature for a number of reasons (Freeman, Liang, Song, and Timmins, 2019; Khanna, Liang, Mobarak and Song, 2021). First, wind direction is determined by nature, and thus it is less likely to be affected local economic activities. Second, those large-scale coal-fired power plants supply electricity to vast areas of China, including many remote areas; many do not even supply electricity to their nearby cities at all, but rather to many regions that are far away from them.[13] Third, the establishment of large-scale power plants and the allocation of electricity supply from them is determined by the central government – it is hard for local governments to influence the placement of large-scale plants and the electricity supply from them. Finally, the spillover from distant power plants on local economic activity is almost negligible, but the pollutants discharged from power

[13] Inter-province electricity transmission is prevalent in China. For example, in 2016, Yunnan province transmitted about half of its power output to other provinces, and Sichuan province transmitted 40% of its power output to other provinces. Large-scale power plants are mainly responsible for the power generation for inter-province electricity transmission in China (Freeman et al., 2019; Khanna et al. 2021).

plants located upwind significantly drives up the level of local air pollution.

We test potential concerns with this instrument in Section 6.2.2. For example, the location and the coal consumption of coal-fired plants may be affected by unobservables of nearby cities, and thus we show robustness to only using power plants that are located at various distance away from cities. Our falsification tests further demonstrate that city economic conditions, population and electricity demand are not associated with the future placement of plants. The government attaches more importance to environmental protection in recent years and in turn may take potential environmental costs into account when siting coal-fired plants, and we demonstrate robustness of our results to using only old power plants, such as those built even 25 years ago. The empirical pattern estimated using the wind direction IV is also insensitive to excluding coal-producing regions, as well as additionally controlling for local electricity demand.

We employ the two instruments discussed above independently as they represent very different sources of variation in air pollution (driven by a meteorological phenomenon versus wind direction).

6. Empirical Results

6.1 Baseline Results

Table 1 presents the baseline estimates of the effects of air pollution on a binary indicator of giving birth within the last 12 months. We use a sample of individuals drawn from the 2010 population census and look at reproductive-age Han women who had never had children one year prior to the census. Panel A shows OLS estimates. Across all four columns, we control for distances to three large seaports and nearest big cities to account for spatial distribution of economic development and add weather amenities to get around potential endogeneity arising from the correlation between weather and air pollution. We additionally add city-tier fixed effects in column (2) and further include age-cohort fixed effects in column (3) to account for differential fertility patterns and socioeconomic conditions among people in different tier of cities and of different ages. We impose a more stringent restriction by controlling for the interaction of city tier- and cohort-fixed effects in column (4). Our OLS results are very robust to different specifications. The change in the amount of PM2.5 over three years leading to the fertility decisions has significantly negative effects on women's fertility outcomes, whereas the effects of contemporaneous level of PM2.5 are statistically insignificant.

Air pollution is likely to be correlated with human economic activities like industrial production, biasing the naïve OLS estimates of pollution and fertility. In Panel B of Table 1, we deal with the endogeneity of pollution by leveraging our first instrumental variable based on the strength of thermal inversions that traps pollution. The IV results show a similar fact—individuals are more responsive to the change of pollution over time rather than the contemporaneous level of pollution. The estimates of the three-year change in PM2.5 are statistically significant and increase substantially in magnitude after dealing with the potential endogeneity. Our IV results indicate that if PM2.5 increases by 10 μg/m3 over three years (leading to fertility choices), the probability that a productive-age woman (who had never had children one year prior) gives birth within the previous 12 months will decline by approximately 12 percentage points. Based the IV estimates, the effect of a 10 μg/m3 increase in local PM2.5 concentration corresponds to about 25% of a standard deviation of the dependent variable of experiencing a new birth and approximately 34% of the mean of the dependent variable.

Table 1 documents that pollution alters individuals' actual fertility behaviors, so it is natural to ask whether it also affects people's reproduction preferences. Table 2 looks at how pollution change the ideal number of children of reproductive-age Han women using data from CLDS. CLDS asks each woman to report her desired number of children if the respondent were not restricted by the OCP and her current economic and health status. Panel A presents the OLS results, and we leverage the plausible exogenous change in thermal inversions to get around the potential endogeneity issue in Panel B. The IV estimates document that the temporal change in pollution is significantly negatively associated with the desired number of children, whereas the implications of the amount of pollution just one year prior are insignificantly different from zero. A 10 μg/m3 increase in PM2.5 over three years raises the desired number of children by 0.12 a reproductive-age woman. As the mean and the standard deviation of the desired number of children are 1.93 and 0.58, respectively, in our sample, the effects of increased pollution on the willingness to reproduce are non-trivial. The results of Table 1 and Table 2 jointly demonstrate that an increase in pollution over time not only affect individuals' actual fertility outcomes but also change their belief about reproduction, whereas the contemporaneous level of air quality does not have any meaningful effects on fertility.

6.2 Sensitivity Analyses

We perform a wide range of meaningful robustness checks to examine the concreteness of the empirical association between air pollution and fertility. We explore alternative sources of variation, additional covariates, different model specifications and data sources and re-estimate the fertility response to pollution for ethnic minorities.

6.2.1 Additional Controls

In this section, we introduce a wide array of control variables that may confound the estimated relationship between air pollution and fertility and test the sensitivity of our empirical pattern. We first re-estimate equation (4) using our baseline sample of reproductive-age Han women, and additionally control for these confounding factors.

In China, housing costs are strongly associated with individuals' fertility decisions, as home ownership and long-term rental status determines one's access to many child-related benefits provided by the government. Air quality tends to be capitalized in housing prices based on the hedonic price theory (Roback, 1982), which may confound the effects of pollution on fertility. To allay this concern, we control for the contemporaneous level and the three-year change in housing prices in Table A3 Panel A. The coefficients on the shift in pollution over time hardly change and parameters of yearly mean pollution are slightly more precisely estimated. Thus, our baseline empirical patterns are not driven by the spatial differences in housing costs.

Cities that experience economic growth may happen to be places have a higher pollution level and a lower fertility rate. We thus check the robustness of our IV estimates to economic controls in Table A3 Panel B. Our results display similar patterns as before after we control for GDP per capita, employment rate, and three-year changes of these indicators. We additionally control for hospital infrastructure in Table A3 Panel C. Our empirical pattern is insensitive to adding the number of hospitals and the number of hospital beds along with their changes within three years.

One may be concerned that fine particle concentration is correlated with local industrial discharges. So as to deal with the confounding effects of local pollutant emissions, we add the level and the three-year change of industrial SO_2 emission and NO_x emissions in Table A3 Panel D. Our coefficient estimates are quantitively and qualitatively similar. Our thermal inversion IV does a good job of isolating the effects of particulate matter concentration.

In Table A4, we assess sensitivity to additional geological and meteorological controls that may be associated with the thermal inversions instrument. These include annual rainfall, wind speed, humidity, three-year changes of these weather variables, fraction of the region covered by water bodies, and whether the city is coastal or not. Adding additional geological and meteorological controls does not affect our results meaningfully.

We then assess the preference for reproduction. Table A5 documents that our predicted relationship between increased pollution over time and people's willingness to reproduce (as measured by their desired number of children) are also robust to controlling for housing costs that may affect their fertility choices and adding local industrial emissions that may be correlated with PM2.5 concentration.

6.2.2 Alternative Sources of Variation

In this section, we leverage an alternative instrumental variable based on the interaction between wind direction and the location and coal consumption of large-scaled coal-fired plants. The wind direction IV has been used in recent work on air pollution in China (Freeman et al., 2019; Khanna et al., 2021; Gao et al., 2021) and as such, has been scrutinized thoroughly in these papers. We re-estimate the relationship between air pollution and fertility in equation (4) using our baseline sample from the census data.

Table A6 shows how the variation of PM2.5 from our second instrumental variable of wind direction and distant thermal power plants affect fertility decisions of individuals. We find a similar empirical pattern—the fertility response is more sensitive to the change of atmospheric contamination over time rather than the contemporaneous level of pollution.

We next examine the identification concern of our second instrumental variable. There is a concern that policy makers may also take the interaction of wind direction, coal consumption and distance to cities into account when siting coal-fired power plants. If that were the case, unobservables of nearby cities like political influence may affect the location and coal consumption of power plants, biasing our IV estimates. We thus exclude power plants located within 60 km, 110 km and 150 km of a given city in the IV construction in Table A7. Excluding nearby power plants (that are more likely to be associated with city-level unobservables) does not systematically change our parameter estimate of the change in pollution over time.

Even though the government may not have considered the three components of our second instrumental variable (wind direction, coal consumption and distance to cities) to locate power plants in the past, they may have taken the potential environmental costs into account when siting power plants in recent years as both the government and the public have recently paid more attention to environmental degradation in China. To address this concern, we exclude power plants built within five, ten, fifteen, twenty and twenty-five years, respectively in Table A8. Using old power plants yields a more conservative empirical strategy, as cities with newly built plants are in the 'control group'. However, our coefficient estimates still document a similar pattern—people are more significantly responsive to the change of pollution over time.

In Table A9, we drop individuals in Shanxi Province (the largest coal producing region in China) to allay the concern that our IV estimates are driven by the concentration of coal production which may affect individual income and in turn their fertility choices. Excluding this coal producing region does little to affect our results. Table A10 documents that our results are also robust to controlling for local electricity demand, measured by industrial electricity consumption and total electricity consumption (including residential electricity and industrial consumption). In Table A11, we conduct a falsification test, and evaluate the effects of city characteristics in 2004 on the ratio of upwind power plants built after 2005, along with the IV constructed only using plants built after 2005. Baseline city characteristics, including GDP, population, and electricity demand do not have a meaningful association with the location and coal consumption of newly built coal-fired plants.

Our two instrumental variables capture very different sources of variation in air pollution (due to wind direction versus a meteorological phenomenon). The consistency in the estimated relationship between pollution and fertility is comforting, which gives us confidence that we are indeed identifying the ceteris paribus effects of air quality on fertility.

6.2.3 Individual Longitudinal Panel

In our baseline analysis, we focus on the fertility choices of women who did not have children previously. In this section we employ an individual-level longitudinal panel including those who had children and those who had not had children prior to their fertility decisions.[14] We use an alternative specification to revisit the effect of pollution on fertility for ethnic Han women. CLDS 2014 asks a retrospective history of locations and fertility outcomes for female respondents. We use this retrospective fertility history to create an individual-level longitudinal panel. Here, we define fertility to be an indicator for whether or not a reproductive-age woman gives birth in a particular year, irrespective of her previous childbearing history. The strengths of the individual-level panel lie in that it enables us to account for individual-specific unobservables that may affect

[14] Our individual longitudinal panel tracks the fertility outcomes of reproductive-age women from 1998 to 2010. All women in the panel data were of reproductive age in 1998. We exclude the observations after 2010, because China changed the regulation of OCP in 2011. The change of OCP regulations may confound our predicted empirical pattern and make it hard to compare the longitudinal panel results with our baseline estimates using 2010 population census.

fertility choices. We combine the longitudinal data with information on city-level yearly PM2.5 and the change in PM2.5 within three years leading to fertility choices.

We employ our first instrumental variable-the strength of thermal inversions to address the endogeneity of air pollution. Table A12 presents the IV estimation of the relationship between air pollution and the fertility behaviors of individuals, controlling for year and individual- fixed effects. Adding individual-specific fixed effects allow us to account for individual-level unobservables (such as taste for fertility or individual preferences for air quality) that may be systematically associated with fertility outcomes. We present results without weather controls in panel A and additionally time-varying weather conditions in panel B. The results are robust and document that once again, an increase in air pollution exposure over time significantly lowers the probability of giving birth for reproductive-age women. The coefficient estimates of the change in PM2.5 is smaller in magnitude compared to our baseline estimates, perhaps as here we include those who had had children previously and are less likely to experience a new birth due to the OCP restrictions.

6.2.4 Results for Ethnic Minorities

In this section, we turn our attention to the fertility behavior of ethnic minorities. In Panel A of Table A13, we employ population census data to replicate the baseline estimation of equation (4) using ethnic minority women of reproductive age who do not have children. Neither the annual mean PM2.5 nor the three-year change in PM2.5 has significant association with the fertility decisions of ethnic minority women. As ethnic minorities are not restricted by the OCP, in Table A12 Panel B, we use the full sample of reproductive-age ethnic minority women regardless of their childbearing histories and additionally control for the number of children they had one year prior to the census. We see a similar empirical pattern between the two samples (used in Panels A and B, respectively) once controlling for age-cohort fixed effects or cohort by city-tier fixed effects—air pollution does not have any meaningful effect on the reproduction outcome of ethnic minorities.

There tends to be two reasons behind the differential effects of pollution on fertility between Han people and ethnic minorities. First, minority groups are likely to settle in remote rural areas with less exposure to air pollution. Second, because they are not restricted by China's OCP, ethnic minorities may have less demand for child quality than Han people, who are subject to that constraint. In Table A14, we restrict our analysis to ethnic minorities who work in urban areas in China, as those minority women are likely to be exposed to the same level of air pollution as the Han people. Our empirical pattern barely changes, thus the heterogeneous fertility response to pollution between Han people and minorities seems to be not driven by their differential exposure to air pollution.[15]

If the OCP drives differential fertility patterns, we would expect that the effects of air pollution on individual fertility decisions would depend on the stringency of the OCP. We use fines for the violation of OCP at the provincial level to measure the stringency of the OCP (as in Ebenstein, 2010), and the OCP penalty measure is zero for ethnic minorities. We then combine Han women and minority women and perform triple-difference regressions by interacting the OCP stringency measure, the three year change in PM2.5, and an indicator for the Han group. As OCP penalties differ by provinces and are likely to be associated with local confounding factors, we employ fines for the OCP violation in the baseline year of 2000 and additionally control for province fixed effects. As reported in Table A15, the coefficients on the triple interaction between the OCP stringency measure, increased PM2.5 over years, and the indicator for Han women are negative and statistically significant different from zero. The results document that China's OCP enhances the implications of air pollution on individuals' fertility decisions, and significantly contributes to the differential fertility response to pollution between Han people and ethnic minorities.

As discussed under the stylized the Q-Q framework in Section. The OCP reduces the number of children for Han people and in turn raises their demand for child quality (conditional upon having a child),[16] which drives up the implications of increased pollution exposure on the shadow price of child number and consequently lowers the reproductive incentives for Han people.

6.3 Mechanisms

In this section, we evaluate the underlying mechanisms through which pollution affects fertility choices and conduct some meaningful tests of the implications of the Quantity-Quality (Q-Q) model of human fertility.

At least three potential mechanisms may drive the effects of air pollution on individuals' fertility decisions. First, air pollution alters the shadow price of having children and in turn distorts people's fertility behaviors. Second, air pollution affects the income of parents and then influences

[15] In Table A17, we random draw a subsample of Han women, the sample size of which is same as the ethnic minority data, to replicate our baseline estimation of Table 1. Even though the number of observations shrinks by up to 90%, we still see a significant relationship between the change in pollution and the reproduction outcomes of Han women. Therefore, the heterogeneous fertility patterns to pollution between Han people and minorities are not due to their differential sample size.

[16] Indeed, we show in Table A16 that people in regions that experience more restrict OCP regulations in baseline year are more likely to attach importance to their children's education.

their fertility decisions. Third, air pollution may lead to the infertility of reproductive age women. In this section, we empirically examine the three mechanisms and find the most consistency with the shadow price mechanism.

6.3.1 The Shadow Price of Having Children

Based on the standard Q-Q model sketched in Section 2, the reproduction decisions of parents depend on the shadow price of children with respect to number. Air pollution can alter the shadow price of child number by increasing parental per child investments in quality (say, education expenditure and health expenditure). We thus empirically test whether air pollution increases the parental expenditure per child. If that were the case, air quality would have a meaningful impact on the shadow price of child number, which would alter the fertility choices of parents. In Table A18, we look at how pollution exposure experienced by children during the age of 0-2 years affects the parental expenditure on them later in their childhood. Early childhood exposure to fine particulate matter significantly increases total parental expenditure per child as well as parents' spending on their education and health care. Therefore, atmospheric contamination raises the shadow price of child number, making reproduction more "expensive" and dampening the desire for children. Although parents do not know the level of prenatal and childhood exposure to pollution faced by their prospective children before they make fertility choices, they can predict the amount of pollution to which their children will be exposed based on the time trend of pollution changes. Thus, increased pollution over time would negatively affect their fertility decisions, as documented in our baseline results.

An important way to mitigate the adverse effects of pollution on children is to adopt indoor air filtration. The impacts of increased exposure to pollution on the shadow price of child number may therefore be stronger in cities with higher prices for indoor air filtration. As in Ito and Zhang (2020), we look at an important product attribute – high-efficiency particulate air (HEPA) filtration, which informs consumers about the purifier's effectiveness in reducing indoor particulate matter. According to the US Department of Energy, a HEPA filter is much more effective for removing particulate matter compared to a non-HEPA filter. We interact the three-year PM2.5 increase with the city-average price of HEPA and non-HEPA filter air purifiers, respectively. Table A19 shows that the impacts of increased pollution exposure on fertility are stronger in cities with higher prices for HEPA filter air purifiers but are not related to the price of non-HEPA filter air purifiers. The results additionally confirm the predictions of the Q-Q model that air pollution can lower fertility by driving up the costs of having children.

The Q-Q model also demonstrates that the implications of pollution for fertility are pronounced for people who have higher preferences over child quality. We expect parents who have higher education levels (Currie and Moretti, 2003), live in places with higher returns to human capital (Becker et al., 1990; Galor and Weil, 2000), or are stringently restricted by the OCP to be likely to have a higher demand for child quality (Rosenzweig and Zhang, J., 2009; Liu 2014). We add an interaction between the temporal change in PM2.5 and years of schooling of mothers in Table A20. The coefficient estimates of the interaction term indicate that high-skilled parents are more sensitive to increased pollution over time. We follow Khanna et al. (2021) and Dahl (2002) to use city-specific return to college education[17] in the baseline year to measure the return to human capital and interact it with the three-year change of PM2.5 in Panel B of Table A20. The interaction between the change in PM2.5 and the return to human capital is significantly positive, indicating that the fertility response to increased pollution is stronger in places that place higher value on the quality of children. Section 6.2.4 Table A16 presents that the stringency level of the OCP result in the heterogeneous reactions of fertility to pollution. The empirical findings in Table A16 and Tables A18-20 are highly consistent with our admitted stylized version of a Q-Q model, suggesting that the shadow price mechanism—pollution raises the shadow price of child number—can explain the observed empirical pattern of pollution and fertility in China.

6.3.2 Other Mechanisms

Income is an important determinant of fertility tendencies. Air pollution can lower the productivity of workers (Zivin and Neidell, 2012) and in turn reduce their income. Nevertheless, recent literature also documents a compensating differential for air pollution in China—people require higher income to compensate for the adverse effects of pollution exposure (Gao, Song and Timmins, 2021). Thus, the direction of the income effects of pollution is uncertain, and a systematic scrutiny of pollution and income is beyond the scope of our work. To test the role played by income, we additionally control for that variable. We examine whether accounting for income affects our empirical patterns of actual individual fertility outcomes in Table A21 and the ideal number of children in Table A22. Adding income does little to affect these patterns, suggesting that fertility reactions to pollution changes are not driven by the income mechanism. Table A23

[17] We run Mincer wage regression city by city using 2005 Mini Population Survey of China and estimate the city-specific Mincerian returns to college education in the baseline year of 2005.

examines the relationship between pollution and infertility. Both the contemporaneous level of pollution and the three-year change in pollution have nothing to do with the probability of infertility of reproductive-age women.[18]

In sum, the shadow price channel does a better job of explaining the observed relationship between pollution and fertility than do the income or infertility mechanisms. Nevertheless, we acknowledge that there may be other mechanisms behind the effects of pollution on fertility that require additional data collection and analysis.

7. Conclusion

In this paper, we embed the exposure to air pollution in the stylized Quantity-Quality fertility framework and document that pollution can distort fertility behaviors by changing the shadow price of child number. Our results suggest a negative and significant effect of the temporal change in air pollution exposure on the fertility of ethnic Han people, who account for approximately 92% of the Chinese population. The rise in PM2.5 exposure over time is not only significantly negatively associated with their actual fertility outcomes but also their willingness to reproduce, as measured by the ideal number of children perceived by women.

Our evidence supports three empirical facts that are consistent with the predictions of the "Quality-Quantity" model of human fertility. First, increased pollution over time significantly raises parental expenditure per child, capturing the shadow price associated with child number. Second, the effects of pollution on fertility are much stronger for Han women who have higher educational attainment and who live in cities with higher returns to human capital, as these two groups are likely to have higher demand for child quality. Third, ethnic minorities are less sensitive to air pollution, and the differential fertility response to fertility between Han people and the minority group is driven by the stringency level of China's OCP, which is positively associated with individuals' demand for child quality.

Recognizing that declining fertility can reduce the working age population, lead to demographic imbalance, and undermine long-term economic development (Bloom et al., 2009), we propose a new channel through which air pollution can have deleterious impacts. Indeed, our results suggest that the costs associated with pollution may be larger than environmental

[18] Our results indicate that the short- and medium-term change in pollution does not result in the infertility of women, but we acknowledge that we cannot rule out the effects of long-term exposure to pollution on infertility.

economists previously thought. Finally, our results also speak to the long-standing debate among labor economists on what explains the coincidence of fertility decline with economic growth (Galor, 2011; Chatterjee and Vogl, 2018). As pollution is an inevitable by-product of production, increased pollution during industrialization may negatively affects people's incentives to reproduce.

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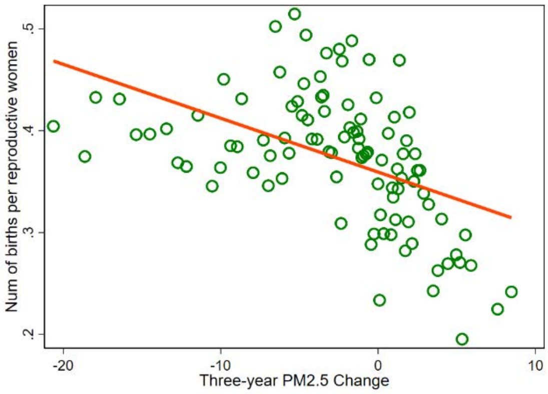
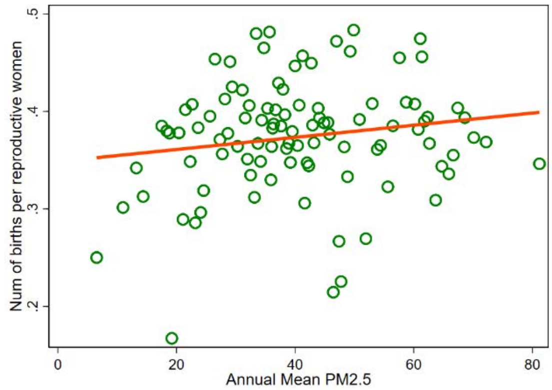
Figure 1: Air Pollution and the Number of Births in China

(a) Three-year Change inPM2.5



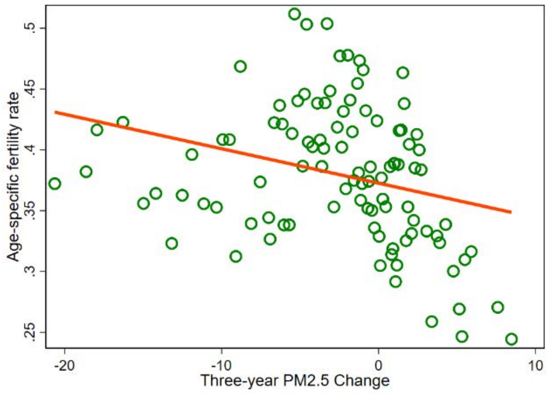
(b) Yearly Mean PM2.5



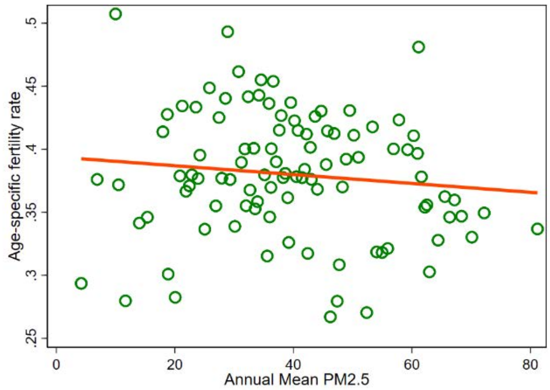
Note: Fertility Data come from National Population Census 2010. PM2.5 data are from the Global Annual PM2.5 Grids. Reproductive-age women are defined as women aged 15-50.

Figure 2: Air Pollution and the Age-Specific Fertility Rate

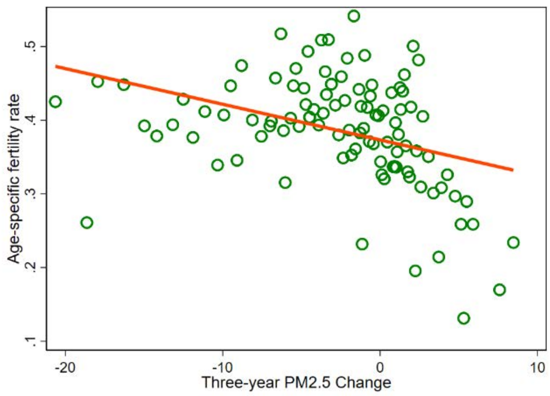
(a) Age 20-25, Three-Year PM2.5 Change



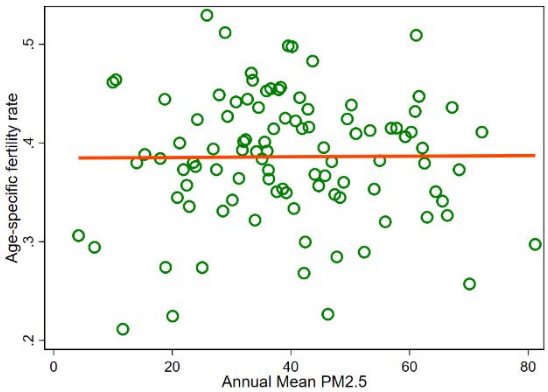
(b) Age 20-25, Yearly PM2.5



(c) Age 26-30, Three-Year PM2.5 Change



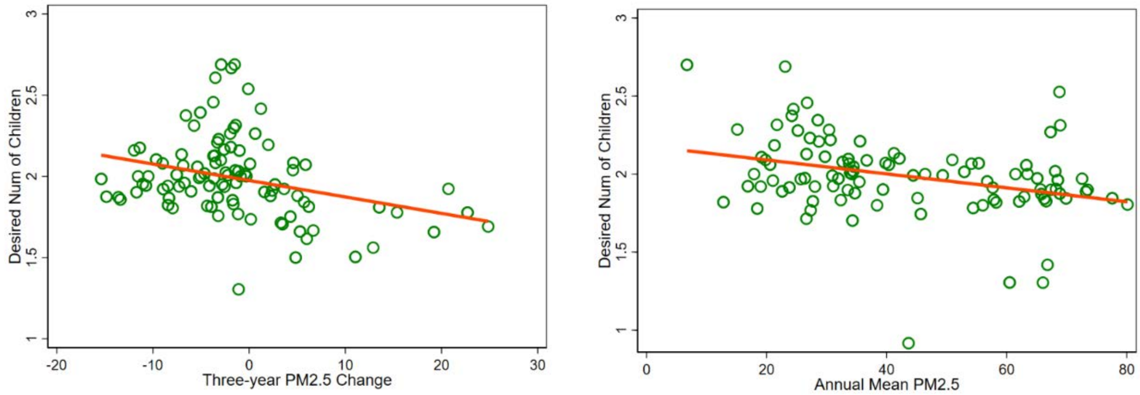
(d) Age 26-30, Yearly PM2.5



Note: Age-specific fertility rate is defined as the number of new births for per woman of a particular age. Fertility Data come from National Population Census 2010. PM2.5 data are from the Global Annual PM2.5 Grids.

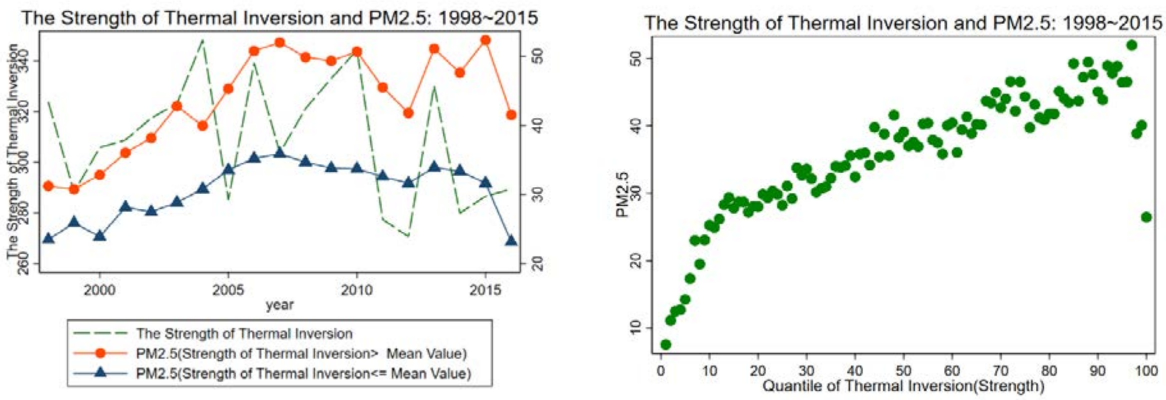
Figure 3: Air Pollution and the Number of Ideal Children

(a) Three-year Change in PM2.5 (b) Yearly Mean PM2.5



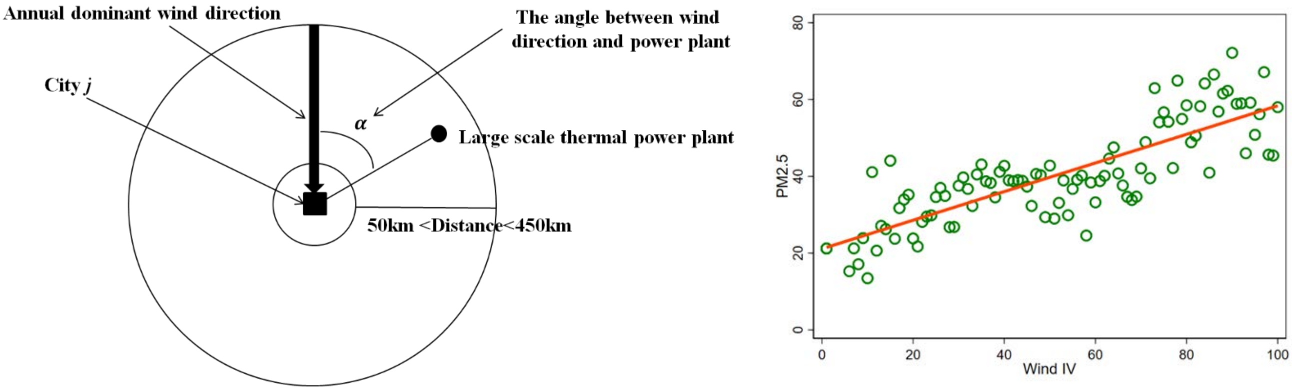
Note: Data on the number of desired children (perceived by reproductive age women) are from China Labor-force Dynamic Survey. PM2.5 data are from the Global Annual PM2.5 Grids.

Figure 4: Thermal Inversions and Air Pollution



Notes: In the left figure, we divide cities into the two groups based on whether or not they lie above the average annual strength of thermal inversions. The red line denotes the yearly mean of PM2.5 in cities where the annual strength of the thermal inversions is above average. The violet line denotes the yearly mean of PM2.5 in cities where the annual strength of thermal inversions is below average. The green-dash line presents the annual strength of thermal inversions. In the right figure, cities are grouped into one hundred groups based on the quantile of the annual strength of thermal inversions. The y-axis denotes the mean value of PM2.5 concentration in each quantile and x-axis denotes the mean strength of thermal inversions in each quantile.

Figure 5: Wind direction, distance, and coal consumption of large coal-fired plants



Notes: In the left figure, the thick arrow is the annual prevailing wind direction of city o. The dark dot is a large-scale thermal power plant located at least 50 km outside city o and within 300 km from the city. The angle α represents the angle between the large-scale power plant and the annual prevailing wind direction of city o. Large-scale thermal power plants are defined as plants whose installed-capacities are larger than 1 million KW. In the right figure, cities are grouped into one hundred groups based on the quantile of the wind direction IV measure. The y-axis presents the mean value of PM2.5 in each quantile in 2010 and x-axis represents the mean value of wind direction IV in each quantile.

Table1: Air pollution and Actual Fertility Choices

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Panel A: OLS regression				
Annual Mean PM2.5	-0.000485	-0.000497	-0.000484	-0.000474
	(0.000344)	(0.000350)	(0.000350)	(0.000346)
Three-year PM2.5 Change	-0.00440***	-0.00441***	-0.00441***	-0.00441***
	(0.000674)	(0.000663)	(0.000666)	(0.000666)
Observations	96,910	96,910	96,910	96,910
Adjusted R-squared	0.0250	0.0250	0.0301	0.0307
Panel B: IV regression				
Annual Mean PM2.5	-0.00269	-0.00266	-0.00261	-0.00247
	(0.00204)	(0.00199)	(0.00200)	(0.00197)
Three-year PM2.5 Change	-0.0121**	-0.0119**	-0.0120**	-0.0115**
	(0.00560)	(0.00543)	(0.00550)	(0.00538)
Observations	96,910	96,910	96,910	96,910
Mean of dependent variable	0.358	0.358	0.358	0.358
Std. of dependent variable	0.480	0.480	0.480	0.480
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE × Year FE	N	N	N	Y

Notes: The instrumental variables specification in the panel B uses the strength of thermal inversions. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Individual data come from 2010 Population Census of China. We use reproductive-age Han women who had not had children one-year prior to the census. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Air pollution and the Ideal Number of Children

	(1)	(2)	(3)	(4)
	Dependent variable: Ideal number of children perceived by women			
Panel A: OLS regression				
Annual Mean PM2.5	0.00456**	0.00489**	0.00454*	0.00488**
	(0.00208)	(0.00205)	(0.00245)	(0.00240)
Three-year PM2.5 Change	-0.00500***	-0.00527***	-0.00430**	-0.00456**
	(0.00167)	(0.00169)	(0.00193)	(0.00193)
Observations	15,700	15,700	15,700	15,700
Adj. R-squared	0.216	0.220	0.216	0.219
Panel B: IV regression				
Annual Mean PM2.5	0.0150	0.0153	0.0172	0.0176
	(0.0116)	(0.0117)	(0.0122)	(0.0124)
Three-year PM2.5 Change	-0.0176**	-0.0179**	-0.0208*	-0.0212*
	(0.00833)	(0.00846)	(0.0115)	(0.0116)
Observations	15,700	15,700	15,700	15,700
Mean of dependent variable	1.933	1.933	1.933	1.933
Std. of dependent variable	0.582	0.582	0.582	0.582
Weather controls	N	N	Y	Y
Residential City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Respondent's Birth City FE	Y	Y	Y	N
Cohort FE	N	Y	N	Y

Notes: The instrumental variables specification in the panel B uses the strength of thermal inversions. We control for the number of children and marital status of each respondent across all specification in columns 1-4. We use individual-level pooled cross-sectional data constructed by CLDS 2014, 2016 and 2018. We use the full sample reproductive-age Han women irrespective of their marital status and childbearing histories. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Table of Contents

A.1 Summary Statistics and First-Stage Results

Table A1: Summary Statistics

Variable name	Description	Mean	Std. dev
Individual fertility choices	Indicator = 1 if a reproductive-age woman who had not had children one year prior gave birth within the last 12 months, =0 otherwise	0.36	0.48
Ideal number of children	Ideal number of children perceived a reproductive-age woman irrespective of her childbearing histories and socioeconomic status and government birth control policies	1.96	0.61
Air pollution exposure	PM2.5 concentration	46.8	15.45
Temperature	Annual mean temperature	149.99	47.87
Sunshine duration	Annual total sunshine hours	19,773.80	4,850.05
Distance to Tianjin seaport		992.52	583.23
Distance to Shanghai seaport		1,016.57	553.54
Distance to Shenzhen seaport		1,336.22	688.07
Distance to the nearest big city		111.83	106.95

Note: Table shows summary statistics for outcome variables and key control variables.

Table A2: The First Stage Across Different Instruments

	(1)	(2)	(3)	(4)
	Dependent variable: PM2.5 concentration			
Panel A: Thermal Inversions IV				
Strength of inversions	0.0607***	0.0561***	0.0558***	0.0558***
	(0.00998)	(0.0102)	(0.0102)	(0.0102)
Observations	96,910	96,910	96,910	96,910
Adjusted R-squared	0.585	0.595	0.596	0.596
F-value	37.06	30.14	30.08	30.13
Panel B: Wind IV				
Wind Direction and Coal Plants	0.0326***	0.0323***	0.0322***	0.0322***
	(0.00311)	(0.00298)	(0.00297)	(0.00296)
Observations	96,910	96,910	96,910	96,910
Adjusted R-squared	0.634	0.664	0.665	0.665
F-value	109.8	117.9	118.1	118.4
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: We use individual data to estimate the first-stage regression of thermal inversion IV in panel A and of wind direction IV in Panel B. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Additional Control Variables

Table A3: Actual Fertility Decisions and Additional Controls

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
	Panel A: Add Housing Costs			
Annual Mean PM2.5	-0.00398*	-0.00390*	-0.00388*	-0.00371*
	(0.00215)	(0.00206)	(0.00206)	(0.00203)
Three-year PM2.5 Change	-0.0118**	-0.0116**	-0.0117**	-0.0112**
	(0.00555)	(0.00540)	(0.00545)	(0.00535)
	Panel B: Add Economic Controls			
Annual Mean PM2.5	-0.00287	-0.00287	-0.00286	-0.00275
	(0.00186)	(0.00187)	(0.00188)	(0.00185)
Three-year PM2.5 Change	-0.0121***	-0.0121***	-0.0122***	-0.0118**
	(0.00466)	(0.00463)	(0.00470)	(0.00459)
Observations	91,869	91,869	91,869	91,869
	Panel C: Add Hospital Infrastructures			
Annual Mean PM2.5	-0.00247	-0.00248	-0.00244	-0.00230
	(0.00166)	(0.00164)	(0.00165)	(0.00163)
Three-year PM2.5 Change	-0.00894*	-0.00893*	-0.00905*	-0.00854*
	(0.00482)	(0.00485)	(0.00491)	(0.00481)
Observations	93,647	93,647	93,647	93,647
	Panel D: Add Emissions Controls			
Annual Mean PM2.5	-0.00278	-0.00277	-0.00272	-0.00258
	(0.00191)	(0.00186)	(0.00187)	(0.00184)
Three-year PM2.5 Change	-0.0115**	-0.0114**	-0.0115**	-0.0110**
	(0.00524)	(0.00520)	(0.00527)	(0.00515)
Observations	92,261	92,261	92,261	92,261
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We use reproductive-age Han women who had not had children one-year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. Housing costs controls include city-specific yearly housing price and three-year change in housing price. Economic controls include GDP per capita, three-year change in GDP per capita, unemployment rate and three-year change in the employment rate. Hospital Infrastructure include the number of hospitals, the number of hospital beds and three-year changes in the two measures of hospital infrastructures. Emissions Controls include industrial SO2 emission, industrial NO_x emission and three-year changes in the two measures of industrial emissions. Standard errors that are clustered at the city level are reported in parentheses p < 0.10, ** p < 0.05, *** p < 0.01.

TableA4 Add Weather and Geological Controls: For Thermal Inversions IV

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Annual Mean PM2.5	-0.00347*	-0.00349*	-0.00348*	-0.00333*
	(0.00185)	(0.00191)	(0.00192)	(0.00188)
Three-year PM2.5 Change	-0.0112**	-0.0113**	-0.0114**	-0.0109**
	(0.00501)	(0.00513)	(0.00520)	(0.00504)
Observations	89,143	89,143	89,143	89,143
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We use reproductive-age Han women who had not had children one-year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. In addition, we control for annual rainfall, wind speed, humidity, three-year changes in rainfall, wind speed, humidity, fraction of the region area under water coverage, and whether on the coast. Standard errors that are clustered at the city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A5: Ideal number of children and Additional Controls

	(1)	(2)	(3)	(4)
	Dependent variable: Ideal number of children perceived by women			
Panel A: Control for housing price				
Annual Mean PM2.5	0.0347	0.0314	0.0472	0.0427
	(0.0274)	(0.0252)	(0.0346)	(0.0306)
Three-year PM2.5 Change	-0.0407*	-0.0379*	-0.0453*	-0.0415*
	(0.0227)	(0.0213)	(0.0265)	(0.0239)
Observations	4,808	4,807	4,808	4,807
Panel B: Control for other pollutant				
Annual Mean PM2.5	0.0101	0.0102	0.0112	0.0112
	(0.0101)	(0.0103)	(0.0185)	(0.0193)
Three-year PM2.5 Change	-0.0134*	-0.0138*	-0.0215*	-0.0224*
	(0.00791)	(0.00812)	(0.0120)	(0.0126)
Observations	12,994	12,994	12,994	12,994
Weather controls	N	N	Y	Y
Demographics	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Birth City FE	Y	Y	Y	Y
Cohort FE	N	Y	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. We control for the number of children and marital status of each respondent across all specification in columns 1-4. We use individual-level pooled cross-sectional data constructed by CLDS 2014, 2016 and 2018. We use the full sample reproductive-age Han women irrespective of their marital status and childbearing histories. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

A.3 Alternative Source of Variation--Wind Direction IV

Table A6: Wind Direction IV

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Annual Mean PM2.5	-0.00337	-0.00369	-0.00373	-0.00340
	(0.00283)	(0.00316)	(0.00322)	(0.00309)
Three-year PM2.5 Change	-0.00915*	-0.00898*	-0.00898*	-0.00850*
	(0.00519)	(0.00501)	(0.00507)	(0.00489)
Observations	96,910	96,910	96,910	96,910
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: Instrumental variables specification using the interaction between wind direction, distance to coal plant, and coal consumption at power plant. Individual data come from 2010 Population Census of China. We use reproductive-age Han women who had not had children one-year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Data come from 2010 Population Census of China. We use individual-level data of Han women who had not had children one-year prior to the census. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Different Distance Bins for Selection of Power Plants

	Dependent variable: Giving birth within the last 12 months (=1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A							
	Baseline Results				Exclude 60km			
Annual Mean PM2.5	-0.00337	-0.00369	-0.00373	-0.00340	-0.00308	-0.00343	-0.00349	-0.00317
	(0.00283)	(0.00316)	(0.00322)	(0.00309)	(0.00276)	(0.00318)	(0.00325)	(0.00313)
Three-year PM2.5 Change	-0.00915*	-0.00898*	-0.00898*	-0.00850*	-0.00883*	-0.00877*	-0.00879*	-0.00834*
	(0.00519)	(0.00501)	(0.00507)	(0.00489)	(0.00482)	(0.00478)	(0.00485)	(0.00469)
	Panel B							
	Exclude 110km				Exclude 150km			
Annual Mean PM2.5	-0.00249	-0.00275	-0.00275	-0.00238	-0.00254	-0.00254	-0.00254	-0.00209
	(0.00330)	(0.00374)	(0.00381)	(0.00370)	(0.00414)	(0.00414)	(0.00425)	(0.00408)
Three-year PM2.5 Change	-0.00893*	-0.00897*	-0.00891*	-0.00847*	-0.00891*	-0.00891*	-0.00887*	-0.00838*
	(0.00505)	(0.00512)	(0.00516)	(0.00504)	(0.00465)	(0.00465)	(0.00472)	(0.00457)
Observations	96,910	96,910	96,910	96,910	96,910	96,910	96,910	96,910
Weather controls	Y	Y	Y	Y	Y	Y	Y	Y
City controls	Y	Y	Y	Y	Y	Y	Y	Y
City-Tier FE	N	Y	N	N	N	Y	N	N
Cohort FE	N	N	Y	N	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y	N	N	N	Y

Notes: Instrumental variables specification using the interaction between wind direction, distance to coal plant, and coal consumption at power plant. Individual data come from 2010 Population Census of China. We use reproductive-age Han women who had not had children one-year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. We replicate the results of Table A7 in columns (1)-(4) of Panel A, exclude plants within 60 km around the city in columns (5)-(8) of Panel B, exclude plants within 110 km in columns (1)-(4) of Panel B, and exclude plants within 150 km in columns (5)-(8) of Panel B. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Excluding Newly Built Power Plants

	Dependent variable: Giving birth within the last 12 months (=1)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A							
	Plants> 5 yrs ago				Plants> 15 yrs ago			
Annual Mean PM2.5	-0.00331	-0.00345	-0.00338	-0.00311	-0.00261	-0.00333	-0.00346	-0.00363
	(0.00248)	(0.00254)	(0.00255)	(0.00246)	(0.00192)	(0.00251)	(0.00253)	(0.00258)
Three-year PM2.5 Change	-0.00948*	-0.00903*	-0.00885*	-0.00842*	-0.00820*	-0.00933*	-0.00957*	-0.0100*
	(0.00528)	(0.00472)	(0.00471)	(0.00457)	(0.00426)	(0.00526)	(0.00537)	(0.00549)
	Panel B							
	Plants> 20 yrs ago				Plants> 25 yrs ago			
Annual Mean PM2.5	-0.00558**	-0.00752	-0.00778	-0.00792	-0.00468	-0.00550	-0.00564	-0.00577
	(0.00276)	(0.00460)	(0.00472)	(0.00481)	(0.00316)	(0.00386)	(0.00391)	(0.00398)
Three-year PM2.5 Change	-0.0132**	-0.0162*	-0.0167*	-0.0170*	-0.0122**	-0.0132**	-0.0135**	-0.0138**
	(0.00528)	(0.00828)	(0.00852)	(0.00868)	(0.00556)	(0.00644)	(0.00655)	(0.00665)
Observations	96,910	96,910	96,910	96,910	96,910	96,910	96,910	96,910
Weather controls	Y	Y	Y	Y	Y	Y	Y	Y
City controls	Y	Y	Y	Y	Y	Y	Y	Y
City-Tier FE	N	Y	N	N	N	Y	N	N
Cohort FE	N	N	Y	N	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y	N	N	N	Y

Notes: Instrumental variables specification using the interaction between wind direction, distance to coal plant, and coal consumption at power plant. Individual data come from 2010 Population Census of China. We use reproductive-age Han women who had not had children one-year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. We use power plants built more than 5 years ago in columns 1-4 of Panel A, plants built more than 15 years ago in columns 5-8 of Panel A, plants built more than 20 years ago in columns 1-4 of Panel A and plants built more than 25 years ago in columns 5-8 of Panel B. Standard errors that are clustered at the city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A9: Excluding Coal Producing Region

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Annual Mean PM2.5	-0.00342	-0.00359	-0.00362	-0.00336
	(0.00237)	(0.00256)	(0.00260)	(0.00251)
Three-year PM2.5 Change	-0.00905*	-0.00885**	-0.00882*	-0.00840*
	(0.00474)	(0.00448)	(0.00453)	(0.00439)
Observations	94,137	94,137	94,137	94,137
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: Instrumental variables specification using the interaction between wind direction, distance to coal plant, and coal consumption at power plant. Individual data come from 2010 Population Census of China. We use reproductive-age Han women who had not had children one-year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A10: Controlling for Electricity Demand

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Panel A: Add Industrial Elec. Cons.				
Annual Mean PM2.5	-0.00367	-0.00399	-0.00402	-0.00369
	(0.00314)	(0.00368)	(0.00375)	(0.00360)
Three-year PM2.5 Change	-0.00998*	-0.00995*	-0.0100*	-0.00953*
	(0.00538)	(0.00536)	(0.00543)	(0.00523)
Observations	93,383	93,383	93,383	93,383
Panel B: Add Elec. Cons.				
Annual Mean PM2.5	-0.00323	-0.00346	-0.00348	-0.00314
	(0.00308)	(0.00353)	(0.00360)	(0.00346)
Three-year PM2.5 Change	-0.00924*	-0.00920*	-0.00925*	-0.00876*
	(0.00527)	(0.00520)	(0.00527)	(0.00507)
Observations	93,383	93,383	93,383	93,383
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: Instrumental variables specification using the interaction between wind direction, distance to coal plant, and coal consumption at power plant. Individual data come from 2010 Population Census of China. We use reproductive-age Han women who had not had children one-year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A11 Baseline Economy and the Wind Direction IV

Dependent variable:	The ratio of upwind plants		Wind direction and coal plants IV	
	(1)	(2)	(3)	(4)
Baseline GDP	-0.00103	-0.00163	-0.245	-0.199
	(0.00318)	(0.00313)	(0.258)	(0.273)
Log Baseline Population	-0.0211	-0.0222	-0.0125	0.0684
	(0.0289)	(0.0293)	(2.170)	(2.194)
Log Baseline Total Elec cons	-0.0504	-0.0627	-2.690	-1.738
	(0.0694)	(0.0735)	(4.721)	(5.134)
Log Baseline Industrial Elec cons	0.0382	0.0465	3.428	2.789
	(0.0563)	(0.0587)	(3.838)	(4.056)
Observations	277	277	277	277
Adjusted R-squared	0.0683	0.0657	0.317	0.315
Region FE	Yes	Yes	Yes	Yes
City-Tier FE	No	Yes	No	Yes

Notes: City-level regression. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Dependent variables are based on power plants built post 2005, and independent variables are measured in the year 2004. We drop cities with missing values in baseline characteristics. Standard errors clustered at the city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

A.4 Results of Individual-Level Longitudinal Panel

Table A12: Results of Individual Longitudinal Panel

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth in a particular year (=1)			
	Panel A: Baseline			
Annual Mean PM2.5	0.0104	0.00918	0.00942	0.00988
	(0.00670)	(0.00589)	(0.00610)	(0.00644)
Three-year PM2.5 Change	-0.00622*	-0.00559*	-0.00562*	-0.00582*
	(0.00354)	(0.00315)	(0.00321)	(0.00338)
	Panel B: Add weather controls			
Annual Mean PM2.5	0.00976	0.00860	0.00877	0.00913
	(0.00627)	(0.00553)	(0.00568)	(0.00586)
Three-year PM2.5 Change	-0.00643*	-0.00581*	-0.00578*	-0.00599*
	(0.00355)	(0.00318)	(0.00321)	(0.00332)
Observations	43,400	43,400	43,400	43,400
Individual FE	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Region × Year FE	Y	Y	Y	N
City-Tier FE × Year FE	N	N	Y	N
Region × City-Tier FE × Year FE	N	N	N	Y

Notes: We use individual-level longitudinal panel data that tracks the childbearing histories of individual women. The panel data are constructed based on information in CLDS 2014. We control for the number of children thar each respondent had one year prior across all specification in columns 1-4. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.5 Results of Ethnic Minorities

Table A13: Fertility Choices of Ethnic Minorities

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Panel A Minority Women Who Hadn't Had Children One-Year Prior				
Annual Mean PM2.5	-0.000102	-0.000465	-0.000623	-0.000739
	(0.00216)	(0.00197)	(0.00209)	(0.00199)
Three-year PM2.5 Change	-0.00160	-0.000614	-0.00337	-0.00315
	(0.0123)	(0.0105)	(0.0105)	(0.0103)
Observations	11,103	11,103	11,103	11,103
Panel B：Minority Women Irrespective of Childbearing Histories				
Annual Mean PM2.5	-0.000556	-0.000610	3.62e-05	2.77e-05
	(0.00116)	(0.00129)	(0.000409)	(0.000419)
Three-year PM2.5 Change	-0.00832*	-0.00809*	0.00165	0.00174
	(0.00472)	(0.00447)	(0.00327)	(0.00330)
Observations	82,523	82,523	82,523	82,523
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Cohort FE	N	N	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We use reproductive-age ethnic minority women. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Using Minority Samples Who Work in Urban Areas

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Panel A Minority Women Who Hadn't Had Children One-Year Prior				
Annual Mean PM2.5	0.00109	0.000935	0.000256	-0.000226
	(0.00737)	(0.00791)	(0.00792)	(0.00852)
Three-year PM2.5 Change	-0.0408	-0.0394	-0.0403	-0.0448
	(0.0417)	(0.0355)	(0.0346)	(0.0397)
Observations	1,499	1,499	1,497	1,494
Panel B Minority Women Irrespective of Childbearing Histories				
Annual Mean PM2.5	-0.000859	-0.000909	-8.52e-05	-6.91e-05
	(0.00165)	(0.00167)	(0.00106)	(0.00103)
Three-year PM2.5 Change	-0.0116	-0.0107	-0.00562	-0.00532
	(0.0109)	(0.00722)	(0.00494)	(0.00482)
Observations	10,645	10,645	10,644	10,643
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We use reproductive-age ethnic minority women. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A15: The OCP and the Differential Fertility Response to Pollution

	(1)	(2)	(3)
	Dependent variable: Giving birth within the last 12 months (=1)		
Three-year PM2.5 Change × Han Indicator × Log OCP Fines	-0.0221*	-0.0218*	-0.0222*
	(0.0126)	(0.0127)	(0.0128)
Observations	21,800	21,799	21,799
Weather controls	Y	Y	Y
City controls	Y	Y	Y
City-Tier FE	Y	Y	Y
Cohort FE	N	Y	N
City Trend	N	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We use the amount of fines for violating the OCP at the provincial level in the baseline year of 2000. We include reproductive-age ethnic minority women and Han women, and restrict the sample to those who had not had children one year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: The OCP and Preferences for the College Education of Children

	(1)	(2)	(3)	(4)
	Dependent variable: College education is useful for children (=1)			
Log OCP fines	-0.0509***	-0.0414***	-0.0338**	-0.0344**
	(0.0144)	(0.0127)	(0.0159)	(0.0160)
Observations	9,928	9,928	9,928	9,928
Adj. R-squared	0.0155	0.0285	0.0286	0.0289
City controls	N	N	Y	Y
City-Tier FE	N	Y	N	Y

Note: We use the amount of fines for violating the OCP at the provincial level in the baseline year of 2000. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Data come from CLDS 2016, as only CLDS 2016 records information on whether parents attach importance to college education. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: A Random Han Sample with the Same Sample Size as the Minorities

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Annual Mean PM2.5	-0.00430	-0.00427	-0.00436	-0.00408
	(0.00308)	(0.00300)	(0.00306)	(0.00298)
Three-year PM2.5 Change	-0.0192**	-0.0191**	-0.0198**	-0.0190**
	(0.00790)	(0.00765)	(0.00785)	(0.00761)
Observations	11,103	11,103	11,102	11,101
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We include reproductive-age Han women who had not had children one year prior to the census. We draw a random Han women sample of which the sample size is the same as the ethnic minority sample. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.6 Tests of Underlying Mechanisms

Table A18: Early Childhood PM2.5 Exposure and Parental Expenditure

	(1)	(2)	(3)	(4)
	Panel A: Total Expenditure per Child			
PM2.5 Exposure (between 0-2 years)	0.0701***	0.0707***	0.0559***	0.0555***
	(0.0240)	(0.0237)	(0.0208)	(0.0206)
	Panel B: Health Expenditure per Child			
PM2.5 Exposure (between 0-2 years)	0.0246	0.0247	0.0338**	0.0344**
	(0.0162)	(0.0165)	(0.0166)	(0.0166)
	Panel C: Education Expenditure per Child			
PM2.5 Exposure (between 0-2 years)	0.0972***	0.0978***	0.0619**	0.0622**
	(0.0340)	(0.0332)	(0.0249)	(0.0248)
Observations	6,538	6,538	6,538	6,538
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Cohort FE	N	N	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Household-level data come from 2014 China Family Panel Studies (CFPS). Total expenditure includes health expenditure, education expenditure and other types of expenditure on children. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Differential Effected of Increased Pollution by Air Purifier Prices

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
	HEPA Purifier		**Non-HEPA Purifier**	
Three-year PM2.5 Change × Log Air Purifier Price	-0.0127*	-0.0125*	-0.00595	-0.00562
	(0.00666)	(0.00653)	(0.00459)	(0.00449)
Observations	40,564	40,564	0.000612	0.000684
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
Cohort FE	Y	N	Y	N
City-Tier FE × Year FE	Y	Y	Y	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We include reproductive-age Han women who had not had children one year prior to the census. We use city-specific average air purifier prices three year prior to the census, the data of which come from a marketing firm in China. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Heterogenous Effects on Fertility Choices

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Panel A: Heterogeneity by mother's education levels				
Annual Mean PM2.5	-0.00144	-0.00141	-0.00126	-0.00118
	(0.00190)	(0.00187)	(0.00184)	(0.00183)
Three-year PM2.5 Change	0.0101	0.0103	0.0112	0.0112
	(0.0110)	(0.0108)	(0.0108)	(0.0106)
Three-year PM2.5 Change ×Years of Schooling of Mothers	-0.00176**	-0.00177**	-0.00182**	-0.00179**
	(0.000853)	(0.000850)	(0.000852)	(0.000835)
Observations	96,910	96,910	96,910	96,910
Panel B: Heterogeneity by rates of return on human capital				
Annual Mean PM2.5	-0.00128	-0.00211	-0.00207	-0.00193
	(0.00180)	(0.00189)	(0.00189)	(0.00188)
Three-year PM2.5 Change	0.0172	0.00142	0.00130	0.00185
	(0.0107)	(0.00804)	(0.00813)	(0.00798)
Three-year PM2.5 Change × Return to College Education	-0.0417***	-0.0191*	-0.0189*	-0.0190*
	(0.0152)	(0.0109)	(0.0110)	(0.0108)
Observations	96,897	96,897	96,897	96,897
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We include reproductive-age Han women who had not had children one year prior to the census. We run Mincer wage regression city by city to estimate the city-specific Mincerian returns to college education in the baseline year of 2005. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses.

Table A21: Accounting for Income Effects on Actual Fertility Choices

	(1)	(2)	(3)	(4)
	Dependent variable: Giving birth within the last 12 months (=1)			
Annual Mean PM2.5	-0.00361*	-0.00354**	-0.00349**	-0.00338**
	(0.00185)	(0.00171)	(0.00172)	(0.00169)
Three-year PM2.5 Change	-0.0113**	-0.0112**	-0.0112**	-0.0108**
	(0.00501)	(0.00479)	(0.00483)	(0.00474)
Observations	89,311	89,311	89,311	89,311
Weather controls	Y	Y	Y	Y
City controls	Y	Y	Y	Y
City-Tier FE	N	Y	N	N
Cohort FE	N	N	Y	N
City-Tier FE× Year FE	N	N	N	Y

Notes: We account for income across all specifications of columns 1-4. Instrumental variables specification using the strength of thermal inversions. Individual data come from 2010 Population Census of China. We include reproductive-age Han women who had not had children one year prior to the census. City controls include the distance to Shanghai, Tianjin and Shenzhen seaport and the distance to the nearest big city. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses

Table A22: Accounting for Income Effects on the Ideal Number of Children

	(1)	(2)	(3)	(4)
	Dependent variable: Ideal number of children perceived by women			
Annual Mean PM2.5	0.0159	0.0160	0.0186	0.0188
	(0.0116)	(0.0116)	(0.0119)	(0.0121)
Three-year PM2.5 Change	-0.0182**	-0.0184**	-0.0214*	-0.0216*
	(0.00828)	(0.00837)	(0.0117)	(0.0117)
Observations	15,420	15,420	15,420	15,420
Weather controls	N	N	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Birth City FE	Y	Y	Y	Y
Cohort FE	N	Y	N	Y

Notes: We account for income across all specifications of columns 1-4. Instrumental variables specification using the strength of thermal inversions. We additionally control for the number of children and marital status of each respondent across all specification in columns 1-4. We use individual-level pooled cross-sectional data constructed by CLDS 2014, 2016 and 2018. We use the full sample reproductive-age Han women irrespective of their marital status and childbearing histories. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Air Pollution and Infertility

	(1)	(2)	(3)	(4)
	Dependent variable: Infertility (=1)			
Annual Mean PM2.5	-0.00293	-0.00303	-0.00237	-0.00241
	(0.00231)	(0.00234)	(0.00413)	(0.00421)
Three-year PM2.5 Change	0.000779	0.000807	-0.00304	-0.00312
	(0.000970)	(0.000985)	(0.00508)	(0.00518)
Observations	9,395	9,393	9,395	9,393
Weather controls	N	N	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Birth City FE	Y	Y	Y	Y
Cohort FE	N	Y	N	Y

Notes: The dependent variable is an indicator for weather a particular reproductive age woman suffers from infertility. Instrumental variables specification using the strength of thermal inversions. Instrumental variables specification using the strength of thermal inversions. We use individual-level pooled cross-sectional data constructed by CLDS 2014, 2016. We use the full sample reproductive-age Han women irrespective of their marital status and childbearing histories. Weather controls include temperature, three-year change in temperature, sunshine duration and three-year change in sunshine duration. Standard errors that are clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.