Pollution, Ability, and Gender-Specific Investment Responses to Shocks

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Abstract

This paper explores how labor market conditions drive gender differences in the human capital decisions of men and women. Specifically, I investigate how male and female schooling decisions respond to an exogenous change in cognitive ability. Using data from Mexico, I begin by documenting that in utero exposure to

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thermal inversions, which exacerbate air pollution, leads to lower cognitive ability in adulthood for both men and women. I then explore how male and female schooling decisions respond differentially to this cognitive shock: for women only, pollution exposure leads to reduced educational attainment and income. I show that this gender difference is explained by the fact that women disproportionately sort into white-collar jobs, where schooling and ability are more complementary than they are in blue-collar jobs.

Keywords: gender, occupational choice, early life, pollution, education, Mexico

JEL Codes: I26, Q53, J24

1. Introduction

In both developed and developing countries, there are systematic differences in the human capital decisions made by men and women. For schooling decisions, specifically, there are well-documented gender differences in schooling levels, schooling returns, and the trends in both of these over time (Psacharopoulos and Patrinos, 2004; Grant and Behrman, 2010; Pitt et al., 2012; Rosenzweig and Zhang, 2013). Importantly, it is also clear that men and women differ in their schooling *responses* to various shocks, including individual early-life health shocks (Bobonis et al., 2006; Maluccio et al., 2009; Field et al., 2009; Maccini and Yang, 2009) and country-wide technological change (Rendall, 2017).

In this paper, I explore how the labor market can drive gender differences in the schooling response to an early-life health shock. After documenting that a negative shock to cognitive ability translates into different schooling responses for men and women, I investigate whether gender-specific labor market opportunities are responsible for these differences.

Using the Mexican Family Life Survey, I first show that in utero exposure to poor air quality reduces adult cognitive ability for both men and women. To do this, I use thermal inversions, a meteorological phenomenon that negatively impacts air quality, as an exogenous source of variation in pollution levels. Exploiting within-municipality variation in thermal inversion exposure across birth cohorts, I find that men and women exposed to more thermal inversions (and thus worse pollution) during their second trimester in utero score significantly lower on Raven's tests of fluid intelligence as young adults. Many studies have shown that in utero exposure to air pollution can negatively affect birth outcomes (like birth weight or infant mortality),[1] but this paper contributes to a smaller body of research that looks at the longer-term impact of such exposure (Sanders, 2012; Isen et al., 2017; Bharadwaj et al., 2017; Peet, 2016; Rosales-Rueda and Triyana, 2018).[2] The importance of this line of research is growing rapidly: recent studies have revealed pollution as one of the main causes of disease and premature death worldwide (Landrigan et al., 2018),[3] but we have much to learn about the long-run effects of early-life exposure, especially in developing countries.

Having established that in utero exposure to pollution drives exogenous changes in cognitive ability, I then ask how male and female schooling decisions respond to this cognitive shock. For women, pollution exposure in the second trimester leads to significantly lower high school completion and income. Men, on the other hand, do not adjust their schooling decisions at all. Male income effects are negative, but not significantly different from zero.

I outline a simple model that highlights three potential labor market features that might explain the gender difference in the high school completion response. Men and women differ in their tendency to take up a white-collar job, their labor force participation, and their opportunity costs of schooling, all of which could be

1. See Chay and Greenstone (2003), Currie and Neidell (2005), Jayachandran (2009), and others summarized in Currie et al. (2014).

2. Another strand of research on long-term effects of pollution has focused on exposure to radiation from nuclear accidents (Almond et al., 2009; Black et al., 2014), a very different and more extreme case of air pollution than what is studied here.

3. In 2015, for example, pollution-related diseases were found to be responsible for 16% of deaths globally (Landrigan et al., 2018). This was three times more than the combination of deaths from AIDS, malaria, and tuberculosis.

responsible for the gender difference that I find. Empirically, however, white-collar sorting tendencies are the only labor market feature that are able to explain this gender difference.

Specifically, when I allow for the effect of pollution to vary across individuals facing different gender-specific white-collar opportunities, the gender difference in the high school completion response completely disappears. In addition, I find that the negative effect of inversions on high school completion is driven by those with more white-collar opportunities. These findings can be explained the fact that schooling and cognitive ability are more complementary in white-collar jobs (favored by women) than blue-collar jobs (favored by men), as these complementarities are what determine how an individual's schooling decision will respond to a cognitive shock. In short, these results provide empirical support for a commonly proposed but rarely tested hypothesis:[4] that gender differentials in the effects of early life shocks can be explained by gender-specific labor market conditions. I am able to rule out other explanations for my results, including son preference and gender differences in other characteristics (labor force participation, youth employment opportunities, marriage, income, and industry choices).

This paper extends the work of two important studies (Pitt et al., 2012; Rosenzweig and Zhang, 2013), which find evidence of gender-specific schooling responses to a physical health shock, similar to what I find in the context of a cognitive ability shock. In these studies, the authors formally model the idea that

4. Several studies have hypothesized that gender differences can stem from the different labor market conditions that men and women face (Bhalotra and Venkataramani, 2013; Cutler et al., 2010; Hoddinott et al., 2008; Bhalotra et al., 2016), but very little evidence for this hypothesis currently exists.

gender-specific occupational sorting might drive differential schooling responses across genders. My work expands on this knowledge by providing an empirical link between schooling responses and job opportunities, which allows me to quantify how much of the gender difference can be explained by this mechanism. In this context, I find that the gender difference is fully explained by these labor market conditions.

By emphasizing the interaction between early-life shocks and labor market opportunities, this paper speaks to two important questions in the literature. First, it sheds light on the substantial heterogeneity – both across and within studies – in the estimated schooling responses reported in the existing literature.[5] Given that labor market conditions vary over time, across space, and across groups, this heterogeneity can be explained by the main result of this paper: individuals facing different labor market opportunities respond differently to early-life shocks.

This paper also addresses the important question of how early-life shocks interact with policy interventions or economic conditions later in life. Whether these events are health or education interventions (Adhvaryu et al., 2018; Rossin-Slater and Wüst, 2019; Gunnsteinsson et al., 2014), economic shocks (Bharadwaj et al., 2019), or the labor market conditions studied in this paper, the fact that they interact with early-life conditions in ways we may not yet fully understand has implications for future policy and the interpretation of existing results.

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5. For example, many studies find that health conditions early in life have a substantial impact on educational attainment (Almond, 2006; Bleakley, 2007), while others find no effect (Venkataramani, 2012; Cutler et al., 2010), or much smaller effects for certain groups (Maluccio et al., 2009; Maccini and Yang, 2009; Field et al., 2009; Bleakley, 2010).

2. Background

In this section, I provide a brief background on the education system and occupations in Mexico, the biological effects of pollution, and the meteorological events known as thermal inversions that will provide the identifying variation for this study.

2.1. Education and Occupations in Mexico

This paper investigates the education decisions of men and women in Mexico. As in most countries, detailed information on exactly how individuals make their schooling decisions is limited,[6] but certain features of the school system and eventual occupation distributions are likely to be relevant to the schooling decision process. The school system in Mexico consists of six years of primary school, three years of junior high school (lower secondary), and four years of high school (upper secondary). Until 1992, compulsory schooling laws required six years of school. This requirement was increased to nine years in 1992, and then to eleven years in 2001. Of the cohorts that make up this study's sample, the majority were attending school during a period when either nine or eleven years were compulsory.

As illustrated in Appendix Figure A1, there is substantial variation in the educational attainment of Mexican adults in the 2000 and 2010 censuses. In the overall population, approximately 20-30% fall into each of the following education categories: no primary, only primary completed, only junior high completed,

6. Attanasio and Kaufmann (2014) use unique survey data from poor Mexican youths to document that schooling decisions depend on the expected returns to schooling and perceived unemployment and earnings risk. The perceptions of parents and children both seem to matter.

and high school completed. These education decisions seem to have important implications for the job an individual eventually obtains. Figure A1 also illustrates the vastly different education distributions for white-collar and blue-collar workers, classified using ISCO codes according to the brains-brawn categorization in Vogl (2014), summarized in Table 1. The vast majority of white-collar workers are high school graduates. 80% of white-collar workers have a high school degree, while only 14% report junior high as their highest level of education, suggesting that a white-collar job is difficult to obtain for those who have not completed high school.

Especially important to this paper are the differences in occupation distributions across gender, reported in Table 1. Here, I report the distribution across ISCO occupation codes for each gender. Female white-collar shares (35%) are much higher than male white-collar shares (20%). As shown in Appendix Figure A2, this is not unique to Mexico: similar patterns hold across several countries.

TABLE 1. Occupation Distributions by Gender

ISCO Occupation Code & Description	Male	Female
White-Collar ("Brains")	**19.85**	**35.34**
1 Legislators, senior officials and managers	3.89	3.49
2 Professionals	7.86	10.86
3 Technicians and associate professionals	3.46	8.74
4 Clerks	4.64	12.25
Blue-Collar ("Brawn")	**80.15**	**64.66**
5 Service workers and shop and market sales	16.41	27.93
6 Skilled agricultural and fishery workers	16.32	2.85
7 Crafts and related trades workers	23.36	8.99
8 Plant and machine operators and assemblers	13.02	4.99
9 Elementary occupations (domestic workers, laborers, etc)	11.04	19.9

Notes: Brain and brawn categorizations from Vogl (2014). Weighted percentages calculated from working adults aged 25 to 65 in the 2000 and 2010 Mexican census.

In Mexico, another important way in which men and women differ is in their labor force participation. In the 2000 and 2010 censuses, male labor force participation was around double the female labor force participation rate. These gender differences are also present for school-aged children. Boys under the age of 18 are also twice as likely to be working compared to girls of the same age, suggesting that the opportunity cost of schooling differs across genders.

2.2. Pollution

Substantial medical and epidemiological evidence demonstrates that in utero exposure to pollution can be harmful to the fetus (Lacasaña et al., 2005; Peterson et al., 2015; Le et al., 2012; Saenen et al., 2015; Backes et al., 2013). Concrete evidence that pins down the biological mechanisms is more limited, but there are a few commonly cited suspected pathways that primarily relate to two types of pollutants: carbon monoxide (CO) and particulate matter (PM-10 or PM-2.5).

As described in detail in Appendix Section B.1, both of these pollutants can disrupt the transport of blood, glucose, or oxygen to the fetus, which could in theory have negative impacts on both the physical and cognitive aspects of fetal development. Whether pollution exposure results in primarily physical or cognitive damage likely depends on the timing of exposure (Dobbing and Sands, 1973). For instance, because most neurogenesis takes place in the second trimester of pregnancy, this trimester is seen as a "critical period for the formation of cortical neurons" (Morgan and Gibson, 1991, p.10). In line with this, medical and economic studies on exposure to radiation flag the second trimester as the most sensitive period for brain development (Otake, 1998; Almond et al., 2009;

Black et al., 2014).[7] Although day-to-day air pollution and radiation are very different types of pollution, these radiation studies offer some generalizable lessons about the critical periods in brain development: second trimester exposure is also particularly detrimental for other external stressors, like influenza (Schwandt, 2018) and nutritional deficiencies (Morgan and Gibson, 1991).[8]

Individuals make different schooling decisions and earn different wages partially because of heterogeneous levels of ability. Any effect that in utero exposure to pollution has on schooling and labor market outcomes is likely working through its biological effect on this unobserved endowment, of which cognitive functioning is an important component.

The ideal data set for an analysis of the long-run effects of in utero exposure would consist of pollution data going back to the in utero months of my sample individuals, who are adults in the 2002 through 2009 waves of the MxFLS. Pollution measurements for CO, O_3, SO_2, NO_2, PM10, and most recently, PM2.5 are available for a total of 16 cities from Mexico's National Institute of Ecology (INECC). However, the majority of this spatially limited data does not go back far

7. Otake (1998) document that weeks 8 to 25 (late first and almost entire second trimester) are particularly crucial for brain development. Black et al. (2014) also find that the 3rd, 4th, and 5th months of pregnancy were the critical periods during which exposure to nuclear fallout resulted in lower IQ as adults.

8. The critical period highlighted by these studies coincides with crucial processes in the development of the fetal brain. The migration of neurons, from their place of origin to their final location in the brain, peaks in the second trimester and is largely complete by the beginning of the third trimester. Similarly, synaptic connections in the cortex are refined and become more permanent starting in the second trimester; this process peaks by the beginning of the third trimester (Tau and Peterson, 2010).

enough to study at-birth exposure of adults in the MxFLS. The earliest pollution measurements date back to 1986, but for only CO in Mexico City, for which there are large sections of missing data until about 1993.

The lack of high quality historical data going back far enough to link adults with their in utero exposure is a major obstacle to identifying the effects of pollution exposure at birth on later life outcomes, in this context as well as more generally. In order to circumvent this issue, I rely on thermal inversions, a meteorological phenomenon known to worsen air quality, as an exogenous source of variation in pollution levels for which there is data for all of Mexico dating back to 1979.

2.3. Thermal Inversions

Air temperature typically falls with altitude, but when a thermal inversion occurs, this relationship reverses, which results in a warm layer of air sitting above cooler air, trapping pollutants released near the surface. That thermal inversions can negatively impact air quality is well-documented, both in the atmospheric sciences literature (Jacobson, 2002) as well as more recently in the economics literature (Jans et al., 2018; Arceo et al., 2016).[9]

In general, inversions are the result of the combination of various atmospheric forces and geographic conditions. I argue that after controlling for all of the relevant main effects (fixed geographic characteristics, time of year, temperature, humidity, cloud coverage, etc.), the occurrence of a thermal inversion is exogenous: essentially the random interaction of all of the necessary conditions. Like Jans et al. (2018) and Arceo et al. (2016), I assume that thermal inversions can only affect my outcomes

9. See Appendix Section B.2 and Jacobson (2002) for a more detailed discussion of the different types and causes of inversions.

of interest through their effect on pollution levels, once I have controlled for all of the weather controls, geographic fixed effects, and non-linear time trends that I include in my regressions.

I identify thermal inversions in Mexico using the North American Regional Reanalysis (NARR) data, which provides air temperatures just above the surface and at various pressure levels above sea-level on a 0.3 x 0.3 degree grid (roughly 30km by 30 km) across the North American continent.[10] Using atmospheric modeling techniques, the NARR combines temperature, wind, moisture, and precipitation data from a number of different sources, including weather balloons, commercial aircraft recordings, ground-based rainfall measurements, and satellite data.[11] The resulting data set records, every three hours for each grid point, a wide array of meteorological variables at the surface, a few meters above the surface, and at 29 pressure levels (extending vertically into the atmosphere), from 1000 hPa (roughly equivalent to sea level) to 100 hPa (about 16,000 meters above sea-level).

To identify thermal inversions, I take the air temperature 2 meters above the surface[12] and subtract this from the air temperature recorded at the pressure level 25 hPa lower (roughly 300 meters higher) than the surface pressure at a given

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10. NCEP Reanalysis data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at http://www.esrl.noaa.gov/psd/.

11. See Mesinger et al. (2006) for more detail about the various data sources and model. See Appendix Section B.2 for a discussion of validation checks.

12. 2-meter temperature is what is reported by meteorologists in weather reports and is distinct from “skin” surface temperature, which the NARR also records.

location.[13] I identify an inversion episode as any time this difference is greater than zero, consistent with the American Meteorological Society's definition of an inversion (Glickman and Zenk, 2000) and how existing literature identifies them (Beard et al., 2012; Devasthale et al., 2010). I use the 25 hPa increment because this is the smallest increment between pressure levels available in the NARR data. Looking further above the surface (50 hPa or 75 hPa, for example) does not detect many additional inversions and therefore, unsurprisingly, leaves my results virtually unchanged. In general, I am most interested in the inversions close to the surface as they are likely to have the largest effects on air quality.

Like Jans et al. (2018), I focus on nighttime inversions. There is greater variation in the occurrence of nighttime (compared to daytime) inversions over time and across space, which makes nighttime inversions much stronger predictors of pollution in my first-stage checks. Moreover, nighttime inversions are much less visible than daytime inversions and are therefore less likely to generate behavioral responses.[14]

In addition to using the NARR to identify thermal inversions, I also utilize this data set's relative humidity, wind speed, and total cloud coverage variables as important controls in all specifications. Although precipitation is also available in the NARR data set, I use ground measurements recorded by Mexico's National

13. Because of varying surface altitude across Mexico, I do not take temperature from the same pressure level for all points. For example, for a municipality at sea level, I use the temperature at 975 hPa, whereas for a higher-altitude location in Mexico City, I use the 700 pressure level because the surface pressure is 725.

14. Daytime inversions are not always visible but are more likely to be seen in warm and humid climates like Mexico's.

Meteorological Service (CONAGUA) to control for rainfall because these should be measured with less error.

As mentioned above, Mexican pollution measures do not date back far enough to enable me to use thermal inversions as an instrument for in utero exposure to pollution, as Arceo et al. (2016) do in their study of the contemporaneous effects of pollution. However, using the pollution measures that do exist, I check whether thermal inversions drive pollution levels in the years and cities for which I have pollution data. To establish a link between thermal inversions (I_{jym}) and pollution levels (P_{jym}) in a given municipality j, during the three-month period starting from month m in year y, I run the following regression:

$$P_{jym} = \alpha_1 I_{jym} + \alpha_2' W_{jym} + \mu_j + \delta_y + \alpha_m + v_{jym}. \tag{1}$$

P_{jym} represents a pollution measure averaged over the three month period starting in month m of year y. I aggregate to the three-month level because my main analysis studies the effects of pollution by trimester. I look at CO (8-hour daily maximum), PM-10 (mean), SO_2 (mean), NO_2 (mean), and O_3 (8-hour daily maximum). I_{jym} represents the average number of days per month with a nighttime inversion in that same three-month period. I include municipality (μ_j), year (δ_y), and month (α_m) fixed effects. W_{jym} is a vector of flexible weather controls (also averaged across the three month period): linear, quadratic, and cubic terms of minimum, maximum, and mean 2-meter temperature, rainfall, relative humidity, wind speed, and total cloud coverage. In this regression, these weather controls are important because they influence the likelihood of a thermal inversion but also have the potential to directly affect pollution levels. In the later analysis, their inclusion is crucial to ensure that thermal inversions are affecting my outcomes of interest only via the pollution channel, and not through these weather variables.

Table 2 reports the results of this regression, using data from 1994, when more complete data was being recorded, to 2009, the last year of available pollution data. Even after controlling for a complete set of fixed effects and weather controls, inversions are positively and significantly related to both CO and PM-10 levels. The F-statistics in this "quasi-first-stage" exceed conventional thresholds for strong instruments. There are no significant effects of thermal inversions on SO_2, NO_2, or O_3, consistent with the findings of Arceo et al. (2016). When I later estimate the reduced form effect of thermal inversions on various outcomes of interest, all of the effects should be interpreted as operating through the effect of thermal inversions on CO and PM-10 (and not the other pollutants).

Table 2. Relationship between Thermal Inversions and Pollution

	(1)	(2)	(3)	(4)	(5)
	CO	PM-10	SO_2	NO_2	O_3
Average Monthly Inversions During 3-Month Period	0.0140***	0.474***	-0.000523	-0.00481	-0.0000252
	(0.00254)	(0.0828)	(0.000406)	(0.00292)	(0.0000457)
N	23821	21292	25083	21939	24294
Mean of DV	2.306	55.17	0.0225	0.0806	0.0544
Fstat	30.449	32.835	1.662	2.717	.304

Notes: * p< 0.1 ** p< 0.05 *** p< 0.01. Standard errors (clustered at municipality level) in parentheses. The dependent variables are three-month averages of CO (8-hour daily maximum, in ppm), PM-10 (mean in $\mu g/m^3$), SO_2 (mean in ppm), NO_2 (mean in ppm), and O_3 (8-hour daily maximum, in ppm). All regressions control for month, year, and municipality fixed effects, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, average monthly relative humidity, average monthly precipitation, and average monthly cloud coverage during each relevant 3-month period.

3. Data

This section outlines the outcome data used to document the effects of thermal inversions on later-life outcomes and pin down the role played by the local labor market. More details are provided in Appendix Section B.3.

3.1. Mexican Family Life Survey

All outcome variables come from the Mexican Family Life Survey (MxFLS), a nationally representative longitudinal household survey that began in 2002 and conducted follow-ups in 2005 and 2009. In addition to collecting standard demographic, schooling, and employment information, this survey also measured several physical biomarkers (like height) and administered Raven's tests of fluid intelligence.

I use scores from the "adult" version of the Raven's test, which was administered in the MxFLS to all individuals aged 13 and older. This test consisted of 12 multiple choice questions taken from the Standard Progressive Matrices.[15] Each question presents a three-by-three matrix of symbols, with one symbol missing, and subjects are asked to pick the correct symbol to fill in the blank. In the MxFLS, respondents took the test on paper, in a quiet location of the house (if possible), and were given 30 minutes to complete the test (though the majority finished in 15 minutes or less).

15. The Standard Progressive Matrices are the original Raven's tests. The easier Colored Progressive Matrices, developed later, were used for children in the MxFLS. The more complicated Advanced Progressive Matrices were not used.

Raven's tests capture what is known as fluid intelligence or analytic intelligence – "the ability to reason and solve problems involving new information, without relying extensively on an explicit base of declarative knowledge derived from either schooling or previous experience" (Carpenter et al., 1990, p.1). These test scores are highly correlated with performance in other complex cognitive tests (Vernon and Parry, 1949; Carpenter et al., 1990).

I use these Raven's test scores, height, educational attainment, and earned annual income as my main outcomes of interest. I include individuals found in any wave of the survey in order to obtain as large of a sample as possible. For all outcomes except for Raven's scores, I take the outcome from the most recent wave in which the individual was interviewed. For Raven's tests, I use each individual's first test score in order to minimize the effect that test-taking experience (either from the survey or elsewhere) may have on their scores.[16]

Another key variable obtained from the MxFLS is municipality of birth, a restricted-use variable that enables me to link adults and adolescents (including those who have migrated) with thermal inversion exposure specific to their birthplace at their time of birth. More details about the construction of individual-level variables are provided in Appendix Section B.3.

Table 3 reports summary statistics, by gender, for the outcomes and main regressors for all individuals with non-missing thermal inversion data (implying a non-missing birth month, birth municipality, and birth year after 1978) and who were at least 15 years of age in the last MxFLS wave in which they appeared. These are the individuals old enough to have been included in the migration module of

16. It should be noted that the same set of 12 questions were used for the Raven's test in all three survey waves.

Table 3. Summary Statistics

Variable Name	Female Mean	Female S.D.	Female N	Male Mean	Male S.D.	Male N
Outcome Variables						
Raven's test score (proportion correct)	0.55	0.229	5455	0.56	0.226	4865
Height (cm)	155.20	7.722	5506	166.06	10.27	4892
Years of schooling	9.52	3.075	5634	9.20	3.074	5081
Annual income	24555.65	22352.4	954	31405.04	74474.1	2043
Control Variables						
Mother's Education	6.00	3.853	5204	6.36	3.804	4566
Father's Education	6.34	4.279	4832	6.69	4.226	4258
Age for Raven's Test variable	17.24	3.319	5455	17.12	3.398	4865
Age for height variable	20.38	4.491	5506	19.86	4.507	4892
Age for schooling variables	20.45	4.424	5634	19.94	4.463	5081
Age for income variable	22.56	3.627	954	22.36	3.693	2043
			Full Sample			
Inversion Variables	Mean	SD	10th pctile	Median	90th pctile	N
Average monthly inversions during trimester 1	18.09	8.206	5.93	19.23	28	10848
Average monthly inversions during trimester 2	17.93	8.235	5.69	18.94	28	10848
Average monthly inversions during trimester 3	17.80	8.288	5.54	18.94	28	10848

Notes: Sample includes individuals with non-missing thermal inversion data who were at least 15 years of age in the last MxFLS wave in which they appeared.

the survey, which obtains information about place of birth. I report raw means for Raven's test scores and height in this table but use standardized variables in the regressions.[17] The sample size for annual income is much smaller compared to the other variables, primarily because I restrict to those who report work as their primary activity in the week prior to the survey.[18] I do this in order to exclude those still in school but working part-time, whose income is likely a poor representation of their labor market productivity or lifetime earning potential.

17. I standardize test scores using the full sample mean and standard deviation. For height, I use WHO standards for everyone under 20 and for the remainder of the sample simply standardize using the gender-specific mean and standard deviation of the sample population 20 and older. I identify and drop gross outliers.

18. They make up about 40% of this relatively young sample. About 1,000 more are dropped due to missing income data.

Note that this restriction does not apply to the rest of the outcome variables. On average, individuals in this sample are exposed to approximately 18 inversion nights per month during any given trimester.

3.2. Census Data

In order to investigate the interaction between labor market conditions and pollution exposure, I use various labor market variables from the 1990, 2000, and 2010 Mexican censuses (Minnesota Population Center, 2015). I collapse to the commuting zone level and link this labor market information to individuals using their commuting zone of residence during their school-aged years. Following Atkin (2016), I use commuting zones instead of individual municipalities because these better represent local labor markets. For instance, large metropolitan areas are often composed of many municipalities, with individuals often working and residing in different ones. I combine all municipalities in the same Zona Metropolitan (according to the 2000 INEGI classification) into a single commuting zone and also combine municipalities where over 10% of the working population in one reports commuting to another for work (according to the more detailed version of the 2000 census, obtained from INEGI).

I calculate zone-specific, gender-specific labor force participation, white-collar shares, youth employment rates (among individuals aged 12-16), and average youth income (among individuals aged 12-16). In my main specifications, I linearly interpolate between census years in order to assign individuals a value from the year in which they turned 12, in their commuting zone of residence at age 12. In robustness checks, I assign values to individuals based on the census conducted closest to the year in which they turned 12. For white-collar shares, I also use a shift-share strategy for predicting values for years in between censuses, which I describe in Appendix Section B.4.

In order to investigate the potential role of son preference, I also use the 1970 census and calculate male-to-female sex ratios among children (under 5 and under 3 years old) for each state.

4. Empirical Strategy

To estimate the effects of pollution, I regress my outcomes of interest on thermal inversion counts over several three month periods prior to and after a child's birth. In addition to helping to overcome the pollution data limitations described above, using thermal inversions also addresses the endogeneity of pollution. Pollution is not randomly assigned: individuals born in highly polluted areas are different from those born in less polluted areas. While location fixed effects can be used to alleviate these residential sorting concerns, they do not control for location-specific trends in pollution that may coincide with trends in the outcomes of interest.

In this framework, thermal inversions can be thought of as an "instrument" that generates exogenous variation in an endogenous variable that I do not observe. This endogenous variable is not a particular pollutant but rather, air quality in general. The approach of this paper is not designed to estimate the dose-response function of specific pollutants: rather, it offers a well-identified way to learn whether being exposed to higher pollution while in utero has discernible effects in the long term.

For individual i, born in municipality j, in year y and month m, whose outcome Y_{ijymw} comes from survey wave w, I estimate the following specification:

$$Y_{ijymw} = \sum_{k=-7}^{3} \beta_k \mathrm{I}_{jym}^{3k} + \sum_{k=-7}^{3} \alpha_k' \mathrm{W}_{jym}^{3k} + \gamma' X_i +$$

$$\mu_j + (\delta_y \text{ x } \nu_w) + \eta_m + \varepsilon_{ijymw}. \tag{2}$$

I_{jym}^{a} represents the average number of monthly thermal inversions that took place in individual i's municipality of birth during the three month period starting a months after the individual's birth month (where negative values indicate months before birth). I include all three month periods starting a year before conception (21 months before birth) until a year after birth in order to identify critical periods and ensure that any effects I find in the in utero period are not being driven by serial correlation in the thermal inversion variable year to year. Omitting the thermal inversion variables from before and after pregnancy could result in their effects loading onto the trimester coefficients. The coefficients on inversions prior to conception also serve as a falsification check, as pollution exposure before a child is conceived should not have direct effects on that child's outcomes.

W_{jym}^{a} is a vector of weather controls (minimum, maximum, and mean temperatures, rain, total cloud coverage, relative humidity, and wind speed), averaged over each three-month period, along with their squares and cubes. In this specification, municipality fixed effects (μ_j) address cross-sectional pollution endogeneity concerns, including residential sorting issues, by ensuring that identification comes from within-municipality variation over time. Year (δ_y) and month fixed effects (η_m) control flexibly for long-term and seasonal time trends. The interaction of year and wave dummies (δ_y x ν_w) capture both wave and age effects.[19] Controls X_i include gender, mother's education, and father's education, for which I set missing values to zero and include dummies for missing values. In more rigorous specifications, I add various combinations of location fixed effects and location-specific trends in order to allow for differential long-term and seasonal trends across geographic areas (including state-by-season fixed effects, state-by-quadratic year trends, municipality-by-season fixed effects, and year-month fixed effects).

I run these regressions for the full sample and then separately for men and women. In order to explore whether gender-specific labor market conditions play a role in determining schooling responses to shocks, I also estimate a specification that interacts various labor market variables with the trimester coefficients of interest.

I cluster the standard errors at the municipality level.[20] As stated above, I am restricted to individuals born in 1979 or later due to the availability of the NARR data, and those who are at least 15 years of age in their most recent MxFLS interview. Because I am identifying off of variation within municipalities over time (controlling non-linearly for year and month effects), I also drop individuals in municipalities with very small numbers of individuals (less than 30), which make up less than 5% of the full sample.

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19. These control for systematic differences across waves as well as systematic differences across ages, in order to improve precision. Results are robust to the exclusion of these interactions.

20. There are 150 municipalities in the final sample.

5. Results

In this section, I begin by documenting the overall and gender-specific effects of thermal inversions. I then investigate the labor market mechanisms driving the gender differences that I find. Finally, I address potential threats to identification.

5.1. Main Results

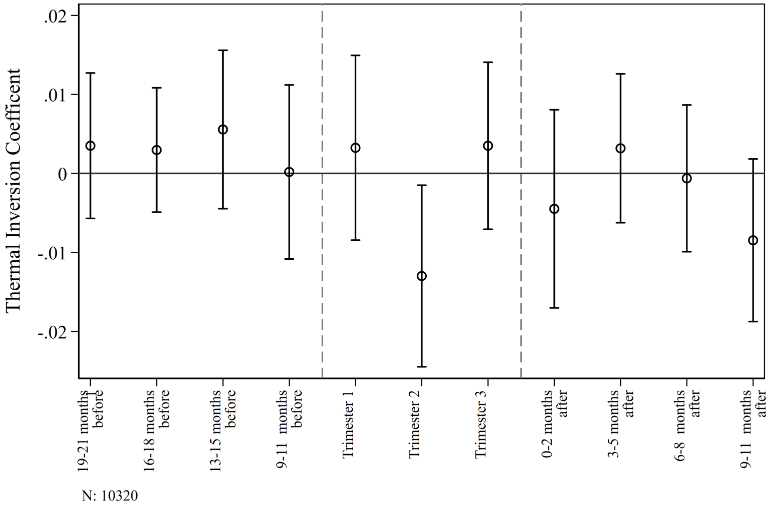

Figure 1. Effects of Thermal Inversions on Raven's Test Z-Scores

Notes: Intervals represent 95% confidence intervals. Controls include: birth month, birth year, municipality of birth, survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, gender, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. See Table A1, column 2, for corresponding estimates.

To display my reduced form results, I graphically illustrate the estimated coefficients from the specification described in equation (2), with the additional inclusion of state-specific quadratic year trends and state-specific quarter of the year dummies, hereafter referred to as season dummies. All corresponding tables, which include estimates from specifications with and without the state-specific trends, are available in Appendix Section A.

Figure 1 reports the estimated effects of thermal inversions on cognitive ability, measured by standardized Raven's test scores. Thermal inversions in the second trimester have a significant negative impact on Raven's test scores. I do not find any significant effects associated with any of the other three-month periods. This is consistent with the medical and economic literature discussed in Section 2.2, which flags the second trimester as a crucial period for brain development (Otake, 1998; Almond et al., 2009; Black et al., 2014; Schwandt, 2018; Morgan and Gibson, 1991).[21]

In contrast, Figure 2 shows no evidence of a robust relationship between inversion exposure (in any period) and height, which is often used as a cumulative measure of the quality of health and nutritional inputs early in life (Thomas and Strauss, 1997; Maccini and Yang, 2009; Vogl, 2014) and has been shown to be causally linked to fetal health measures like birth weight (Behrman and Rosenzweig, 2004; Black et al., 2007). These results suggest that thermal inversions did not substantially hinder the *physical* development of fetuses and therefore that the negative impact of in utero inversion exposure was primarily cognitive.

In order to study differences across gender, I run these regressions separately for men and women. In the following figures, I plot the coefficients (and 95% confidence intervals) for males and females on the same graph, reporting only the three

21. In the following set of results, I show that it is also the second trimester coefficient, specifically, that has a significant impact on schooling and income outcomes, alleviating concerns that its statistical significance in the cognitive ability regression is simply a result of multiple hypothesis tests and Type 1 error.

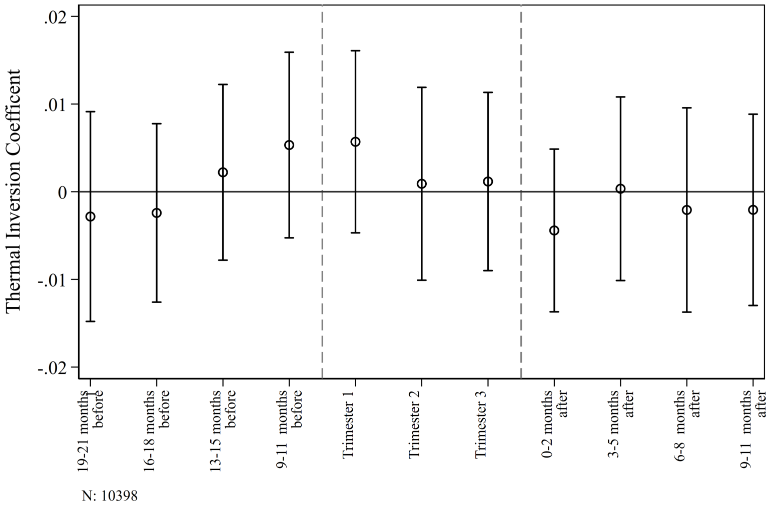

Figure 2. Effects of Thermal Inversions on Height Z-Scores

Notes: Intervals represent 95% confidence intervals. Controls include: birth month, birth year, municipality of birth, survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, gender, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. See Table A1, column 4, for corresponding estimates.

trimester coefficients (even though all regressions control for the remaining three-month periods). In the Appendix, I report these trimester coefficients, along with their differences and associated standard errors. The first panel of Figure 3 shows that the second trimester estimates for the effect of inversions on Raven's scores are very similar in magnitude for males and females: -0.011 for females compared to -0.013 for males, which are not significantly different from each other. Neither coefficient is significant individually, likely due to the smaller sample sizes, but given the significance of the negative effect in the full sample, the main takeaway from this figure is that cognition appears to be affected by inversions in similar ways for men and women. For height, in the second panel of Figure 3, there are no significant gender differences.

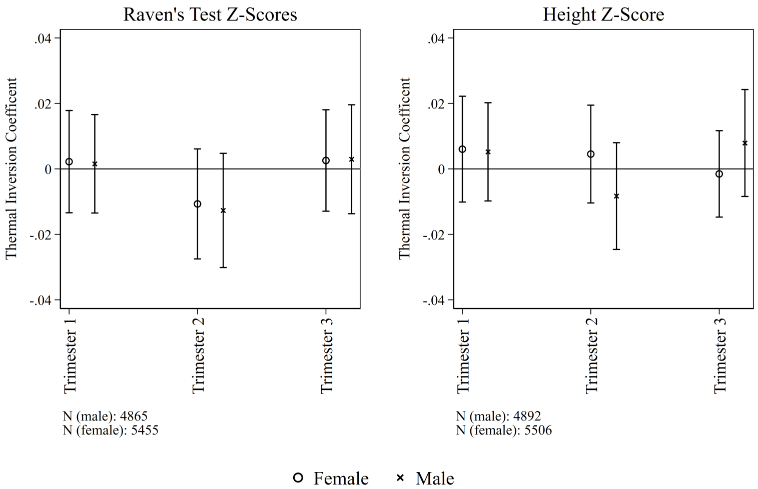

FIGURE 3. Effects of Thermal Inversions on Cognitive and Physical Health, by Gender

Notes: Separate regressions are conducted for men and women. * p< 0.1, ** p< 0.05, *** p< 0.01 are used to denote significant differences across genders. Intervals represent 95% confidence intervals. Controls include: birth month, birth year, municipality of birth, survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. See Table A2, columns 2 and 4, for corresponding estimates. Although not plotted here, inversions in all other three-month periods are included in these regressions and reported in Table A10.

It is important to note that the effects being estimated here are reduced form effects: they are the result of the biological effects of pollution (via thermal inversions) as well as a series of investments made by parents up until the age at which the Raven's tests are administered and height is measured.[22] The purpose of this analysis is not to tease out the biological effect from the investment responses, as the data is not well-suited for this question: for the sample that I am using, information on early parental investments is not available. What is important for the goals of this paper is the fact that thermal inversions provide exogenous

22. See Cunha and Heckman (2007), Cunha and Heckman (2008), and Cunha et al. (2010) for a commonly used dynamic framework for the production function of skill.

variation in cognitive ability, which allows me to study how schooling decisions respond to exogenously determined cognitive endowments.

In addition to the reduced form nature of these estimates, there are several issues that complicate the interpretation of magnitudes. The quasi "first-stage" regression of pollution on inversions uses data from a different time period than the reduced form regressions discussed in this section. In addition, they show that inversions affect more than one pollutant. This makes the calculation of a dose-response function for a single pollutant impossible, if we acknowledge that pollutants may interact in ways that are not well understood and that the effect of inversions on pollution may change over time. Focusing only on the reduced form effect of thermal inversions, however, a few useful comparisons can be made. First of all, the coefficient on the thermal inversion variable is about one-third of the effect of an additional year of maternal schooling. Secondly, Arceo et al. (2016) document that an additional thermal inversion in a given week increased infant mortality by 2% in that week, which suggests an additional thermal inversion in a month would have increased infant mortality by 0.5%. Given this, a 0.01 standard deviation decrease in cognitive ability resulting from an additional average monthly inversion during the second trimester seems reasonable: mortality is an extreme event, and cognitive ability is measured much later in life, after a number of (potentially reinforcing) investments could have been made. Finally, for all of the coefficient estimates (in the previous as well as upcoming figures), it is not clear how informative the exact point estimates are, given that the confidence intervals are all rather wide.

With regard to magnitudes, another important consideration is that the effect of thermal inversions on pollution may vary across space and over time (across areas with varying levels of baseline pollution, for example). This means that the reduced form effects of thermal inversions may also vary across space and time. As I argue in Section 2.3, the occurrence of a thermal inversion, after controlling for all of the relevant fixed effects and weather controls, is random, and therefore exogenous to any effect heterogeneity that may exist. The fact that my estimates are not sensitive to the inclusion of state-specific trends, which controls for differential trends across states that industrialized at different rates, for example, supports this argument. Given this, I am able to recover consistent estimates of the average reduced form effect of inversions across locations and time periods. The estimates discussed in this section, therefore, should be interpreted as the average effect of thermal inversions on the outcomes of interest, across all of the time periods and locations included in this sample.

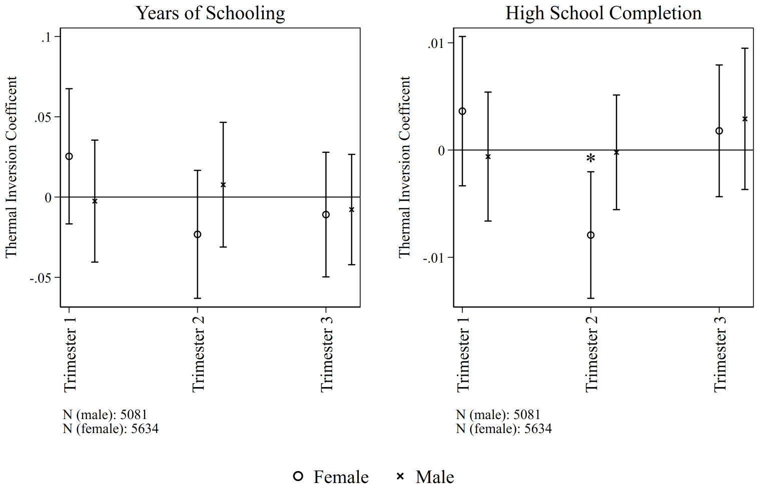

FIGURE 4. Effects of Thermal Inversions on Educational Attainment, by Gender

Notes: Separate regressions are conducted for men and women. * p< 0.1, ** p< 0.05, *** p< 0.01 are used to denote significant differences across genders. Intervals represent 95% confidence intervals. Controls include: birth month, birth year, municipality of birth, survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. See Table A3, columns 2 and 4, for corresponding estimates. Although not plotted here, inversions in all other three-month periods are included in these regressions and reported in Table A10.

Having established that in utero exposure to thermal inversions acted as a negative and primarily cognitive endowment shock that did not affect men and women differentially, I next ask whether there were any differences in male and female schooling responses to this shock. Clear gender differences are apparent in Figure 4. Though both panels depict a similar pattern, the result is more pronounced in the regression on high school completion: thermal inversions had a significant negative impact on high school completion for women only. Like in the cognitive ability regressions, the effect of an additional inversion on female high school completion is equivalent to about one-third of the effect of an additional year of maternal schooling. The male coefficient, on the other hand, is statistically indistinguishable from zero, and significantly different from the female coefficient at the 10% level.

High school graduation appears to be the only milestone affected by pollution: Appendix Table A5 shows that in utero thermal inversions had no significant impact on elementary school or junior high school completion for either gender. Compulsory schooling laws are one potential reason why the effects only show up for high school completion. Because most of the individuals in my sample were required to attend at least 9 or 11 years of school, this could have limited the responsiveness of milestones earlier than these required levels of schooling. At the end of Section 6.2, I discuss another reason for the absence of effects on early milestones of schooling: these effects are primarily driven by individuals expecting to go into a white-collar job, who would be on the margin of completing high school.

Figure 5 reports the effects of thermal inversions on income, again by gender, among those who reported work as their primary activity in the previous week. This deliberately excludes individuals who may be working part time while still in school and whose annual income would not be an appropriate measure of their labor market productivity. Once again, I find that thermal inversions in the second trimester have a significant negative effect on female income. The fact that it is the second trimester coefficient that is significant in this regression (as well as in the cognitive ability and female high school completion regressions) alleviates concerns that these statistically significant coefficients are just a result of Type 1 error from multiple hypothesis tests.

The effect of second trimester inversions on men is smaller in magnitude and not significantly different from zero, but still negative, sizable, and not significantly different from the female coefficient. Unlike the high school completion results, Figure 5 does not offer clear-cut evidence for stark gender differences. Although it appears that inversions affected incomes primarily for women, there are also some non-negligible effects on men, which would be consistent with existing examples of early-life circumstances that significantly affected male labor market outcomes despite having very little effect on their schooling decisions (Hoddinott et al., 2008; Rosenzweig and Zhang, 2013; Politi, 2015).

These results should be interpreted with caution. Because this is a young sample (aged 15 to 34), the estimated coefficients represent the effect of thermal inversions on early career outcomes, which might be very different from the effects on lifetime income. In particular, the career wage trajectories of men and women likely differ; the direction and magnitude of the gender differences found here may not be the same as those in lifetime income effects. These regressions also ignore selection into the sample of working individuals: I do not, however find evidence that thermal inversions affected the working decision for either gender (results available upon request). Because of the limitations associated with the income analysis, I focus in Section 6 on explaining the well-identified gender difference in the schooling response.

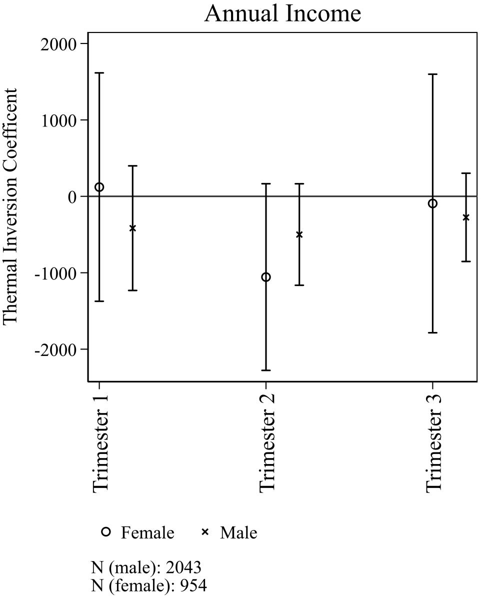

FIGURE 5. Effects of Thermal Inversions on Income, by Gender

Notes: Separate regressions are conducted for men and women. * p< 0.1, ** p< 0.05, *** p< 0.01 are used to denote significant differences across genders. Intervals represent 95% confidence intervals. Controls include: birth month, birth year, municipality of birth, survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. See Table A4, column 2, for corresponding estimates. Although not plotted here, inversions in all other three-month periods are included in these regressions and reported in Table A10.

5.2. Threats to Identification

5.2.1. Fertility Timing. The validity of the above analysis relies on the assumption that mothers in a given municipality who experience many thermal inversions during their second trimester are not systematically different from mothers in that same municipality who experience fewer thermal inversions in that same period. One way of testing this is to regress observable maternal characteristics on the thermal inversion variables of interest. Columns 1 and 3 of Table 4 report the results of regressions of maternal years of schooling and an indicator for whether an individual's mother ever worked on thermal inversions in the second trimester.[23] In both columns, there is no systematic relationship between inversion exposure and these two maternal characteristics. In Columns 2 and 4, I report the regression results from running the entire specification used for the above analysis (excluding the maternal and paternal schooling controls), with these two maternal characteristics as dependent variables. None of the trimester coefficients are significantly different from zero (and all are small in magnitude), suggesting that, conditional on all of the fixed effects and weather controls, thermal inversion exposure is truly exogenous to these maternal characteristics.

Of course, these two characteristics may not represent all of the observed or unobserved dimensions that could be systematically correlated with thermal inversion exposure. Perhaps the more relevant variables are those related to the characteristics of the mother in the year before the child's birth, which are not available in this data set. For example, thermal inversions are more common in winter, and pregnant mothers who are in their second trimester during winter give birth in the spring. In areas where the maize harvest is in the spring, mothers who choose to give birth in the spring might be less likely to be working in agriculture, for example, than mothers who choose instead to give birth in the fall. In the current specification, month fixed effects help account for this, but are an incomplete solution if these seasonal effects vary over time or space. In order to better control for time-varying or municipality-specific seasonal effects, I run two additional specifications. In the first specification, I replace the state-season fixed effects with municipality-season fixed effects. In the second specification, I

23. These are the only two maternal characteristics which are recorded in a comparable way for individuals with parents living in the household and individuals whose parents do not live in the same household.

Table 4. Maternal Characteristics and Thermal Inversions

	(1)	(1)	(2)	(2)
Average monthly inversions…	Mother's Education	Mother's Education	1(Mother Worked)	1(Mother Worked)
BEFORE CONCEPTION				
19-21 months before birth		-0.00165		0.00145
		(0.0172)		(0.00235)
16-18 months before birth		-0.0181		-0.00253
		(0.0191)		(0.00211)
13-15 months before birth		-0.0318*		-0.00182
		(0.0185)		(0.00270)
10-12 months before birth		-0.0148		0.000651
		(0.0180)		(0.00256)
DURING PREGNANCY				
Trimester 1		-0.00139		-0.00160
		(0.0224)		(0.00262)
Trimester 2	-0.000340	-0.00590	-0.0000635	0.00234
	(0.0175)	(0.0218)	(0.00132)	(0.00233)
Trimester 3		0.00846		0.00269
		(0.0205)		(0.00284)
AFTER BIRTH				
0-2 months after birth		-0.0101		-0.00275
		(0.0175)		(0.00245)
3-5 months after birth		-0.00435		-0.000335
		(0.0195)		(0.00272)
6-8 months after birth		0.0122		0.00123
		(0.0160)		(0.00256)
9-11 months after birth		0.0211		-0.00249
		(0.0193)		(0.00249)
N	10322	9770	11104	10496
Mean of dependent variable	6.105	6.170	0.462	0.466
Basic Controls	No	Yes	No	Yes

Notes: Standard errors (clustered at municipality level) in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$. The "Basic Controls" included in columns 2 and 4 include: birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, gender, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period.

keep these municipality-season fixed effects and replace the year and month fixed effects with interacted year-month dummies. The latter allows for monthly trends to differ non-linearly over time, which would be important if the incentives to time births have changed over the two decade period spanning the birth years in my sample. As Appendix Figures A3 and A4 show, my main results are robust to these specification changes: pollution significantly reduces Raven's test scores for the whole sample and high school completion for women only.

5.2.2. Mortality Selection. Given that in utero exposure to pollution is known to affect infant mortality, one important concern is whether my results are being driven by selective mortality. First, it is worthwhile to note that if the infants that do not survive as a result of pollution exposure are mostly from the left tail of the ability distribution, my estimated effects should be an underestimate of pollution's true impact. However, in order to verify whether selective mortality is an issue in my setting, I check whether thermal inversions before birth have any effect on cohort size or cohort gender composition. Using all individuals in the MxFLS born 1979 to 1998 (the range of birth years in my sample), I calculate the total number of individuals and fraction that is male for each birth municipality, birth month, and birth year combination. With each observation representing a year-month-municipality, I regress these aggregate values on thermal inversions during pregnancy and in the year before and after. My results, reported in Table 5, show no evidence for selective mortality in this sample.

While the absence of any pollution-driven changes in cohort size may seem inconsistent with previous studies documenting a positive link between pollution and infant mortality (Arceo et al., 2016; Jayachandran, 2009; Currie and Neidell, 2005; Chay and Greenstone, 2003), it does not necessarily rule out the possibility that thermal inversions led to higher infant mortality in this sample as well. These null effects are consistent with a situation in which thermal inversions increased infant mortality by accelerating the deaths of infants who would have died before reaching adolescence or adulthood in the absence of pollution. By the time I observe my sample, pollution-driven changes in its composition do not appear to be a substantial concern.

Table 5. Effects of Thermal Inversions on Cohort Size and Gender Composition

	(1)	(2)
Average monthly inversions…	Cohort size	Fraction male
BEFORE CONCEPTION		
19-21 months before birth	-0.00365	-0.000975
	(0.00317)	(0.00271)
16-18 months before birth	-0.00162	0.000462
	(0.00309)	(0.00258)
13-15 months before birth	0.00464	-0.00186
	(0.00313)	(0.00275)
10-12 months before birth	0.00358	0.00171
	(0.00347)	(0.00251)
DURING PREGNANCY		
Trimester 1	0.00194	-0.000884
	(0.00319)	(0.00244)
Trimester 2	0.00170	-0.000700
	(0.00345)	(0.00279)
Trimester 3	-0.00536	-0.000376
	(0.00447)	(0.00236)
AFTER BIRTH		
0-2 months after birth	-0.000776	-0.000238
	(0.00384)	(0.00241)
3-5 months after birth	0.000450	-0.00199
	(0.00363)	(0.00262)
6-8 months after birth	-0.000941	-0.000740
	(0.00327)	(0.00247)
9-11 months after birth	-0.00427	-0.00102
	(0.00347)	(0.00301)
N (municipality-year-months)	11078	11067
Mean of dependent variable	1.323	0.477

Notes: Standard errors (clustered at municipality level) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ In these regressions, each observation represents a unique municipality-month-year combination. All regressions control for month, year, and municipality fixed effects, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period.

5.2.3. Adjusted Raven's Scores. Previous work has documented significant gender differences in performance on Raven's tests (Mackintosh and Bennett, 2005), driven by different success rates with specific types of questions. In particular, males often outperform females on questions that require the use of two rules (addition or subtraction of figures, and distribution of two – see Mackintosh and Bennett (2005) for a more detailed discussion). As shown in Table 3, males perform slightly better than females in my sample. Though small in magnitude, this difference is statistically significant.

Fortunately, these gender differences do not affect the identification of gender differences in the effects of thermal inversions on high school completion (which are analyzed separately from Raven's test scores). One concern, however, might be that Raven's tests are a poor measure of cognitive ability for women (due to the issue described above) and that I am underestimating the effect of thermal inversions on female cognitive ability.[24] In other words, the true effect of thermal inversions on female scores could be significantly larger than the true effect for men, which could mean that my high school completion differences are simply the result of larger cognitive ability effects for women. Because this has important implications for the investigation of mechanisms in the next section, I investigate in Table A6 whether this alternative interpretation is plausible. To do this, I adjust the Raven's test scores by removing the two questions that require the use of the addition or subtraction of figures or the distribution of two rules. This narrows the gender gap in Raven's test scores in my sample. I then repeat the analysis on these adjusted scores and report the results in Table A6. Like in Figure 3, the difference between the male and female coefficients is small in magnitude and not statistically significant, suggesting that the initial results were not masking larger underlying gender differences in the cognitive effects.

24. This would require non-classical measurement error in the Raven's as a measure of true cognitive ability for women but not for men.

6. Labor Market Mechanisms

Having established that the schooling decisions of men and women respond differently to an exogenous shock to cognitive ability, I now investigate what labor market conditions might be driving this gender difference. I begin with a simple model, which highlights three potential labor market explanations. I then move on to empirical tests of these different channels.

6.1. Conceptual Framework

Suppose individuals are born with an ability endowment θ, which I measure in the data using Raven's test scores. As adults, individuals can work in one of two occupations: white-collar ($k = w$) or blue-collar ($k = b$), defined by the categorizations in Table 1.[25] They can also remain out of the labor force ($k = n$). Each alternative has a different wage function, where schooling S and ability θ are rewarded differently.

These functions capture the idea that worker characteristics command different prices in different occupations (Heckman and Scheinkman, 1987) and that schooling and ability may exhibit non-separabilities that vary across sectors, which is reflected in the descriptive evidence in Figure 6. This figure illustrates the relationship between income and ability for individuals with different jobs and different levels of education. I plot the relationship between annual income and Raven's test scores, separately for four different schooling-occupation combinations: white-collar high

25. Note that blue-collar jobs include both agricultural and factory work. Women who carried out agricultural activities for no pay to help with household consumption are counted as working, in both the MxFLS and the census.

school graduates, white-collar non-graduates, blue-collar high school graduates, and blue-collar non-graduates. Interestingly, the gap between high school graduates and non-graduates is *increasing* in ability in white-collar occupations, but *decreasing* in ability in blue-collar occupations. This can be seen in the widening of the gap between the two white-collar lines and the slight narrowing of the gap between the two blue-collar lines. Although this figure does not take into account selection into occupation types or schooling, it offers suggestive evidence that the complementarity between schooling and ability is higher in white-collar than in blue-collar jobs.[26]

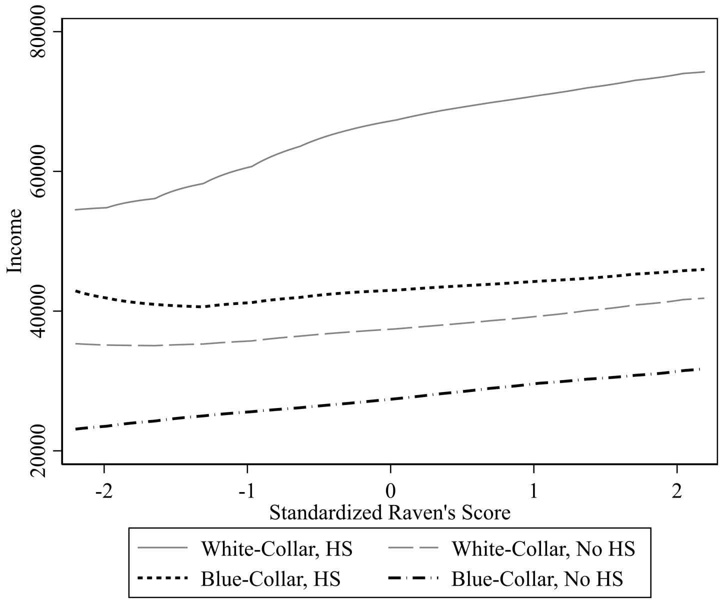

FIGURE 6. Income-Ability Relationship

Notes: Lines depict local linear regressions using individuals aged 25 to 65 in the MxFLS. Blue-collar and white-collar jobs are identified using CMO codes and the classifications in Table B1. Income is total earned annual income measured in 2002 Mexican pesos and winsorized at the 99th percentile.

26. These conclusions are also supported by the estimates from a dynamic discrete choice model that endogenizes schooling and occupational choice (Molina, 2019).

I denote the occupation-specific expected wage functions as

$$W_k(S, \theta)$$

Individuals can also remain out of the labor market, denoted by $k = n$. The reward function in the home sector takes a similar form ($W_n(E, \theta)$), and can be interpreted as the utility individuals would enjoy if they did not work (which could be a function of their marriage decisions, bargaining power in marriage, productivity in home production, etc.).

The opportunity cost of schooling takes the following form:

$$c(S, \theta),$$

where $\partial c/\partial S > 0$ and $\partial^2 c/\partial S^2 > 0$.

Expected wages are given by

$$qpW_w(S, \theta) + q(1-p)W_b(S, \theta) + (1-q)W_n(S, \theta),$$

where q represents the expected probability of an individual entering the labor force and p represents the expected probability of an individual going into a white-collar job, conditional on being in the labor market.[27]

27. For parsimony, p and q are fixed parameters. In a previous draft of this paper, I work with a model that allows for p and q to vary with S and θ and reach similar conclusions (Molina, 2019).

Individuals pick the optimal level of education S to maximize their expected future rewards, net of the cost of schooling, as in the maximization problem below:[28]

$$\max_{S} \quad E\left[W(S,\theta)\right] - c(S,\theta).$$

The optimal schooling response to a positive shock to cognitive ability (θ) is:

$$\frac{dS^*}{d\theta} = -\left[\frac{\partial^2 E\left[W(S,\theta)\right]}{\partial S \partial \theta} - \frac{\partial^2 c}{\partial S \partial \theta}\right]\left[\frac{\partial^2 E\left[W(S,\theta)\right]}{\partial S^2} - \frac{\partial^2 c}{\partial S^2}\right]^{-1}. \tag{3}$$

The sign of this term depends on the numerator (as the denominator is negative by assumption). The numerator involves the cross-partials between schooling and

28. By choosing to model only the schooling decision, which is the focus of this paper, I assume that any major investments parents might make to change θ take place before the crucial schooling decisions are made. This assumption is consistent with the well-documented finding that there are higher returns to investing in a child's skill formation early in life (before primary school) compared to later on (Cunha et al., 2010; Heckman, 2006). Moreover, for children in Mexico, the end of primary school marks the first critical schooling transition period when many drop out (Behrman et al., 2011).

ability in the various wage functions and in the opportunity cost function:[29]

$$pq\frac{\partial^2 W_w}{\partial S\partial\theta} + (1-p)q\frac{\partial^2 W_b}{\partial S\partial\theta} + (1-q)\frac{\partial^2 W_n}{\partial S\partial\theta} - \frac{\partial^2 c}{\partial S\partial\theta}. \tag{4}$$

There are three clear ways the expression in (4) might vary for men and women. As discussed in Section 2.1, men and women differ in their labor force participation rates (in adulthood as well as in school), as well as in their tendencies to take up white-collar over blue-collar jobs. This has implications for their expected probability of entering the labor force (q), their expected probability of taking a white-collar job (p), and their opportunity cost function ($c(S,\theta)$).

6.1.1. Labor Force Participation. In Mexico, during the decade spanned by the three waves of the MxFLS, men are much more likely to be in the labor force than women, which means they face a higher q (expected likelihood of labor force participation). Because q acts as a weight on the various cross-partials in (4), this would generate larger schooling responses for women than men if certain conditions hold: specifically, if the degree of complementarity between schooling and ability is higher in the home sector than in the labor force. Unlike wages, home-sector rewards are abstract and difficult to measure; it is not clear, therefore, whether this condition is likely to hold. However, what I am able to test is whether the

29. It is important to note that this schooling response depends on the *cross-partials* between schooling and ability in the various wage and cost functions, not the returns to ability in each job type ($\partial W_k/\partial\theta$). To state this in terms of the data used in this analysis, the response of schooling to changes in Raven's scores depends on how fluid intelligence and schooling interact in the various alternative-specific wage functions and opportunity cost function ($\partial^2 W_k/\partial S\partial\theta$ and $\partial^2 c/\partial S\partial\theta$). Notably, this does not require Raven's scores to capture a type of ability valued more in one job type than another (which depends on differences in $\partial W_k/\partial\theta$ across k).

schooling response to thermal inversions (a cognitive ability shock) varies with proxies for q, which will help shed light on the importance of this mechanism.

6.1.2. White-Collar versus Blue-Collar Decision. Conditional on being in the labor force, women are much more likely to be in a white-collar job than men, both in Mexico (Table 1) and more generally across the globe (Appendix Figure A2). Because women have a higher p (expected likelihood of a white-collar job) than men, they should exhibit larger schooling responses to a cognitive shock if schooling and ability are more complementary in white-collar jobs than in blue-collar jobs ($\partial^2 W_w/\partial S\partial\theta > \partial^2 W_b/\partial S\partial\theta$). The descriptive evidence in Figure 6 suggests that this is indeed the case.[30]

With respect to the data used in the empirical analysis, this condition ($\partial^2 W_w/\partial S\partial\theta > \partial^2 W_b/\partial S\partial\theta$) means that schooling amplifies the returns to fluid intelligence in white-collar jobs to a greater extent than in blue-collar jobs. I argue this is consistent with the following intuition. Suppose that fluid intelligence captures an individual's ability to learn new skills, and that education provides individuals with knowledge and skills that are useful primarily in white-collar jobs, not blue-collar jobs, and difficult to learn elsewhere. Then, a high-ability individual with little education will not earn higher wages than a low-ability individual with little education in a white-collar job, as neither have had the opportunity to learn skills that are important for that type of job. For educated individuals, however, ability will increase the amount (or quality) of skills acquired and therefore eventual wages in a white-collar job. In contrast, in blue-collar jobs, where the knowledge and

30. Structural estimates from a previous version of this paper, which account for the endogeneity of the schooling and occupation choice, also reveal significantly higher complementarities in white-collar than blue-collar jobs (Molina, 2019).

skills learned through education are not as important, ability can improve wages for an individual regardless of education. This will generate a complementarity between fluid intelligence and schooling in white-collar jobs, but not in blue-collar jobs, where schooling and ability would be more substitutable.

6.1.3. Opportunity Costs. Finally, men and women might face different opportunity cost functions ($c(S, \theta)$). As discussed in Section 2.1, school-aged boys are more likely to be working than school-aged girls, which suggests that potential wages in the child labor market (perhaps the most important component of the opportunity cost) are different. In particular, the higher employment rates among school-aged boys could reflect a greater complementarity between schooling and ability in the opportunity cost function. If this complementarity ($\partial^2 c/\partial S \partial \theta$) is higher for boys than for girls, this would also drive larger female schooling responses to a cognitive shock.

6.2. Empirical Evidence

In order to empirically investigate how these three mechanisms contribute to the gender difference that I document, I allow for the effect of thermal inversions to vary by various gender-specific labor market characteristics that proxy for q, p, and $\partial^2 c/\partial S \partial \theta$.

To proxy for an individual's expected probability of going into the labor force (or a white-collar job), I calculate the gender-specific share of adults that are in the labor force (or a white-collar job) in an individual's local labor market during a critical school transition period.[31] Like Rosenzweig and Zhang (2013), I focus on

31. Although it is difficult to capture expectations without subjective expectations data, the existing literature suggests current labor market conditions can serve as a reasonable proxy

the local labor market in which a child is residing at age 12. In Mexico, the end of primary school is a critical transition period during which a large proportion of children drop out (Behrman et al., 2011). Moreover, for the majority of individuals in my sample, I have data on their municipality of residence at age 12 specifically. That is, I know whether individuals were living in their municipality of birth (which I have in the data) at age 12, their municipality of current residence (which I have in the data) at age 12, or neither. For individuals in the last category, who make up less than 10% of the sample, I assign them to their municipality of birth, acknowledging that there will be some measurement error, because municipality of residence at age 12 is a restricted-use variable.

Expectations about the cross-partial between schooling and ability in the opportunity cost function are less straightforward to measure. To proxy for these expectations, I use the gender-specific employment rate among school-aged youth (aged 12-16) and gender-specific average income among school-aged youth in an individual's local labor market at age 12. I argue that higher employment probabilities and wages are an indication of a child labor market that rewards worker skill (rather than just paying a fixed child wage rate), which would allow for greater complementarity between schooling and ability.

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for these expectations about future employment. For example, Jensen (2010) finds that 70% of survey respondents in the Dominican Republic report that people in their community were their main source of information about expected earnings. Similarly, Nguyen (2008) shows that information about current labor market conditions can affect parental and child expectations about future returns. In a slightly different context, Attanasio and Kaufmann (2017) use current conditions in the marriage market – gender ratios for various education categories – to proxy for marriage market expectations.

For the following analysis, I use data from the Mexican census to calculate these gender-specific local labor market characteristics. As described in Section 3.2, I use linear interpolation between census years in the main specification. I create an indicator equal to 1 if the relevant gender-specific labor market measure falls in the top quartile of the overall distribution. Appendix Table A7 repeats the analysis using other methods of interpolation and continuous instead of discrete variables.

I begin by reporting, in column 1 of Table 6, the trimester coefficients from the fully-interacted specification used to generate the second panel of Figure 4, which demonstrates the significant gender difference in the effect of thermal inversions on high school completion. In the remaining columns, I add interactions between inversions in each period and one of the four gender-specific labor market indicators described above. This allows me to investigate the extent to which the initial gender difference is being driven by gender-specific labor market opportunities.

Column 2 of Table 6 investigates the effect of labor force participation expectations (q). After the inclusion of these labor force participation interaction terms, the effect of inversions on female high school completion is still negative and significant, and the gender difference (though no longer statistically significant) is still large in magnitude. Notably, there is no significant heterogeneity in the effect of second trimester inversions across individuals facing different probabilities of entering the labor force. Expectations about labor force participation do not appear to be an important determinant of schooling responses.

The limited role of labor force participation could be an indication that adult female labor force participation rates do not adequately represent the labor force participation expectations of young girls, especially during a period of rapidly changing female labor market opportunities. For example, a 2005 survey

TABLE 6. Effects of Thermal Inversions on High School Completion, by Gender-Specific Labor Market Characteristics

Average monthly inversions…	(1) HS Completion	(2) HS Completion	(3) HS Completion	(4) HS Completion	(5) HS Completion
Trimester 1	0.363	0.338	0.215	0.342	0.292
	(0.353)	(0.354)	(0.486)	(0.355)	(0.353)
Trimester 2	-0.792***	-0.802***	-0.0368	-0.809***	-0.775**
	(0.299)	(0.299)	(0.431)	(0.299)	(0.310)
Trimester 3	0.179	0.164	-0.0141	0.165	0.162
	(0.311)	(0.313)	(0.508)	(0.314)	(0.316)
Trimester 1	-0.423	-0.438	-0.384	-0.335	-0.580
x 1(Male)	(0.478)	(0.562)	(0.566)	(0.486)	(0.543)
Trimester 2	0.771*	0.680	0.177	0.692*	0.920**
x 1(Male)	(0.405)	(0.477)	(0.477)	(0.407)	(0.438)
Trimester 3	0.112	0.0426	0.171	0.0582	0.0254
x 1(Male)	(0.431)	(0.471)	(0.522)	(0.426)	(0.493)
Trimester 1		-0.0146	0.182	-0.325	0.290
x 1(Labor market variable in top quartile)		(0.443)	(0.391)	(0.482)	(0.377)
Trimester 2		0.197	-0.901**	0.460	-0.250
x 1(Labor market variable in top quartile)		(0.437)	(0.380)	(0.477)	(0.360)
Trimester 3		0.118	0.198	0.165	0.0943
x 1(Labor market variable in top quartile)		(0.434)	(0.401)	(0.475)	(0.348)
N	10715	10689	10677	10689	10689
Dependent variable mean	26.58	26.51	26.47	26.51	26.51
Labor market variable	None	Labor force participation	White-collar proportion	Youth (12-16) employment	Youth (12-16) income

Notes: Standard errors (clustered at municipality level) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficients scaled to represent percentage points. All regressions control for the following variables and their interactions with a male indicator (as well as the main effect of gender): birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period, as well as inversions in all other three-month periods. The main effect of the relevant labor market dummy and its interactions with inversions in all other three-month periods are also included. Individuals are assigned to labor market variables in their commuting zone of residence at age 12, and linear interpolation is used to interpolate between census years.

that collected subjective expectations data in Mexico shows that teenage boys and girls had identical expected probabilities of going into the labor force as adults (Attanasio and Kaufmann, 2014), which could indicate that the males and females in my sample actually had similar expectations about future labor force participation (despite the higher actual rates of labor force participation among men). Another possibility relates to the complementarity terms: equation (4) shows that labor force participation expectations (q) will only affect the schooling response if there is a gap between the schooling-ability complementarities in the labor market and in the home sector. However, home sector complementarities might simply be a reflection of the complementarities in the labor market, if (for example) a woman's potential wage influences the quality of her spouse (Chiappori et al., 2012; Lam, 1988) and bargaining power in a marriage, even if she does not work (Qian, 2008; Heath and Mobarak, 2015; Majlesi, 2016). Under these conditions, even for women who do not participate in the labor force, the home sector reward function might closely reflect the expected wage functions (conditional on labor force entry), resulting in little scope for different labor force participation expectations to drive gender differences in the schooling response.

Unlike labor force participation, white-collar proportions do seem to be important. In column 3 of Table 6, the negative effect of second trimester inversions on high school completion is concentrated among individuals more likely to go into a white-collar job. The coefficient on the second trimester interaction is negative and significant at the 5% level, while the main effect (which represents the effect on women with limited white-collar opportunities) is much smaller and insignificant. The finding that the negative effect of thermal inversions is concentrated on individuals with more exposure to white-collar jobs helps explain why inversions only had effects on high school completion (and not lower schooling milestones): individuals who expect to go into a white-collar job (where the vast majority of workers have a high school degree, as shown in Figure A1) are likely to be on the margin of high school completion. A cognitive shock for these individuals should therefore have the strongest effects on this margin.

Importantly, the gender difference that appears in column 1 completely disappears when the white-collar interactions are included in column 3: the male interaction is much smaller in magnitude than the white-collar interaction and insignificant. The drastic decrease in the second trimester male interaction with the inclusion of the white-collar interactions demonstrates that the gender difference in this context is driven by the different occupational choices made by men and women.

Finally, columns 4 and 5 investigate the role of the opportunity cost function, by including interactions with youth employment rates and average youth wages. Like labor force participation, these variables do not appear to be important in explaining the gender difference that appears in column 1, which remains significant after the inclusion of each set of child-labor-related interactions. In addition, the effect of second trimester inversions does not exhibit any heterogeneity with respect to these variables: the interactions between second trimester inversions and these indicators are small and statistically insignificant. I acknowledge, of course, that these variables are not direct measures of $\partial^2 c/\partial S \partial \theta$, which could result in an underestimation of the importance of this channel.

In summary, this empirical exercise provides support for only one of the three labor market mechanisms discussed above. Gender-specific white-collar proportions fully explain the gender difference in the schooling response to second trimester thermal inversions. The significant negative effect of inversions on high school completion is driven by individuals more likely to go into white-collar jobs, where schooling and ability are more complementary.

6.3. Alternative Explanations

In this investigation of labor market mechanisms, I have interpreted the gender-specific white-collar shares as representing individuals' expected probabilities of going into a white-collar job. This interpretation may be flawed, however, if these white-collar shares are simply capturing the effects of omitted variables that are correlated with these shares.

6.3.1. Non-Linear Thermal Inversion Effects. For example, if white-collar proportions are correlated with higher pollution levels (due to greater economic activity and urbanization, for example), we might expect to see stronger negative effects in high white-collar areas due to a non-linear relationship between thermal inversions and pollution. That is, if thermal inversions exacerbate pollution more in highly polluted areas (compared to less polluted areas), this would lead to larger reduced form effects in highly polluted areas. It is important to note, however, that while this could explain the significant negative coefficient on the interaction between white-collar proportions and thermal inversions, it would not be able to explain why the gender difference disappears after controlling for these variables.

In addition, this alternative explanation is ruled out by the evidence presented in Table A8. Here, I repeat the analysis conducted in Table 6, instead using cognitive ability as the dependent variable. If the high white-collar proportions were simply capturing larger effects in more polluted areas, there should also be stronger negative effects on cognitive ability in high white-collar areas. However, in the cognitive ability regression in Table A8, I find no differential effect across white-collar shares, and the effect sizes (for males and females) are not affected by the inclusion of these labor market controls.

6.3.2. Correlated Labor Market Variables. White-collar shares might also be correlated with other labor market characteristics. In order for an omitted variable to be driving both the significant negative white-collar interaction and the disappearance of the gender difference in Table 6, it has to be gender-specific (like the white-collar proportion variables I construct) and on average different for men and women. In particular, I need only to be concerned about variables that are correlated with white-collar proportions, within each gender, and which have different means for men and women. Variables that are positively (negatively) correlated with white-collar proportions *and* which are on average higher (lower) for women than for men are a concern. Fortunately, most correlates of white-collar shares do not fulfill this criteria.

For example, one might be concerned that high white-collar shares for a particular gender represent higher income or better job opportunities, specifically for that gender. Unlike white-collar shares, however, incomes are on average higher for men than women, which means that this variable would not be able to generate the pattern of results in Table 6. Another concern is that high white-collar shares could be related to features of the marriage market. Specifically, high white-collar shares for a particular gender may be associated with later marriage or later parenthood for that gender. However, in order for this to produce the pattern of results in Table 6, men would have to marry and have children at a younger age than women on average, which is not the case. It is unsurprising, then, that the coefficient estimates remain similar to those in Column 3 of Table 6, when I include thermal inversions interacted with zone-level gender-specific average income and zone-level gender-specific shares of ever-married individuals aged 18-25 (see columns 1 and 2 of Appendix Table A9).[32]

Though gender-specific incomes and gender-specific marital and fertility behavior were unlikely to be valid alternative explanations for my results in Column 3 of Table 6, gender-specific agricultural industry shares do satisfy the criteria of being negatively correlated with white-collar proportions (within gender) and on average lower for women than men. If agricultural shares (which are defined by industry) rather than white-collar shares (which are defined by occupation type) are responsible for the results in Table 6, this would rule out white-collar shares as the main mechanism. I therefore repeat the analysis conducted in Table 6, this time including interactions between thermal inversions and agricultural industry shares. The inclusion of these interactions does not affect any coefficients from the previous regressions. In column 3 of Appendix Table A9, I still find that there are significantly larger negative effects for individuals living in high white-collar areas, and no significant differences across individuals exposed to different agricultural industry shares.

6.3.3. Son Preference. Another explanation that may come to mind is son preference: only female schooling is negatively affected by cognitive shocks because males are treated preferentially. It is difficult to reconcile this explanation with the finding that the gender difference becomes insignificant with the inclusion of the white-collar share interactions. If the larger negative effect of inversions on

32. I use the gender-specific share of ever-married individuals aged 18-25 as a proxy for early marriage and parenthood because the decennial census does not include questions about age of first marriage or first child for both men and women. Results are robust to the use of younger age cutoffs.

female schooling was driven by son preference, or parental beliefs that men should complete high school no matter their ability level, the gender difference would persist even after controlling for gender-specific white-collar opportunities.

However, if preferences for particular genders are correlated with white-collar shares, this could still generate this specific pattern of results – but only under specific conditions, which I argue are unlikely. Suppose white-collar shares are correlated with a "preference" or "cultural norms" variable: either the preference for a specific gender in a specific location, or the cultural expectation that a given gender will complete high school in that location. The results in Table 6 revealed that there were stronger negative effects for those exposed to high white-collar shares. In addition, women have higher white-collar shares than men. For these two facts to be consistent with a son preference argument, high white-collar shares would have to be proxying for *lower* preference, which is somewhat counter-intuitive. If a particular gender is preferred or expected to complete high school regardless of ability, the natural assumption would be that they would also be expected to go into higher-paying white-collar jobs.

In addition, if son preference were the main reason for the gender difference that I find, the gender difference should be largest in regions with more gender inequality. Frias (2008) constructs a gender equality index for each of the 32 Mexican states and documents substantial heterogeneity across the states. I use this index, along with several other indicators, to test whether gender differences are strongest in states with higher gender inequality. In addition to the Frias (2008) index, I also calculate state-level male-to-female sex ratios for children under 3 and children under 5 years old, using the 1970 census, which was the last census that preceded all of the birth years in my sample. Differential child mortality due to son preference would manifest in higher male-to-female sex ratios. For my last measure of son preference, I calculate each state's average rank across all three measures. Using each of these measures, I split the states at the median and repeat my gender-specific regressions for above-median (high inequality) and below-median (low inequality) states. Appendix Figure A5 summarizes the results of this exercise. Keeping in mind that splitting the sample into two groups (and then cutting by gender) substantially reduces statistical power for detecting significant gender differences, I interpret the results by comparing the magnitudes of the coefficients as well as the gender gaps. Across all groups (both high and low inequality according to various definitions), the second trimester inversion coefficients for women are of very similar magnitudes. The coefficient that is largest in magnitude is, in fact, estimated from a low inequality group (defined by the under 5 sex ratio), which is the opposite of what we would expect if son preference were an important mechanism. Importantly, the gaps between the male and female coefficients are also fairly constant across high and low inequality groups. None of these results are consistent with son preference being the driving force behind the schooling gender difference.

6.3.4. Gender-Specific Returns to Reservation Wage. For parsimony, the model above made important simplifying assumptions, including the assumption that labor force participation probabilities are not affected by schooling or ability. However, reservation wages might vary for men and women (given their vastly different labor force participation rates), and in addition, these reservation wages might be differentially affected by schooling and ability for each gender. As the model does not allow for labor force participation probabilities to vary with ability or schooling, I investigate empirically the extent to which gender differences in the schooling-participation relationship could be driving my results.[33] The answer to this depends crucially on how the effect of schooling on labor force participation varies across gender, geographic area, and correlates with white-collar proportions across areas.

Figure A6 sheds some light on these relationships. In this scatterplot, the y-axis represents white-collar probabilities and the x-axis represents the schooling coefficient in a regression of labor force participation on years of schooling (controlling for age fixed effects) – that is, an estimate of the return to schooling in terms of labor force participation (which reflects reservation wages). Each point represents a different gender-state combination from the census. First, I note that the coefficients, which represent the effect of schooling on labor force participation, are all smaller for men than for women. In order for these gender-specific schooling effects on labor force participation to be driving the main results documented above (which rely on geographic variation in labor market conditions),[34] they would have to demonstrate sufficient variation across geographic areas, and be positively correlated with white-collar shares within each gender.

Figure A6 shows that neither of these conditions appear to hold. First, there is not much variation across the coefficient estimates across states: for both women and men, the range is less than 2 percentage points. Second, the correlations between these estimates and white-collar shares are neither strong nor consistent across genders: they are 0.08 for women and -0.17 for men. For comparison, the

33. Because census data is required for this analysis, I am unable to conduct the analogous analysis for the ability-participation relationship, as cognitive ability is only available in the MxFLS.

34. Both the gender difference and its disappearance after controlling for white-collar shares

variables explored in Table 6 (income, agricultural industry shares, and ever-married shares of 18-25 year-olds) are much more strongly correlated with white-collar shares, and these correlations are consistent in sign across genders.[35]

The small magnitudes and opposing signs of the correlations depicted in Figure A6 provide no support for the hypothesis that the gender difference in the schooling response is being driven by different returns to schooling in the reservation wages (and therefore labor force participation probabilities) of men and women. Unfortunately, I am unable to conduct the same test using cognitive ability, which is not available in the census. Therefore, I cannot definitively rule out gender-specific returns to cognitive ability in the reservation wage as an alternative explanation. However, the fact that the reservation wage returns to schooling are largely uncorrelated with white-collar proportions and demonstrate limited variation across geographic regions does help alleviate concerns about this being a major driver of the results.

7. Conclusion

Using thermal inversions as an exogenous source of variation in pollution levels, this paper documents that in utero exposure to pollution leads to significantly lower cognitive ability in adolescence and adulthood. Although there exists substantial prior evidence documenting the large, contemporaneous health costs of pollution (in terms of disease and premature death), this striking result expands our knowledge

35. For agricultural industry shares, the correlation is -0.78 for men and -0.71 for women; for income, 0.59 for men and 0.57 for women; for ever-married shares, -0.58 for men and -0.21 for women.

on this topic by providing evidence of long-run consequences, evidence of effects on cognitive ability, and evidence from a middle-income country.

Even though the negative effects on cognitive ability are present (and similarly sized) for both men and women, in utero pollution exposure appears to only affect the schooling decisions and income of women. Importantly, I show that the gender difference in the schooling response is driven by the different labor market opportunities men and women face. In particular, women are more likely to end up in white-collar jobs, where schooling and ability exhibit a higher degree of complementarity than in blue-collar jobs, and therefore adjust their schooling more in response to this early-life cognitive shock. In fact, gender-specific white-collar shares turn out to fully explain the gender difference in the schooling response that I document.

This is an important finding for the early-life literature, where gender differences are often documented but where proposed explanations for these differences are rarely tested. In general, these results help explain the substantial heterogeneity in the magnitudes of the estimated effects of early life shocks, both across and within studies. Much of the variation could be due to heterogeneity in labor market conditions across settings or sub-groups, which highlights the importance of considering the labor market when interpreting existing results or designing future interventions.

This paper joins Pitt et al. (2012) and Rosenzweig and Zhang (2013) in underscoring that gender-specific comparative advantage affects how males and females respond to shocks. It also offers evidence that parents and individuals respond to expectations about future labor market opportunities, which is consistent with related studies that use subjective expectations data (Kaufmann, 2014; Attanasio and Kaufmann, 2014). Finally, the results also speak to a broader literature documenting that labor market conditions, including current and future job opportunities, affect schooling decisions in general (Jensen, 2012; Atkin, 2016; Shah and Steinberg, 2015).

These results contribute to the literature on gender gaps in labor market outcomes by providing another potentially important explanation for the large relative gains in female education and employment outcomes that have been observed across the globe over the past few decades (Goldin, 1995; Mammen and Paxson, 2000; Rendall, 2017; Olivetti, 2014; Bhalotra et al., 2015; Pitt et al., 2012; Rosenzweig and Zhang, 2013).[36] Because female schooling responds more strongly to cognitive ability shocks than male schooling does, a sustained improvement in population intelligence levels, which has been observed in many contexts, repeatedly documented, and dubbed the “Flynn effect” (Trahan et al., 2014; Flynn, 1984), could have given rise to these larger improvements for women.

36. Previous literature has emphasized other important explanations for this phenomenon. For instance, many of the aforementioned studies argue that economic growth can generate improved economic outcomes for women precisely because it spurs the rise of a less physical sector, while Pitt et al. (2012) and Rosenzweig and Zhang (2013) argue that improvements in physical health and nutrition have played a role in these large relative improvements for women.

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Online Appendix

Pollution, Ability, and Gender-Specific Investment Responses to Shocks

Teresa Molina

Appendix A: Additional Figures and Tables

- Figure A1 illustrates the education distributions of adults aged 25-65 in the 2000 and 2010 Mexican census – for the overall population, for white-collar workers, and for blue-collar workers.
- Figure A2 reports white-collar to blue-collar ratios among men and women aged 25-65, across six countries using the 2010 census.
- Figures A3 and A4 show the robustness of the main results (on cognitive scores and high school completion) to the inclusion of additional fixed effects.
- Figure A5 reports the second trimester coefficients in the male and female regressions on high school completion, separately for states with above-median and below-median son preference (defined in four different ways).
- Figure A6 depicts the relationship between state-level, gender-specific white-collar shares and the coefficient in a (state- and gender-specific) regression of labor force participation on schooling (controlling for age fixed effects), using the 2000 and 2010 Mexican census.
- Tables A1 to A4 provide the coefficient estimates, standard errors, and observation counts for the graphs in Section 5.1. For each variable, the first column includes the basic fixed effects (municipality, month, and year) and the second adds state-specific season fixed effects and state-specific quadratic

trends. Table A5 provides the coefficient estimates from identical regressions that use elementary and junior high school completion as dependent variables.

- Table A6 reports the coefficient estimates in a regression of adjusted Raven's test scores on thermal inversions, using the basic specification (with state-specific trends in column 2). Adjusted Raven's test scores remove 2 questions of a particular type that have been noted to exhibit gender differences (Mackintosh and Bennett, 2005).
- Table A7 demonstrates the robustness of the labor market mechanism results to the use of alternative methods of constructing the labor market variables. Columns 1, 4, 6, and 8 assign individuals with the relevant labor market variable from the closest census to the year in which they turned 12. Columns 3, 5, 7, and 9 report the results from using a continuous version of the discrete measure used in Table 6. Column 2 uses a discrete measure that assigns inter-censal white-collar proportions using the shift-share strategy described in Section B.4.
- Table A8 repeats the analysis conducted in Column 3 of Table 6, except using Raven's test scores as the dependent variable.
- Table A9 repeats the analysis conducted in Column 3 of Table 6, but adds interactions between thermal inversions and three other variables: gender-specific average income, the gender-specific share of 18-25 year-olds who were ever married, and gender-specific agricultural industry shares.
- Table A10 reports all of the pre-conception and post-birth coefficients from the male and female regressions on Raven's scores, height, years of schooling, high school completion, and annual income.

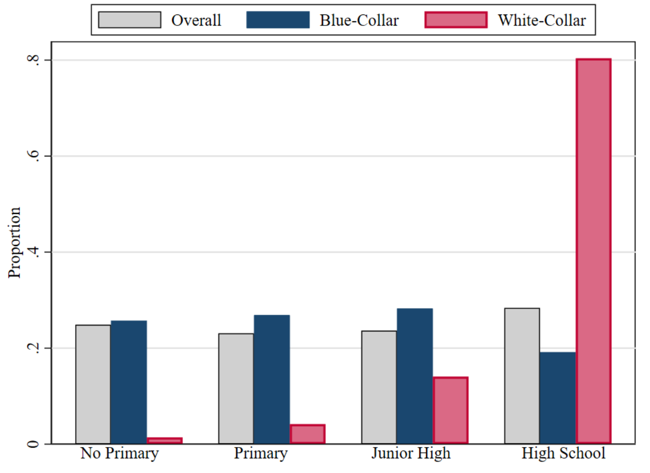

FIGURE A1. Education Distributions by Occupation Type

Notes: Weighted proportions calculated from adults aged 25 to 65 in the 2000 and 2010 Mexican census. Blue-collar and white-collar jobs are identified using ISCO occupation codes and the classifications in Table 1.

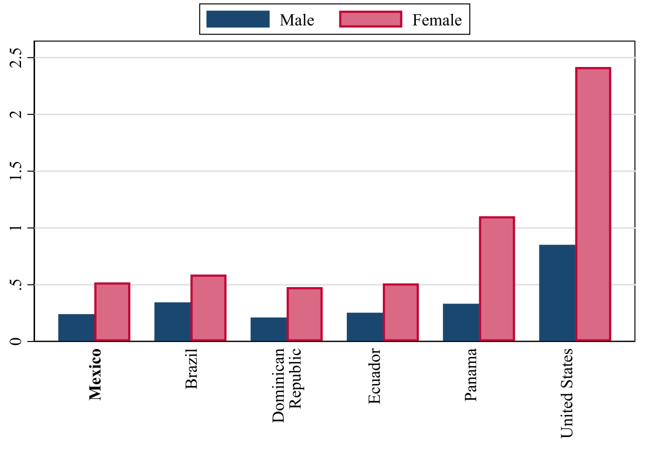

FIGURE A2. White-Collar to Blue-Collar Ratios Across Countries, by Gender

Notes: Ratios calculated using weighted counts of adults aged 25 to 65 in the 2010 censuses of the listed countries. Blue-collar and white-collar jobs are identified using ISCO occupation codes and the classifications in Table 1.

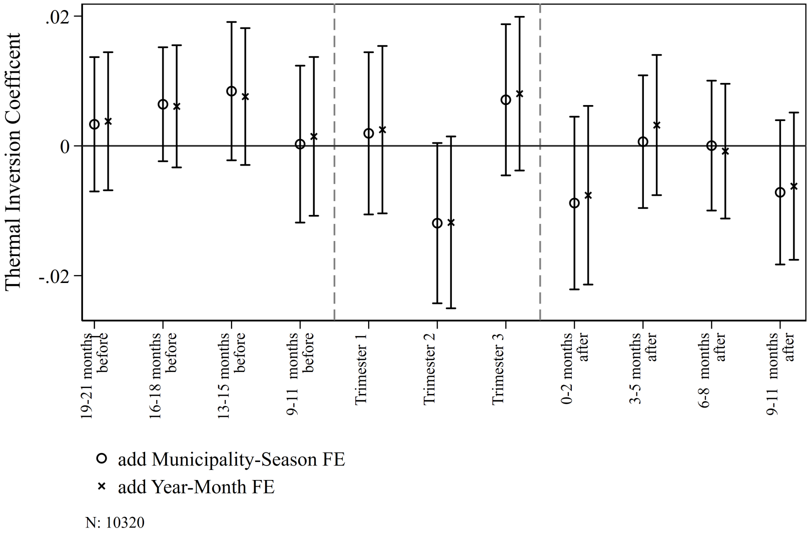

FIGURE A3. Effects of Thermal Inversions on Raven's Test Z-Scores, with Additional Fixed Effects

Notes: Intervals represent 95% confidence intervals. All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-by-quadratic year trends, gender, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period.

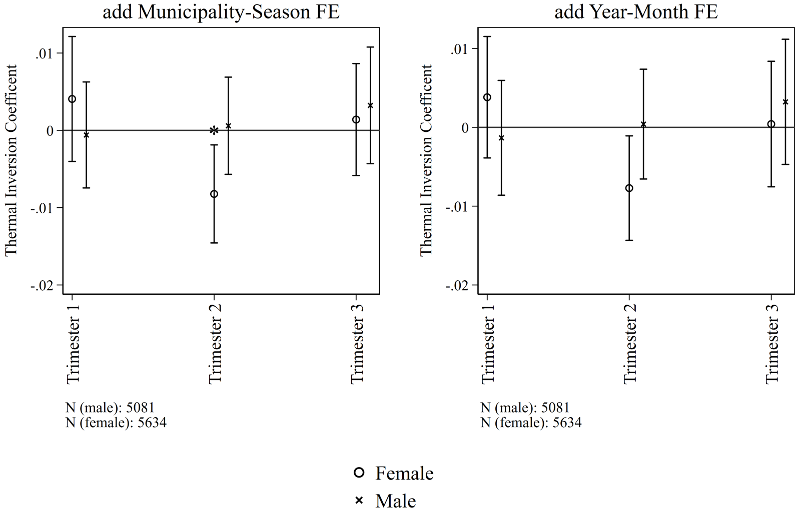

FIGURE A4. Effects of Thermal Inversions on High School Completion by Gender, with Additional Fixed Effects

Notes: Separate regressions are conducted for men and women. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ are used to denote significant differences across genders. Intervals represent 95% intervals. Controls include birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-by-quadratic year trends, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period.

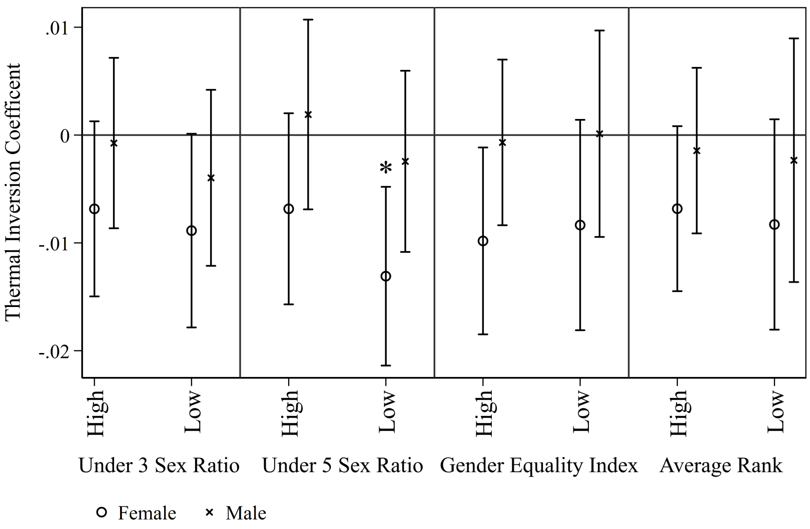

Figure A5. Effects of Thermal Inversions on High School Completion by Gender, Across High and Low Son Preference States

Notes: * p< 0.1, ** p< 0.05, *** p< 0.01 are used to denote significant differences across genders. Only the second trimester coefficients are reported, though inversions in all other three-month periods are included. Separate regressions are conducted for men and women. Intervals represent 95% confidence intervals. Controls include: birth month, birth year, municipality of birth, survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. States are classified into high (above-median) and low (below-median) son preference by ranking them according to the following indicators: male-to-female sex ratio of children under 3, male-to-female sex ratio of children under 5, gender equality index used in Frias (2008), and the average rank across the previous three indicators.

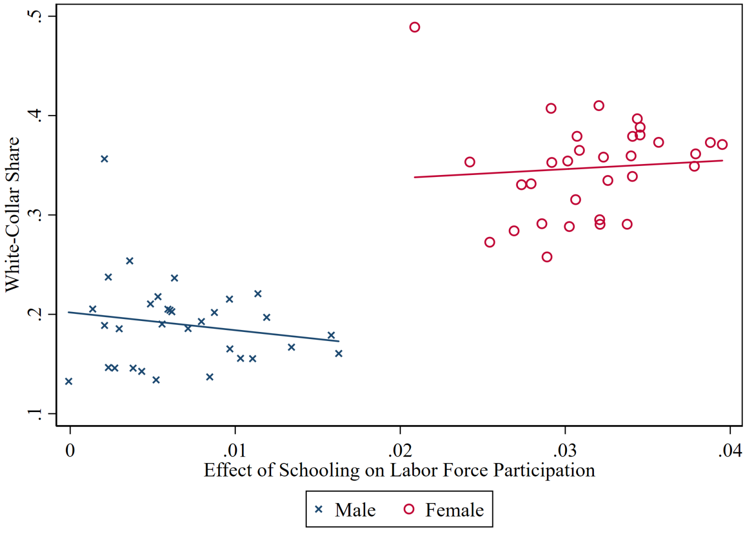

FIGURE A6. State-Level, Gender-Specific White-Collar Shares and Schooling Effects on Labor Force Participation

Notes: The x-axis represents the coefficient estimate on schooling in a regression of labor force participation on years of schooling (controlling for age fixed effects). Sample consists of adults aged 25-65 in the 2000 and 2010 Mexican censuses. Blue-collar and white-collar jobs are identified using the ISCO occupation codes, which are defined as blue-collar or white-collar using the classifications in Vogl (2014), summarized in Table 1.

Table A1. Effects of Thermal Inversions on Cognitive and Physical Health

Average monthly inversions…	(1) Raven's test z-score	(2) Raven's test z-score	(3) Height z-score	(4) Height z-score
BEFORE CONCEPTION				
19-21 months before birth	0.00453	0.00351	-0.00105	-0.00283
	(0.00463)	(0.00466)	(0.00580)	(0.00605)
16-18 months before birth	0.00435	0.00297	-0.00177	-0.00242
	(0.00387)	(0.00398)	(0.00519)	(0.00515)
13-15 months before birth	0.00767	0.00556	0.00356	0.00221
	(0.00497)	(0.00507)	(0.00501)	(0.00507)
10-12 months before birth	0.00284	0.000185	0.00888*	0.00533
	(0.00542)	(0.00557)	(0.00527)	(0.00536)
DURING PREGNANCY				
Trimester 1	0.00398	0.00324	0.00519	0.00570
	(0.00595)	(0.00592)	(0.00542)	(0.00526)
Trimester 2	-0.0119**	-0.0130**	0.00187	0.000907
	(0.00561)	(0.00581)	(0.00550)	(0.00557)
Trimester 3	0.00465	0.00350	0.00254	0.00116
	(0.00543)	(0.00535)	(0.00519)	(0.00514)
AFTER BIRTH				
0-2 months after birth	-0.00349	-0.00448	-0.00196	-0.00442
	(0.00615)	(0.00634)	(0.00467)	(0.00470)
3-5 months after birth	0.00321	0.00318	0.000718	0.000341
	(0.00457)	(0.00477)	(0.00539)	(0.00530)
6-8 months after birth	0.000462	-0.000623	-0.000524	-0.00208
	(0.00466)	(0.00470)	(0.00571)	(0.00589)
9-11 months after birth	-0.00594	-0.00846	-0.00133	-0.00207
	(0.00502)	(0.00521)	(0.00539)	(0.00552)
N	10320	10320	10398	10398
Mean of dependent variable	0.0164	0.0164	-1.008	-1.008
Additional Fixed Effects	None	state-by-season, state-by-quadratic-year	None	state-by-season, state-by-quadratic-year

Notes: Standard errors (clustered at municipality level) in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$. All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, gender, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period.

Table A2. Effects of Thermal Inversions on Cognitive and Physical Health by Gender

Average monthly inversions…	(1) Raven's test z-score	(2) Raven's test z-score	(3) Height z-score	(4) Height z-score
FEMALE				
Trimester 1	0.00464	0.00221	0.00182	0.00603
	(0.00774)	(0.00790)	(0.00810)	(0.00818)
Trimester 2	-0.00971	-0.0107	0.00565	0.00453
	(0.00832)	(0.00850)	(0.00729)	(0.00756)
Trimester 3	0.00392	0.00257	-0.00178	-0.00153
	(0.00770)	(0.00784)	(0.00668)	(0.00668)
N	5455	5455	5506	5506
Dependent variable mean	-0.00429	-0.00429	-1.043	-1.043
MALE				
Trimester 1	0.00193	0.00155	0.00746	0.00521
	(0.00754)	(0.00761)	(0.00754)	(0.00759)
Trimester 2	-0.0139*	-0.0127	-0.00539	-0.00830
	(0.00814)	(0.00883)	(0.00805)	(0.00825)
Trimester 3	0.00438	0.00294	0.0107	0.00790
	(0.00862)	(0.00842)	(0.00831)	(0.00826)
N	4865	4865	4892	4892
Dependent variable mean	0.0397	0.0397	-0.970	-0.970
MALE-FEMALE DIFFERENCE				
Trimester 1	-0.00272	-0.000663	0.00564	-0.000822
	(0.0101)	(0.0109)	(0.0111)	(0.0115)
Trimester 2	-0.00422	-0.00199	-0.0110	-0.0128
	(0.0117)	(0.0122)	(0.0108)	(0.0110)
Trimester 3	0.000465	0.000376	0.0124	0.00943
	(0.0120)	(0.0120)	(0.0105)	(0.0106)
N	10320	10320	10398	10398
Additional Fixed Effects	None	state-by-season, state-by-quadratic-year	None	state-by-season, state-by-quadratic-year

Notes: Standard errors (clustered at municipality level) in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$ All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. Separate regressions are conducted for men and women.

Table A3. Effects of Thermal Inversions on Schooling by Gender

	(1)	(2)	(3)	(4)
Average monthly inversions…	Years of Schooling	Years of Schooling	HS Completion	HS Completion
FEMALE				
Trimester 1	0.0296	0.0254	0.375	0.363
	(0.0217)	(0.0213)	(0.352)	(0.352)
Trimester 2	-0.0165	-0.0232	-0.773**	-0.792***
	(0.0208)	(0.0202)	(0.305)	(0.298)
Trimester 3	-0.0140	-0.0109	0.0748	0.179
	(0.0210)	(0.0196)	(0.307)	(0.311)
N	5634	5634	5634	5634
Dependent variable mean	9.521	9.521	28.79	28.79
MALE				
Trimester 1	-0.000200	-0.00251	-0.0848	-0.0607
	(0.0194)	(0.0192)	(0.298)	(0.304)
Trimester 2	0.00665	0.00771	-0.0714	-0.0211
	(0.0183)	(0.0196)	(0.261)	(0.270)
Trimester 3	-0.00524	-0.00777	0.315	0.291
	(0.0178)	(0.0174)	(0.320)	(0.333)
N	5081	5081	5081	5081
Dependent variable mean	9.199	9.199	24.13	24.13
MALE - FEMALE DIFFERENCE				
Trimester 1	-0.0298	-0.0279	-0.460	-0.423
	(0.0304)	(0.0293)	(0.476)	(0.478)
Trimester 2	0.0231	0.0309	0.702*	0.771*
	(0.0281)	(0.0295)	(0.393)	(0.405)
Trimester 3	0.00874	0.00314	0.240	0.112
	(0.0256)	(0.0243)	(0.429)	(0.431)
N	10715	10715	10715	10715
Additional Fixed Effects	None	state-by-season, state-by-quadratic-year	None	state-by-season, state-by-quadratic-year

Notes: Standard errors (clustered at municipality level) in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. In high school completion regressions, coefficients are scaled to represent percentage points. All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. Separate regressions are conducted for men and women.

Table A4. Effects of Thermal Inversions on Income by Gender

	(1)	(2)
Average monthly inversions…	Annual income	Annual income
FEMALE		
Trimester 1	-3.039	121.3
	(552.6)	(755.3)
Trimester 2	-1112.9*	-1056.2*
	(601.5)	(617.4)
Trimester 3	-187.4	-93.30
	(746.8)	(855.1)
N	954	954
Dependent variable mean	24555.6	24555.6
MALE		
Trimester 1	-97.25	-416.4
	(333.3)	(412.4)
Trimester 2	-251.4	-499.6
	(299.5)	(335.9)
Trimester 3	36.15	-275.0
	(267.8)	(292.0)
N	2043	2043
Dependent variable mean	31405.0	31405.0
MALE - FEMALE DIFFERENCE		
Trimester 1	-94.21	-537.6
	(601.9)	(710.1)
Trimester 2	861.5	556.6
	(641.3)	(671.4)
Trimester 3	223.6	-181.7
	(741.4)	(827.0)
N	2997	2997
Additional Fixed Effects	None	state-by-season, state-by-quadratic-year

Notes: Standard errors (clustered at municipality level) in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$. All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. Separate regressions are conducted for men and women.

Table A5. Effects of Thermal Inversions on Early Educational Attainment, by Gender

Average monthly inversions…	(1) Elementary School Completion	(2) Elementary School Completion	(3) Junior High School Completion	(4) Junior High School Completion
FEMALE				
Trimester 1	-0.0130	-0.0326	0.264	0.210
	(0.207)	(0.203)	(0.326)	(0.325)
Trimester 2	0.217	0.167	0.0556	-0.0529
	(0.179)	(0.187)	(0.343)	(0.342)
Trimester 3	-0.173	-0.129	-0.285	-0.324
	(0.180)	(0.179)	(0.361)	(0.344)
N	5634	5634	5634	5634
Dependent variable mean	92.90	92.90	70.94	70.94
MALE				
Trimester 1	-0.0277	-0.0402	-0.475	-0.493
	(0.187)	(0.197)	(0.344)	(0.351)
Trimester 2	0.185	0.122	0.229	0.188
	(0.208)	(0.221)	(0.364)	(0.373)
Trimester 3	-0.252	-0.303	-0.175	-0.162
	(0.209)	(0.208)	(0.283)	(0.293)
N	5081	5081	5081	5081
Dependent variable mean	90.85	90.85	66.42	66.42
MALE - FEMALE DIFFERENCE				
Trimester 1	-0.0147	-0.00758	-0.739	-0.702
	(0.300)	(0.307)	(0.470)	(0.486)
Trimester 2	-0.0324	-0.0447	0.174	0.241
	(0.262)	(0.283)	(0.550)	(0.545)
Trimester 3	-0.0790	-0.174	0.111	0.162
	(0.256)	(0.243)	(0.450)	(0.441)
N	10715	10715	10715	10715
Additional Fixed Effects	None	state-by-season, state-by-quadratic-year	None	state-by-season, state-by-quadratic-year

Notes: Standard errors (clustered at municipality level) in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficients scaled to represent percentage points. All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. Separate regressions are conducted for men and women.

Table A6. Effects of Thermal Inversions on Adjusted Raven's Test scores by Gender

	(1)	(2)
Average monthly inversions…	Adjusted Raven's test z-score	Adjusted Raven's test z-score
FEMALE		
Trimester 1	0.00772	0.00516
	(0.00814)	(0.00837)
Trimester 2	-0.0125	-0.0139
	(0.00828)	(0.00849)
Trimester 3	0.00296	0.00147
	(0.00756)	(0.00770)
N	5455	5455
Dependent variable mean	0.00291	0.00291
MALE		
Trimester 1	0.00143	0.000715
	(0.00776)	(0.00785)
Trimester 2	-0.0125	-0.0121
	(0.00800)	(0.00874)
Trimester 3	0.00516	0.00346
	(0.00824)	(0.00811)
N	4865	4865
Dependent variable mean	0.0354	0.0354
MALE-FEMALE DIFFERENCE		
Trimester 1	-0.00628	-0.00444
	(0.0107)	(0.0114)
Trimester 2	-0.0000322	0.00176
	(0.0117)	(0.0122)
Trimester 3	0.00220	0.00199
	(0.0115)	(0.0115)
N	10320	10320
Additional Fixed Effects	None	state-by-season, state-by-quadratic-year

Notes: Standard errors (clustered at municipality level) in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$. Adjusted Raven's scores omit two questions of a specific type that has been previously noted to exhibit gender differences. All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. Separate regressions are conducted for men and women.

TABLE A7. Effects of Thermal Inversions on High School Graduation, by Alternative Labor Market Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Average monthly inversions...	HS Completion	HS Completion	HS Completion	HS Completion	HS Completion	HS Completion	HS Completion	HS Completion	HS Completion
Trimester 1	0.155	0.447	-0.0602	0.338	0.132	0.342	0.134	0.505	0.330
	(0.498)	(0.553)	(0.494)	(0.354)	(0.524)	(0.354)	(0.439)	(0.358)	(0.356)
Trimester 2	0.0500	-0.0896	-0.445	-0.802***	-1.068**	-0.818***	-0.724**	-0.777**	-0.826***
	(0.441)	(0.435)	(0.448)	(0.299)	(0.520)	(0.299)	(0.330)	(0.310)	(0.297)
Trimester 3	0.216	0.0764	0.230	0.164	-0.0689	0.156	0.434	0.253	0.171
	(0.546)	(0.579)	(0.423)	(0.313)	(0.496)	(0.313)	(0.368)	(0.318)	(0.313)
Trimester 1	-0.337	-0.429	-0.0493	-0.326	0.112	-0.373	-0.130	-0.266	-0.405
x 1(Male)	(0.584)	(0.621)	(0.584)	(0.535)	(1.109)	(0.499)	(0.582)	(0.491)	(0.500)
Trimester 2	0.112	0.221	0.419	0.602	1.427	0.618	0.627	0.700	0.906**
x 1(Male)	(0.481)	(0.483)	(0.523)	(0.469)	(1.187)	(0.428)	(0.456)	(0.424)	(0.406)
Trimester 3	0.000468	0.0707	-0.00416	0.376	0.640	-0.0478	-0.315	0.106	0.0888
x 1(Male)	(0.531)	(0.584)	(0.511)	(0.485)	(1.095)	(0.437)	(0.500)	(0.436)	(0.434)
Trimester 1	0.238	-0.0643	2.261	-0.189	-1.116	-0.156	-2.688	-0.630*	-0.000343
x 1(Labor market variable)	(0.389)	(0.476)	(1.695)	(0.426)	(2.075)	(0.417)	(3.380)	(0.372)	(0.000845)
Trimester 2	-0.971**	-0.891**	-1.755	0.331	-1.343	0.524	1.416	0.0565	-0.00115
x 1(Labor market variable)	(0.378)	(0.370)	(1.620)	(0.398)	(2.380)	(0.401)	(2.612)	(0.360)	(0.000890)
Trimester 3	-0.0640	0.0691	-0.355	-0.543	-1.181	0.349	3.900	-0.266	0.00000833
x 1(Labor market variable)	(0.435)	(0.455)	(1.437)	(0.445)	(2.054)	(0.449)	(2.713)	(0.339)	(0.000865)
N	10677	10572	10677	10689	10689	10689	10689	10689	10689
Dependent variable mean	26.47	26.42	26.47	26.51	26.51	26.51	26.51	26.51	26.51
Labor market variable	White-collar proportion			Labor force participation		Youth Employment		Youth Income	
Variable construction	Top quartile indicator, closest census	Top quartile indicator, shift-share predictor	Continuous, linear interpolation	Top quartile indicator, closest census	Continuous, linear interpolation	Top quartile indicator, closest census	Continuous, linear interpolation	Top quartile indicator, closest census	Continuous, linear interpolation

Notes: Standard errors (clustered at municipality level) in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. Coefficients scaled to represent percentage points. All regressions control for the following variables and their interactions with a male indicator (as well as the main effect of gender): birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period, as well as inversions in all other three-month periods. The main effect of the relevant labor market dummy and its interactions with inversions in all other three-month periods are also included. Individuals are assigned to labor market variables in their commuting zone of residence at age 12, and intercensal years are predicted using the methods described in the "Variable Construction" row. "Closet census" uses the census closest to the year in which the individual turned 12. See Section B.4 for a description of the "shift-share" method. Continuous labor market variables are de-meaned.

Table A8. Effects of Thermal Inversions on Cognitive Ability, by White Collar Shares

	(1)	(2)
Average monthly inversions…	Raven's test z-score	Raven's test z-score
Trimester 1	0.00221	0.00770
	(0.00793)	(0.0110)
Trimester 2	-0.0107	-0.0134
	(0.00853)	(0.0107)
Trimester 3	0.00257	0.00932
	(0.00786)	(0.0134)
Trimester 1 x 1(Male)	-0.000663	-0.00551
	(0.0109)	(0.0127)
Trimester 2 x 1(Male)	-0.00199	0.000519
	(0.0122)	(0.0129)
Trimester 3 x 1(Male)	0.000376	-0.00531
	(0.0120)	(0.0153)
Trimester 1 x 1(Labor market variable in top quartile)		-0.00555
		(0.00904)
Trimester 2 x 1(Labor market variable in top quartile)		0.00377
		(0.00795)
Trimester 3 x 1(Labor market variable in top quartile)		-0.00761
		(0.0111)
N	10320	10281
Dependent variable mean	0.0164	0.0165
Labor market variable	None	White-collar proportion

Notes: Standard errors (clustered at municipality level) in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. All regressions control for the following variables and their interactions with a male indicator (as well as the main effect of gender): birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period, as well as inversions in all other three-month periods. The main effect of the relevant labor market dummy and its interactions with inversions in all other three-month periods are also included. Individuals are assigned to labor market variables in their commuting zone of residence at age 12, and linear interpolation is used to interpolate between census years.

Table A9. Effects of Thermal Inversions on High School Graduation, by White Collar Shares and Additional Labor Market Variables

	(1)	(2)	(3)
Average monthly inversions…	HS Completion	HS Completion	HS Completion
Trimester 1	0.244	0.0574	0.207
	(0.487)	(0.518)	(0.488)
Trimester 2	-0.0820	0.0243	0.0191
	(0.442)	(0.451)	(0.442)
Trimester 3	0.0267	-0.0183	-0.0858
	(0.499)	(0.566)	(0.530)
Trimester 1	-0.134	-0.247	-0.439
x 1(Male)	(0.627)	(0.601)	(0.567)
Trimester 2	0.129	0.129	0.127
x 1(Male)	(0.520)	(0.495)	(0.479)
Trimester 3	0.587	0.172	0.163
x 1(Male)	(0.645)	(0.575)	(0.518)
Trimester 1	0.265	0.263	0.185
x 1(White collar variable in top quartile)	(0.415)	(0.397)	(0.395)
Trimester 2	-0.900**	-0.939**	-0.944**
x 1(White collar variable in top quartile)	(0.376)	(0.385)	(0.398)
Trimester 3	0.351	0.240	0.273
x 1(White collar variable in top quartile)	(0.434)	(0.423)	(0.424)
Trimester 1	-0.327	0.617	0.521
x 1(Other variable in top quartile)	(0.387)	(0.545)	(0.857)
Trimester 2	0.109	-0.166	-0.475
x 1(Other variable in top quartile)	(0.431)	(0.577)	(0.801)
Trimester 3	-0.575	0.00000664	0.950
x 1(Other variable in top quartile)	(0.363)	(0.646)	(1.165)
N	10677	10677	10677
Dependent variable mean	26.47	26.47	26.47
Other Variable	Average income	Ever-married shares (among ages 18-25)	Agricultural industry shares

Notes: Standard errors (clustered at municipality level) in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$. Coefficients scaled to represent percentage points. All regressions control for the following variables and their interactions with a male indicator (as well as the main effect of gender): birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period, as well as inversions in all other three-month periods. The main effect of both relevant labor market dummies and their interactions with inversions in all other three-month periods are also included. Individuals are assigned to labor market variables in their commuting zone of residence at age 12, and linear interpolation is used to interpolate between census years.

Table A10. Pre-Conception and Post-Birth Coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average monthly inversions…	Raven's test z-score	Raven's test z-score	Height z-score	Height z-score	Years of Schooling	Years of Schooling	HS Completion	HS Completion	Annual Income	Annual Income
BEFORE CONCEPTION										
19-21 months before birth	0.00608	0.00234	-0.000422	-0.00740	0.0177	0.00837	0.0626	0.329	-536.3	-4.214
	(0.00708)	(0.00736)	(0.00804)	(0.00846)	(0.0223)	(0.0202)	(0.354)	(0.318)	(546.0)	(323.0)
16-18 months before birth	0.00531	0.00260	0.00487	-0.00454	0.00965	-0.00498	0.235	-0.0787	478.7	-191.2
	(0.00573)	(0.00656)	(0.00674)	(0.00797)	(0.0188)	(0.0194)	(0.305)	(0.326)	(653.6)	(317.8)
13-15 months before birth	0.00968	0.000691	0.00760	-0.00598	0.0176	-0.00192	0.155	-0.0680	-272.2	203.6
	(0.00655)	(0.00861)	(0.00666)	(0.00802)	(0.0185)	(0.0198)	(0.326)	(0.323)	(560.5)	(376.7)
10-12 months before birth	0.00390	-0.00616	0.0114	-0.00246	-0.0104	-0.0307*	-0.274	-0.167	-516.8	176.5
	(0.00713)	(0.00834)	(0.00817)	(0.00753)	(0.0234)	(0.0183)	(0.373)	(0.303)	(505.5)	(327.6)
AFTER BIRTH										
0-2 months after birth	0.00143	-0.00735	0.00278	-0.0158**	0.0179	0.0148	0.187	0.0606	373.9	-167.0
	(0.00744)	(0.00924)	(0.00706)	(0.00721)	(0.0209)	(0.0186)	(0.376)	(0.283)	(631.2)	(359.0)
3-5 months after birth	-0.000108	0.00681	0.00723	-0.00716	-0.0144	0.0232	-0.0542	0.192	-362.7	404.6
	(0.00610)	(0.00768)	(0.00721)	(0.00814)	(0.0201)	(0.0181)	(0.347)	(0.290)	(552.5)	(368.3)
6-8 months after birth	-0.00179	-0.00413	-0.00118	-0.00744	0.00736	-0.0256	0.479	0.0446	66.02	549.1
	(0.00686)	(0.00657)	(0.00652)	(0.00808)	(0.0196)	(0.0185)	(0.319)	(0.302)	(518.0)	(332.1)
9-11 months after birth	-0.0129*	-0.00188	0.00513	-0.0108	-0.00533	0.0178	-0.179	0.0871	-202.1	-35.78
	(0.00774)	(0.00860)	(0.00832)	(0.00789)	(0.0204)	(0.0184)	(0.316)	(0.232)	(613.5)	(388.1)
N	5455	4865	5506	4892	5634	5081	5634	5081	954	2043
Gender	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male

Notes: Standard errors (clustered at municipality level) in parentheses. * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$. In high school completion regressions, coefficients are scaled to represent percentage points. All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-specific quadratic year trends, state-specific season dummies, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. Separate regressions are conducted for men and women.

Appendix B: Background and Data Appendix

B.1. Pollutants

CO is a colorless and odorless gas that binds more readily to hemoglobin than oxygen and hinders the body's ability to carry oxygen. CO is produced in combustion, and its main source (especially in urban areas) is vehicle emissions. In a pregnant woman, CO can hinder the delivery of oxygen to the fetus, leading to long-term neurological and skeletal damage (Aubard and Magne, 2000).

Particulate matter refers to a mixture of solid and liquid particles in the air, which includes fine particles known as PM-2.5 (with diameters less than 2.5 micrometers) and inhalable coarse particles known as PM-10 (with diameters less than 10 but greater than 2.5 micrometers). These particles can be emitted directly from a source, like fires or construction sites. They can also form as a result of chemical reactions in the atmosphere. When inhaled by a pregnant woman, particulate matter can cause inflammation or infection. This can thicken blood and plasma, hindering blood flow and glucose transport to the placenta (Lacasaña et al., 2005). The effects of one particular component of particulate matter, polycyclic aromatic hydrocarbons (PAHs), can be especially dangerous. PAHs are thought to increase the prevalence of DNA adducts, which are associated with negative birth outcomes like low birth weight and decreased head circumference (Perera et al., 1998; Le et al., 2012; Lacasaña et al., 2005). Moreover, PAHs can cross the placental barrier and damage the fetal brain by causing inflammation, oxidative stress, or damaging blood vessels. Recent evidence has shown this can result in lower cognition later in childhood (Peterson et al., 2015).

B.2. Thermal Inversions

There are three common types of inversions that are associated with worsened air quality; they form in slightly different circumstances but all result in a warm layer of air above a cooler layer. Radiation inversions take place at night, as the surface cools by emitting thermal infrared radiation. Unlike during the day, when radiation from the sun tends to have a stronger opposing effect, this results in cooler air near the surface than further above ground. Radiation inversions are more common during long, calm, and dry nights, when there is more time for the cooling to take place, less mixing in the air, and little water vapor to absorb the thermal infrared energy. Subsidence inversions take place when air descends and warms as it compresses, creating a warm layer above cooler air. This can happen in mountainous regions, when air flows down the side of a slope, or in high pressure systems,[37] which are characterized by this descending movement and compression of air. Over coastal areas, marine inversions take place when air above the sea, which is cooler than the air above land, flows inland and pushes the warm inland air upward.

B.2.1. NARR Validation Checks. I use the NARR data to identify inversions. Detailed validation exercises have concluded that the NARR data closely matches observational data and offers a considerable improvement over prior global reanalysis data sets (Mesinger et al., 2006). Because all of these checks have included the United States and Canada, which may dominate the validation exercises due to their size, I verify that these conclusions are still valid when I

37. High pressure systems are associated with high temperatures, clear skies, and light winds at the surface

restrict to only Mexico. First, using temperature data that is available on the same INECC pollution database described above, I find a very high correlation (0.87) between the NARR 2-meter temperature and these ground-level measurements. Secondly, I compare my measure of inversions to a measure calculated using temperature readings from satellite data: NASA's Atmospheric Infrared Sounder (AIRS), used by Jans et al. (2018) to identify thermal inversions in Sweden. Because the AIRS was launched in 2002, the data is too recent to use as my measure of inversions or to instrument for my current measure of inversions, but for two overlapping years (2002 and 2003), I find correlations between the NARR and AIRS inversions measures of around 0.7.[38]

B.2.2. Construction of Thermal Inversion Variables. As described in the main body of the paper, the NARR dataset provides temperature values on a 0.3 by 0.3 degree grid for 29 pressure levels (extending vertically into the atmosphere), every three hours. For each latitude-longitude grid point and for each recorded hour, I create an indicator equal to 1 if the 2-meter temperature (equivalent to what is usually reported in weather reports) is higher than the temperature at the first pressure level above the surface, which lies roughly 300 meters above the surface. Because surface pressure varies across space, I use the temperatures from

38. It should be noted that there are several factors that complicate the comparison between the NARR and AIRS data. First of all, the times at which the AIRS and NARR data recorded temperatures do not match up exactly. Secondly, the AIRS data has a 1 by 1 degree resolution, substantially larger than the NARR's 0.3 by 0.3 degree resolution. Finally, the AIRS data records temperatures at fewer pressure levels than the NARR. If anything, these factors are likely to weaken the correlation between the two measures, suggesting that a correlation of 0.7 may be an underestimate.

different pressure levels depending on the altitude at a particular grid point. For a municipality at sea level (1000 hPa), I use the temperature at 975 hPa, but for a higher altitude location in Mexico City, for example, I use the temperature at 700 hPa (if surface pressure is 725 hPa). After creating inversion indicators for every recorded hour, I then collapse to two indicators per day – one for any daytime inversion and one for any nighttime inversion. I then match each Mexican municipality to its four closest grid points and assign each municipality with the inverse-distance weighted average of the nighttime inversion indicator for each day. I sum this indicator over the month and then average over three-month periods.

I assign inversions to individuals based on municipality of birth, a restricted use variable obtained from the migration module of the MxFLS, which is directed to individuals aged 15 and older. For the individuals who are missing this variable,[39] I assign them the inversions in their municipality of residence. I do this instead of dropping these individuals because over 80% of individuals who move municipalities between birth and the survey date report that they are currently living in their state of birth and about 70% report living in their municipality of birth. Therefore, for over half of the individuals with missing birth municipalities, using municipality of residence is the correct imputation, while a majority of the remainder only moved short distances (i.e. within state).

39. Less than 5% of individuals in each wave of the migration module listed either no municipality at all or a municipality name that could not be mapped to a unique municipality code. A slightly larger percentage of individuals in my final sample were missing this variable simply because they had not completed a migration module in any wave, despite being older than 15 by the most recent wave.

To create trimester-specific inversion variables for each individual, because I do not have the actual date of conception or date of birth, I simply count backwards, in three month increments, from an individual's month of birth and average over each three month period.

B.3. Construction of Individual-Level Variables

I merge all waves of data for each individual and extract the relevant information from the relevant waves. For variables that should be consistent across waves (gender, birth year), I use data from all available waves and resolve inconsistencies by prioritizing values that are consistent across at least two waves. For other variables, I pick one wave for each individual. In particular, I use the Raven's test score from the first wave the individual took the test (to avoid capturing any learning effects). For all other reduced-form outcome variables (schooling and income), I use the variable from the most recent survey wave available, with one important exception.

In 2009, the share of individuals in the MxFLS who report being a technician in their main job rises by 11 percentage points, from 1% in 2005 and 2% in 2002. This dramatic increase does not show up when comparing the share of technicians in the 2000 and 2010 censuses and therefore seems to be driven by a change in coding, rather than an actual increase in the share of individuals in this occupation. In order to avoid using variables that are coded differently across survey waves, I ignore all work-related variables for individuals who report working as a technician in 2009. This does not mean that I drop these individuals from the sample – this simply means that their work-related variables (income and occupation category, which are used to create Figure 6) are taken from the most recent available wave prior to 2009.

To represent occupation types, the MxFLS uses a different categorization system from the ISCO codes that are used in the census (summarized in Appendix Table 1). Appendix Table B1 lists how I map these Mexican Classification of Occupations (CMO) codes to the white-collar and blue-collar categories. This mapping was fairly straightforward, based simply on comparing CMO descriptions to ISCO descriptions (and then using the Vogl (2014) classification to categorize into white-collar and blue-collar).

B.4. Predicting White Collar Proportions

The results in column 2 of Table A7 combine census data with national-level growth rates from Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) to predict intercensal years. ENIGH is a nationally representative household survey that was first conducted by Mexico's National Institute of Statistics and Geography (INEGI) in 1982, and every two years since 1992. For each year y (measured relative to the most recent census), I calculate national-level growth rates of six major industries[40] (subscripted by j). I denote these growth rates g_{jy}. From the census, in addition to the gender-specific proportions of white collar jobs in each decade in each zone z (p_{gz0}), I also calculate the zone-specific and gender-specific share of brain-intensive jobs in each industry: s_{jgz0}. The predicted proportion, $\hat{p}_{gzy}$, is simply:

40. The six broad industry categories I use are: (1) agriculture, (2) oil, natural gas, and construction, (3) education, health, and government, (4) manufacturing, (5) service and hospitality, and (6) trade.

Table B1. Mexican Classification of Occupation (CMO) Codes

CMO Code and Description	
White-Collar ("Brains")	
11	Professionals
12	Technicians
13	Education Workers
14	Arts, sports, performance, and sports workers
21	Employees and directors of the public, private, and social sectors
61	Department chiefs, coordinators and supervisors of the administrative activities and services
62	Workers in the support of the administrative activities
Blue-Collar ("Brawn")	
41	Agricultural, cattle activities, foresting, hunting, and fishing workers
51	Chiefs, supervisors, and other control workers in craft and industrial manufacture and in maintenance and repairing activities
52	Craftsmen and manufacturers in the transformation industry and workers of maintenance and repairing activities
53	Operators of fixed machinery of continuous movement and equipment in the process of industrial production
54	Assistants, laborers, and similar in the process of artisan and industrial manufacture and in repairing and maintenance activities
55	Conductors and assistants of conductors of movable machinery and means of transport
71	Retailers, employees in commerce, and sales agents
72	Street sales and services workers
81	Workers in personal establishments
82	Workers in domestic services

Notes: CMO codes are first matched to ISCO codes. Brain and brawn categorizations from Vogl (2014).

$$\hat{p}_{gzy} = p_{gz0} + \sum_{j=1}^{6} s_{jgz0} g_{jy}. \tag{B.1}$$