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

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Abstract

The long-term effects of early-life health shocks on later-life human capital are well-documented, but the reasons why men and women often respond differently to these shocks are less well-studied. Using data from Mexico, I show that exposure to pollution in the second trimester of gestation leads to significantly lower cognitive ability in adulthood for both men and women. For women only, however, this shock to cognitive ability also leads to lower high school completion and income. I identify two labor market features that explain why women adjust their schooling decisions more than men: (1) women sort into the white-collar sector at higher rates, and (2) schooling and ability are more complementary in the white-collar sector than in the blue-collar sector. I verify the higher degree of complementarity in white-collar jobs by structurally estimating the wage parameters for each sector, using a dynamic discrete choice model of education and occupational choice.

*University of Southern California Department of Economics: 3620 S. Vermont Ave. KAP 300, Los Angeles, CA 90089; email: tsmolina@usc.edu; This paper would not exist without the guidance, support, and patience of my advisor, John Strauss, and Achyuta Adhvaryu and Anant Nyshadham. I am also grateful to Dan Bennett, Tushar Bharati, Joe Cummins, Yu-Wei Hsieh, Katie Lim, Matt Kahn, Gaurav Khanna, Mallory Montgomery, Jeff Nugent, Geert Ridder, Neeraj Sood, and Jorge Tamayo for helpful conversations and feedback on previous drafts. Thanks to seminar participants at USC, SoCCAM, the WEAI Annual Meeting and Graduate Student Workshop, and CSU Long Beach. I gratefully acknowledge funding from the USC Provost's Ph.D. Fellowship, the USC Dornsife INET graduate student fellowship, and the Oakley Endowed Fellowship. Special thanks to Graciela Teruel and the MxFLS Support Team for providing me with restricted-use data. **This is a preliminary draft. Please do note cite without the author's permission.** All errors are my own.

1 Introduction

Shocks experienced early in life can impact a wide range of outcomes in adulthood,[1] by directly affecting physical and cognitive ability (Almond and Currie, 2011), as well as by influencing the human capital investment decisions made throughout an individual's life (Almond and Mazumder, 2013). Early life exposure to pollution has become a particularly salient example of this. Many studies show that *in utero* exposure to air pollution can negatively affect birth outcomes (like birth weight or infant mortality),[2] but there are only a handful that look at the longer-term impact of this particular early-life shock (Sanders, 2012; Isen et al., 2014; Bharadwaj et al., 2014; Peet, 2016).[3] There is still much to be learned, particularly in developing countries, about the effects of pollution exposure on human capital in adulthood.

Focusing on Mexico, this paper estimates the long-term effects of *in utero* exposure to air pollution on adult cognitive ability, educational attainment, and income. I use thermal inversions, a meteorological phenomenon that negatively impacts air quality, as an exogenous source of variation in pollution levels. 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. For women only, however, this cognitive shock also leads to lower high school completion and income.

Larger female schooling responses to early-life health shocks have been commonly documented in existing literature (Bobonis et al., 2006; Maluccio et al., 2009; Field et al., 2009; Maccini and Yang, 2009; Anderson, 2012; Hoynes et al., 2016), but the reasons for these gender differences are less well-explored. My paper finds evidence that the different labor market conditions faced by men and women influence how they respond to early-life shocks. Specifically, women exhibit larger schooling responses because they are more likely to enter the white-collar sector, where I show that the optimal schooling response to an ability shock is larger than in the blue-collar sector. In fact, once I allow for the effect of pollution to vary by the gender-specific availability of white-collar opportunities, the gender difference

[1] In the medical and epidemiological literature, research on the hypothesis (popularized by Barker (1990)) that fetal conditions can have long-term consequences dates back to discoveries of links between birth defects and *in utero* conditions (Jones et al., 1973; McBride, 1961; Von Lenz and Knapp, 1962). Around the same time, a series of studies on the Dutch famine in 1944 linked exposure to the famine with negative outcomes in adulthood (Stein et al., 1975). Almond and Currie (2011) provide a more detailed history of the literature and the economic evidence that followed. See Heckman (2006) and Currie and Vogl (2013) for other reviews of the evidence.

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

[3] The bulk of existing 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 much more extreme case of air pollution than what we might be interested in for policy reasons.

in the schooling response disappears.

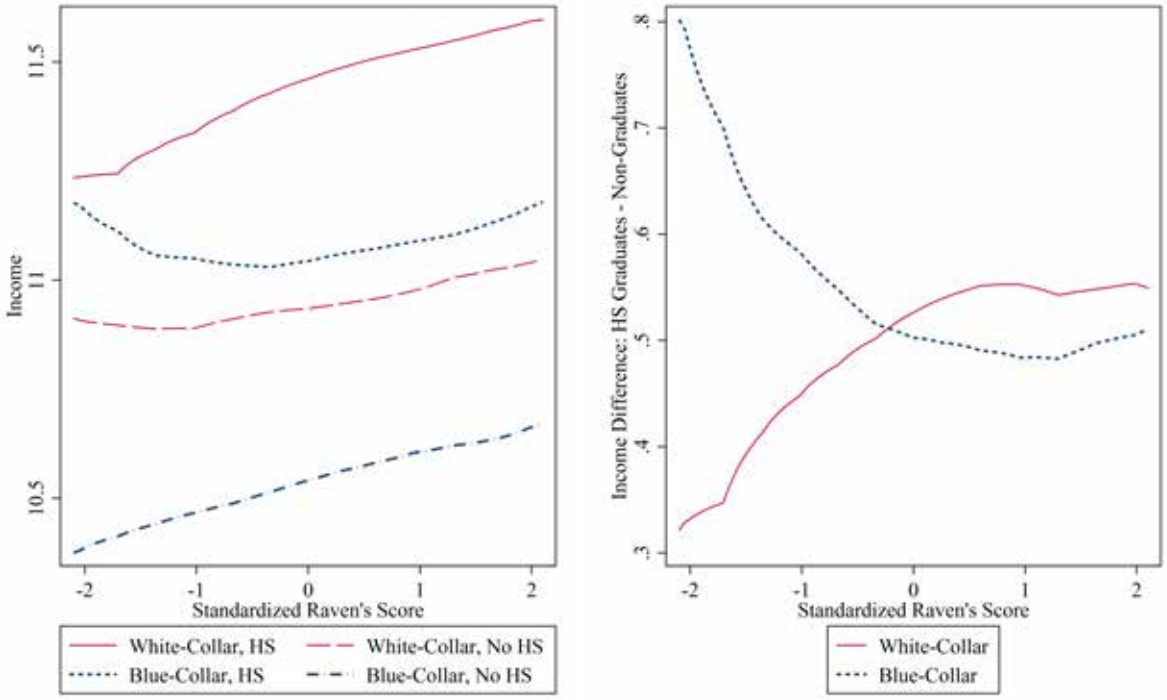
Sectoral choice plays an important role in determining optimal schooling responses to early-life shocks because white-collar jobs (which tend to be favored by women) reward schooling and ability differently than blue-collar ones do. Figure 1 offers descriptive evidence to support this idea, using data from the Mexican Family Life Survey (MxFLS). In the left panel, I plot the relationship between annual income and Raven's test scores, separately for four different schooling-sector combinations. The right panel plots the difference between the two schooling lines for each sector. The striking difference between the two sectors is clear: the income boost enjoyed by high school graduates is *increasing* in ability in the white-collar sector, but *decreasing* in ability in the blue-collar sector. Although these figures do not take into account selection into sectors or schooling, they offer suggestive evidence that the complementarity between schooling and ability may be higher in the white-collar than in the blue-collar sector.

Sectoral differences in the complementarity between schooling and ability could generate important gender differences in responses to early-life shocks because men and women make different occupational choices, as demonstrated by Figure 2. In all but one of the eight countries shown, working women participate in the white-collar sector at much higher rates than working men do. Taken together, the two features of the labor market illustrated in Figures 1 and 2 have important implications for how men and women respond to their cognitive endowments. A boy and girl of the same age growing up in the same village could respond differently to an early-life cognitive shock because of the different sectors they expect to enter.

To formalize this hypothesis, I develop a model in which the key parameters that drive differential schooling responses to endowment shocks are the cross-partials between schooling and ability in the white-collar wage function and the blue-collar wage function. In order to take into account the endogeneity of schooling and sectoral choice, which the descriptive exercise in Figure 1 does not do, I use a dynamic discrete choice model to structurally estimate these parameters of interest. I find that schooling and ability are complements in the the white-collar sector, but not in the blue-collar sector, which is consistent with the finding that schooling responses to pollution are largest for those likely to go into white-collar jobs.

In the existing literature, it is common for authors to use gender-specific labor market conditions to explain gender differentials in the estimated effects of early-life shocks (Bhalotra and Venkataramani, 2013; Cutler et al., 2010; Hoddinott et al., 2008), but very few studies directly test for this link. My paper joins two recent exceptions (Pitt et al., 2012; Rosenzweig and Zhang, 2013), which formally model

Figure 1 Income-Ability Relationship



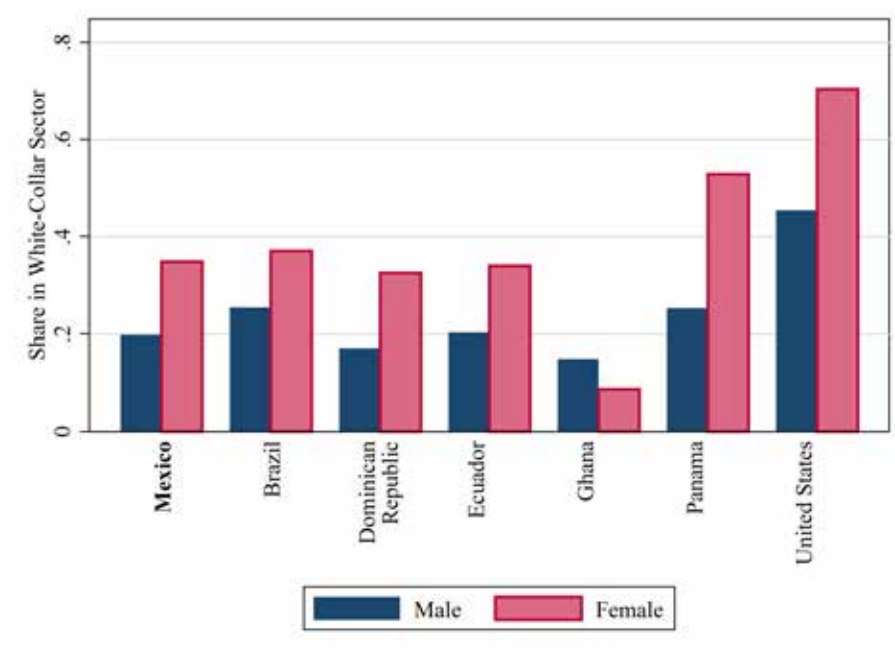
Notes: These local linear regressions use individuals aged 30 to 50 in the MxFLS. The white-collar and blue-collar sectors are defined using the classifications in Vogl (2014), summarized in Table A1. Income is measured using the inverse hyperbolic sine of total earned annual income.

the idea that the sectoral sorting tendencies of men and women might explain differential schooling responses across genders. The authors 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. A major contribution of the model I develop in this paper is the identification of sector-specific complementarities, along with gender differences in occupational choice, as a reason why men and women may adjust their schooling differently in response to a shock. To my knowledge, I am the first to estimate these sector-specific complementarities and show that the gender-specific schooling responses I find are driven primarily by differences in male and female sectoral choice.

By emphasizing the interaction between early-life shocks and labor market opportunities more generally, this paper addresses two other broad questions in the early life literature. First, how do early-life shocks interact with policy interventions or economic conditions later in life (Adhvaryu et al., 2015; Bharadwaj et al., 2014; Rossin-Slater and Wüst, 2015; Gunnsteinsson et al., 2014)? Second, what can explain the substantial heterogeneity – both across and within studies – in the estimated schooling responses reported in the existing literature?[4] Given that labor market opportunities vary over time,

[4]Many studies find that negative (positive) shocks decrease (increase) schooling (Almond, 2006; Bleakley, 2007), while

Figure 2 Cross-Country White-Collar Shares, by Gender



Weighted shares calculated from employed adults aged 30 to 50 in the 2010 censuses of the listed countries. White-collar jobs are identified using the ISCO occupation codes, which are defined as white-collar or blue-collar using the classifications in Vogl (2014), summarized in Table A1.

across space, and across groups, this heterogeneity can be partially explained by the main result of this paper: individuals facing different labor market opportunities respond differently to early-life shocks.

The structural model in this paper allows me to evaluate the policy implications of this result. Using this model, I simulate the effects of an intervention designed to improve the cognitive ability of a disadvantaged population.[5] My results reveal that an intervention like this would have larger effects on female schooling and employment and would therefore have the added benefit of reducing the gender gap in economic outcomes. The finding that women benefit more from improvements in cognitive ability is consistent with the argument that large relative gains in female education and employment outcomes, in the United States and across the globe, have been driven by changes that favor brain-based jobs, in which women have a comparative advantage (Goldin, 1995; Mammen and Paxson, 2000; Rendall, 2010; Olivetti, 2014; Bhalotra et al., 2015). Several of these studies have argued that economic growth can

others find no effect (Venkataramani, 2012), or much smaller effects for certain groups (Maluccio et al., 2009; Maccini and Yang, 2009; Field et al., 2009; Cutler et al., 2010; Bleakley, 2010).

[5]The simulated policy is similar in motivation to the United States Head Start program and Mexico's *Oportunidades* program, which both target the poor, but more closely maps to the smaller-scale intensive interventions conducted in Jamaica and Guatemala, which were actually able to improve cognitive ability in the long run (Walker et al., 2005; Maluccio et al., 2009).

generate improved economic outcomes for women precisely because it spurs the rise of a less physical sector,[6] and I suggest yet another channel through which economic development may improve female outcomes. If economic development raises the cognitive skills of a population by improving early-life health and human capital investment, this should generate larger improvements for women than for men.

In the next section, I outline a conceptual framework that illustrates how local labor market conditions can influence the way schooling decisions respond to an early-life shock. The remainder of the paper provides empirical support for the model predictions, using pollution exposure as a shock to cognitive ability. In section 3, I provide background information on pollution and describe my data sources. The reduced form and structural estimation strategies are described in section 4. Results are discussed in section 5. Section 6 concludes.

2 Model

The model outlined in this section illustrates that local labor market opportunities can affect how schooling decisions respond to a cognitive endowment shock. Because men and women tend to sort into sectors differently (as shown in Figure 2), male and female schooling decisions should respond differently to an early-life shock to cognitive ability.

Individuals are born with an ability endowment θ. As adults, individuals can work in one of two sectors: a white-collar ($k = w$) or a blue-collar sector ($k = b$), which I define using the sector categorizations in Vogl (2014), described in Table A1. Each sector has a different wage function, where educational attainment E and ability θ are rewarded differently. This captures the idea that worker characteristics command different prices in different sectors, which is reflected in the descriptive evidence in Figure 1, as well as in the existing economic literature (Heckman and Scheinkman, 1987). I denote the sector-specific expected wage functions as

$$W_k(E, \theta; \beta_k), \tag{1}$$

where $\frac{\partial W_k}{\partial E} > 0$, $\frac{\partial W_k}{\partial \theta} > 0$, $\frac{\partial^2 W_k}{\partial E \partial E} < 0$, and $\frac{\partial^2 W_k}{\partial \theta \partial \theta} < 0$ for $k = w, b$. β_k are the parameters that map ability and schooling to wages (i.e. the returns to each of these inputs and the cross-partial between the two).

[6] A number of studies have documented a U-shaped relationship – both across and within countries – between economic development and female labor force participation (Goldin, 1995; Mammen and Paxson, 2000; Olivetti, 2014). The positively sloped part of the U is often attributed to an expanding services sector, which is less developed in the left half of the curve.

The opportunity cost of schooling takes the following form:

$$c(E, \theta; \alpha),$$

where $\frac{\partial c}{\partial E} > 0$ and $\frac{\partial^2 c}{\partial E \partial E} > 0$.

Individuals pick the optimal E to maximize their expected future wages, net of the cost of schooling, as in the maximization problem below. 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).

The maximization problem can be written

$$\max_{E} \quad p_{jg} W_w(E, \theta; \beta_w) + (1 - p_{jg}) W_b(E, \theta; \beta_b) - c(E, \theta; \alpha).$$

p_{jg} represents the probability that an individual goes into the white-collar sector. In this simple set-up, this probability only depends on the child's gender g and location j, but I later explicitly model the sectoral choice and allow this to be endogenously determined. The location j subscript captures variation in the availability of white-collar jobs across space (and over time). The g subscript captures different sectoral sorting across gender.

The first order conditions for optimal schooling are:

$$p_{jg} \frac{\partial W_w}{\partial E} + (1 - p_{jg}) \frac{\partial W_b}{\partial E} - \frac{\partial c}{\partial E} = 0$$

Using the implicit function theorem, I can show how optimal schooling will respond to a positive shock to θ:

$$\frac{dE^*}{d\theta} = - \left[p_{jg} \frac{\partial^2 W_w}{\partial E \partial \theta} + (1 - p_{jg}) \frac{\partial^2 W_b}{\partial E \partial \theta} - \frac{\partial^2 c}{\partial E \partial \theta} \right] \left[p_{jg} \frac{\partial^2 W_w}{\partial E \partial E} + (1 - p_{jg}) \frac{\partial^2 W_b}{\partial E \partial E} - \frac{\partial^2 c}{\partial E \partial E} \right]^{-1},$$

where the denominator is negative by assumption. With wage functions that differ across sectors, it

is clear that differences in p_{jg}, which captures expectations about the local labor market, will result in different schooling responses. In particular, if schooling and ability are more complementary in white-collar than blue-collar jobs ($\frac{\partial^2 W_w}{\partial E \partial \theta} > \frac{\partial^2 W_b}{\partial E \partial \theta}$), then individuals exposed to higher p_{jg} will increase their schooling more in response to a positive ability shock (higher $\frac{dE^*}{d\theta}$). The intuition is simple: higher p_{jg} places more weight on the cross-partial between schooling and ability in the white-collar wage function ($\frac{\partial^2 W_w}{\partial E \partial \theta}$) and less weight on the cross-partial in the blue-collar wage function ($\frac{\partial^2 W_b}{\partial E \partial \theta}$). If the opposite is true ($\frac{\partial^2 W_w}{\partial E \partial \theta} < \frac{\partial^2 W_b}{\partial E \partial \theta}$), then higher p_{jg} will translate to a lower schooling response ($\frac{dE^*}{d\theta}$).

It should be noted that these model predictions remain unchanged if I relax the assumption of a fixed p_{jg} across individuals within location-gender groups. In particular, I can allow p_{jg} to take the following form: $p_{jg} = \bar{p}_{jg} + p(E, \theta)$, which means that there is a gender- and location-specific constant that does not depend on schooling or ability, and a separate term (which does not vary over j or g) that governs how sectoral choice depends on schooling and ability. Using this functional form for p_{jg}, it can be shown that individuals facing a higher $\bar{p}_{jg}$ will exhibit higher $\frac{dE^*}{d\theta}$ if schooling and ability are more complementary in the white-collar than blue-collar sector. In the structural estimation described in section 4.2, I do not rely on this functional form assumption and instead explicitly model the sectoral choice.

As Figure 2 and Table A1 clearly show, women are on average more likely to enter the white-collar sector than men, implying that $p_{jf} > p_{jm}$. Given this, women should exhibit larger $\frac{dE^*}{d\theta}$ than men if there is a higher degree of complementarity between schooling and ability in the white-collar sector. I test this hypothesis in two steps. First, I document that there are gender differences in the schooling response to an exogenous cognitive shock (*in utero* exposure to pollution) which are driven by differences in the white-collar opportunities available to men and women. Second, I structurally estimate the sector-specific cross-partials ($\frac{\partial^2 W_k}{\partial E \partial \theta}$) in order to confirm that the signs of these parameters are consistent with the gender differences that I find. In the next section, I outline the biological reasons for considering pollution exposure as a shock to cognitive ability and describe the data I use to estimate these effects.

3 Background and Data

3.1 Pollution and Thermal Inversions

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).

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).

Disrupting the transport of blood, glucose, or oxygen to the fetus 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, medical and economic studies on exposure to radiation (Otake, 1998; Almond et al., 2009; Black et al., 2014) flag the second trimester as the most sensitive period for brain

development.[7] Although day-to-day air pollution and radiation are very different types of pollution, these radiation studies highlight generalizable findings regarding critical periods in brain development, which appear to also be relevant for other external stressors, like influenza (Schwandt, 2016). In fact, 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).

As outlined in section 2, individuals make different schooling decisions and earn different wages partially because of heterogeneous levels of skill. 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 ability is an important component.

A major obstacle to identifying the effects of exposure at birth on later life outcomes is the lack of high quality historical data going back far enough to link adults with their *in utero* exposure. 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 dating back to 1979.

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., 2014; Arceo et al., 2016). 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.[8]

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,

[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] See Jacobson (2002) for a more detailed discussion of the different types and causes of inversions.

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,[9] 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.

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. (2014) and Arceo et al. (2016), I assume that thermal inversions can only affect my outcomes 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.

3.2 Data

This section outlines the pollution, weather, individual-level, and labor market data used to document the effects of an exogenous shock to θ and pin down the role played by the local labor market.

3.2.1 Pollution and Weather Data

The ideal data set for this analysis would consist of pollution data going back to the *in utero* months of adults observed in my data set, the MxFLS. Currently, pollution measurements for CO, O_3, SO_2, NO_2, PM10, and most recently, PM2.5 are publicly available on Mexico's National Institute of Ecology (INECC) website for a total of 16 cities. However, the majority of this spatially limited data does not go back far enough to study at-birth exposure of adults. 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.

As a result of these limitations, I rely on thermal inversions as an exogenous driver of pollution for which I have data going back to 1979 for all of Mexico. I use the INECC pollution measurements to verify the link between inversions and pollution in my data. The INECC database also includes

[9] High pressure systems are associated with high temperatures, clear skies, and light winds at the surface

temperature measurements for six cities, which I use to validate the temperature data set described in the next sub-section.

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 location.[13] I identify an inversion episode as any time this difference is greater than zero. 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. (2014), 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]

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

[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.

[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.

[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.

the validation exercises due to their size, I verify that these conclusions are still valid when I 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. (2014) 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.[15]

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 Meteorological Service (CONAGUA) to control for rainfall because these likely involve less measurement 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:

$$P_{jym} = \alpha_1 I_{jym} + \alpha_2' W_{jym} + \mu_j + \delta_y + \alpha_m + v_{jym}. \tag{2}$$

I aggregate to three-month periods here because I eventually analyze the effects of pollution by trimester. P_{jym} represents CO (8-hour daily maximum) or PM-10 (24-hour mean) averaged over the three month period starting in month m of year y. I_{jym} represents the total number of days (per

[15]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.

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. I aggregate to the three-month level because my main analysis studies the effects of pollution by trimester.

Table 1 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.

Table 1 Relationship between Thermal Inversions and Pollution, 3-Month Periods

	CO	PM-10
Average Monthly Inversions During 3-Month Period	0.0140***	0.474***
	(0.00254)	(0.0828)
N	23821	21292
Mean of DV	2.306	55.17
Fstat	30.449	32.835

Notes:
* p< 0.1 ** p< 0.05 *** p< 0.01
Standard errors (clustered at municipality level) in parentheses.
CO and PM-10 represent three-month averages of the 8-hour daily maximum (in ppm) and 24-hour daily mean (in $\mu g/m^3$), respectively. 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.

3.2.2 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 these measures of cognitive ability and height, along with 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.

Table 2 reports summary statistics 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 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. On average, individuals in this sample are exposed to approximately 18 inversion nights per month during any given trimester.

3.2.3 Mexican Labor Market Data

In order to investigate the interaction between labor market conditions and pollution exposure, I use occupation information (specifically, white-collar shares) from the 1990, 2000, and 2010 Mexican censuses (Minnesota Population Center, 2015). Following Atkin (2016), 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. Commuting zones, which I discuss in more detail in Appendix section B.1, are

[16] It should be noted that Raven's tests were identical across waves.

[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.

Table 2 Summary Statistics for Reduced Form Sample

Variable Name	Mean	Standard Deviation	N
Outcome Variables			
Raven's test score (% correct)	0.56	0.228	10320
Height (cm)	160.31	10.52	10398
Years of schooling	9.37	3.078	10715
Annual income	27761.21	61580.8	3155
Control Variables			
Mother's Education	6.17	3.834	9770
Father's Education	6.50	4.258	9090
1(Male)	0.47	0.499	10848
Age for Raven's Test variable	17.18	3.357	10320
Age for height variable	20.13	4.506	10398
Age for schooling variables	20.21	4.449	10715
Age for income variable	22.45	3.698	3155
Dependent Variables			
Average monthly inversions during trimester 1	18.09	8.206	10848
Average monthly inversions during trimester 2	17.93	8.235	10848
Average monthly inversions during trimester 3	17.80	8.288	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.

municipalities or groups of municipalities that better represent local labor markets: for instance, large metropolitan areas or neighboring municipalities.

In some specifications, I directly use the gender-specific share of white-collar workers calculated from the census. I assign these values to individuals based on the census conducted closest to the year in which they turned 12. In other specifications, I predict values for years in between censuses and assign individuals to the predicted values from the exact year they turned 12. To calculate these predicted values, I use a shift-share strategy, similar to Bartik (1991) and others, which involves predicting economic variables for geographic regions (like states or, in this case, commuting zones) by combining national industry-level growth rates and baseline industry compositions for these regions of interest (see section B.1 for more details). I calculate national industry-level growth rates from Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH), 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. I cannot obtain municipality-level data directly from this data set because it is only representative at the national level (and at the state level for a limited number of states and years).

4 Empirical Strategy

4.1 Reduced Form Analysis

To estimate the effects of pollution, I directly regress my outcomes of interest on thermal inversion counts over 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:

$$Y_{ijymw} = \alpha_0 + \sum_{k=-7}^{4} \beta_k \mathrm{I}_{jym}^{3k} + \sum_{k=-7}^{4} \alpha_k' \mathrm{W}_{jym}^{3k} + \gamma' X_i + \mu_j + (\delta_y \text{ x } \nu_w) + \eta_m + \epsilon_{ijymw}. \tag{3}$$

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. 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.

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.[19] 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

[19]There are 150 municipalities in the final sample.

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.

4.2 Structural Estimation

In order to verify whether the results of the reduced form strategy described above are consistent with the model predictions in section 2, consistent estimates of the sector-specific cross-partials between schooling and ability are needed. This section describes the structural model, estimation methods, and sample used to obtain these parameters.

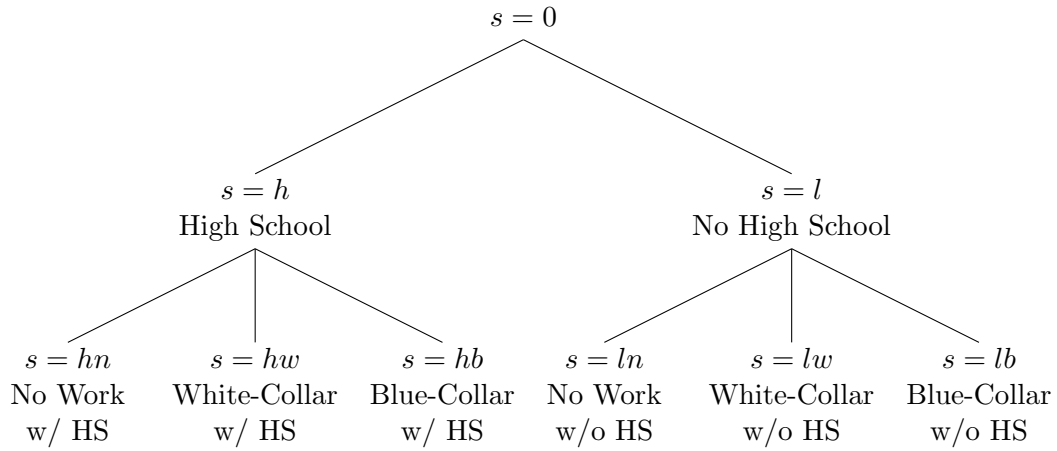
Schooling and occupational choice are endogenous decisions, potentially made jointly. As a result, sector-specific Mincer-style regressions may not yield consistent estimates of the parameters of interest. The endogeneity of schooling in a wage regression has long been acknowledged as an important issue to consider when attempting to obtain causal estimates of the return to schooling (Griliches and Mason, 1972). Studies have used both structural approaches and instrumental variables strategies to deal with this issue (Belzil, 2007). Similarly, self-selection into sectors is also recognized as a potential source of bias in the estimation of sector-specific wage parameters (Roy, 1951; Heckman and Sedlacek, 1985), for which structural approaches are, again, a common solution. In order to deal with both sources of endogeneity, taking into account that schooling decisions may also depend on expected sectoral choice, I use a two-period dynamic discrete choice model. This dynamic model moves away from the static setting used in section 2, allowing individuals to choose their schooling in the first period (based on expected future wages) and their occupational sector in the second period. In order to facilitate estimation, I collapse the continuous schooling decision into a binary choice about whether to obtain a high school degree.[20]

4.2.1 Decision Tree

The agent's decision tree is outlined in Figure 3. I use a similar set-up to that of Eisenhauer et al. (2015), which models several discrete schooling decisions from high school enrollment to college completion. I focus on a single schooling decision (high school completion) but expand the model to include a labor

[20] High school completion is the only schooling milestone affected by the cognitive shock in the reduced form analysis. See section 5.1.

Figure 3 Decision Tree



market decision after graduation or dropout. In the first period, individuals decide whether to obtain a high school degree. In the second period, they decide whether to work in the white-collar sector, work in the blue-collar sector, or remain out of the labor force.

Figure 3 highlights that using a two-period model requires some drastic simplifications. For example, once individuals have chosen their employment status and occupation, they do not change it. While this is certainly a strong assumption, the majority of individuals in my sample do not switch sectors across waves, as I discuss in more detail in section 4.3. Like the model in Eisenhauer et al. (2015), this framework can be viewed as a deliberately simplified version of the dynamic discrete choice model of education and occupational choice in Keane and Wolpin (1997). These simplifications make it possible to estimate a joint schooling and occupational choice model when I do not have the long-run annual panel data that is typically required of papers aiming to model and predict the evolution of wages over the life cycle. Because these life cycle predictions are not the focus of this paper, I use a simpler model which allows me to estimate sector-specific wage parameters while accounting for the endogeneity of schooling and sectoral choice, using only one cross-section of individuals.

4.2.2 Wage Equations

In this model, the value of each state depends on the immediate net rewards, as well as the expected future value of all feasible states made available by entering that state. I denote the current state $s \in S = \{0,\ h,\ l,\ hn,\ hw,\ hb,\ ln,\ lw,\ lb\}$. When an individual picks s', they earn net rewards

$$R(s') = Y(s') - C(s').$$

In the four states in which the individual is working, $Y(s')$ is simply equal to the discounted sum of annual income earned during their working lives (which I assume to be from age 30 to 50) given that they have chosen s'. In other words, if they choose the white-collar sector,

$$Y(s') = W_w(E(s'), \theta; \beta_w) = \sum_{t=0}^{20} \delta^t w_w(E(s'), \theta, t; \beta_w) \quad \forall s' \in \{hw,\ lw\}\,, \tag{4}$$

and if they choose the blue-collar sector,

$$Y(s') = W_b(E(s'), \theta; \beta_b) = \sum_{t=0}^{20} \delta^t w_b(E(s'), \theta, t; \beta_b) \quad \forall s' \in \{hb,\ lb\}\,, \tag{5}$$

where now E is an indicator equal to 1 for high school completion and $w_k(E(s), \theta, t; \beta_k)$ is the income earned in state s (which determines the sector k) at time t,[21] expressed as a linear function of observed characteristics and an unobserved component. Like in equation 1 in the static model, wages depend on schooling and ability θ. Unobserved by the researcher but known to the agent, ability is captured by an individual's Raven's test score plus a standard normal error, ν:

$$\theta = \text{Raven's Score} + \nu,$$

in order to include other dimensions of skill in this measure of labor market ability. In this model, θ is assumed to be the only source of dependency among the unobservables in the model.

Let A_1 to A_3 represent three indicator variables for each of the three 5-year age categories spanning ages 36 to 50, which leaves the age group 30 to 35 as the omitted category. As in the Eisenhauer et al. (2015) framework, which allows for a different set of coefficients for each state, I allow for the effects of ability and experience to vary not only by sector but also by schooling level. Stochastic shocks $\epsilon(s, t)$ are independently normally distributed with mean zero (and variance normalized to 1). These components form the per-period wage functions for each sector:

$$\begin{aligned} w_w(E(s), \theta, t; \beta_w) = {} & \beta_{w0} + \beta_{w1} E(s) + \beta_{w2}\theta + \beta_{w3} E(s)\theta + \\ & \sum_{j=4}^{6} \beta_{wj} A_{j-3}(t) + \sum_{j=7}^{9} \beta_{wj} A_{j-6}(t) E(s) + \sum_{j=10}^{k_w} \beta_{wj} X_{wj} + \epsilon(s, t) \\ & \forall s \in \{hw,\ lw\} \end{aligned} \tag{6}$$

[21] Time, measured in years from the beginning of an individual's working life, is equal to age minus 30.

$$w_b(S(s), \theta, t; \beta_b) = \beta_{b0} + \beta_{b1} E(s) + \beta_{b2}\theta + \beta_{b3} E(s)\theta + \sum_{j=4}^{6} \beta_{bj} A_{j-3}(t) + \sum_{j=7}^{9} \beta_{bj} A_{j-6}(t) E(s) + \sum_{j=10}^{k_b} \beta_{bj} X_{bj} + \epsilon(s,t)$$
$$\forall s \in \{hb,\ lb\}\,. \tag{7}$$

The coefficients that map schooling and ability to wages are sector-specific, which implies that a fixed set of characteristics will map to a different level of wages in the white-collar and blue-collar sector. This is consistent with the existence of two types of skill: one that is rewarded in the white-collar sector and one that is rewarded in the blue-collar sector, each formed by different functions of individual characteristics. Individuals are therefore choosing their sector in a generalized version of the Roy (1951) economy.

In terms of tying my reduced form results to the predictions of the conceptual framework, β_{w3} and β_{b3} are the key parameters in question. These represent the non-separability between schooling and ability in each sector, or $\frac{\partial^2 W_w}{\partial E \partial \theta}$ and $\frac{\partial^2 W_b}{\partial E \partial \theta}$ using the previous notation. Values greater than zero indicate the existence of complementarities between schooling and ability in the wage function. Most importantly, however, the difference between β_{w3} and β_{b3} will indicate whether schooling and ability are more complementary in one sector than the other.

Individuals do not earn "adult" income in period 1, while high-school-aged. Even if they do earn "adolescent" wages during this period, I do not observe this for the vast majority of individuals in the data. However, I do allow for opportunity cost of schooling – which includes foregone wages – to vary across individuals, as shown in the cost functions below.

4.2.3 Relative Cost Equations

At each node, I normalize the non-stochastic portion of the cost of one state (states l, hb, and lb for nodes $s = 0$, $s = h$, and $s = l$, respectively) to equal zero because only relative costs can be identified. Relative costs depend on θ, a vector of observed characteristics Q_s, and stochastic shocks $\eta(s)$. $c(h)$ represents the total cost of obtaining a high school degree. $c(hw)$ and $c(lw)$ represent the costs of going into the white-collar sector, relative to the blue-collar sector, for individuals with and without high

school degree.

$$c(h) = c_h + \alpha_h \theta + \sum_{j=1}^{q_h} \delta_{hj} Q_{hj} + \eta(h) - \eta(l) \tag{8}$$

$$c(hw) = c_{hw} + \alpha_{hw} \theta + \sum_{j=1}^{q_{hw}} \delta_{hwj} Q_{hwj} + \eta(hw) - \eta(hb) \tag{9}$$

$$c(lw) = c_{lw} + \alpha_{lw} \theta + \sum_{j=1}^{q_{lw}} \delta_{lwj} Q_{lwj} + \eta(lw) - \eta(lb) \tag{10}$$

Net rewards for states hn and ln are defined below. Although individuals do receive non-monetary rewards in these two states, I do not observe these rewards and cannot separately identify them from costs. Instead, I allow for net rewards $(Y(s') - C(s'))$ to be a function of E, θ, and observable characteristics:

$$Y(hn) - c(hn) = -(c_{hn} + \alpha_{hn} \theta + \sum_{j=1}^{q_{hn}} \delta_{hnj} Q_{hnj} + \eta(hn) - \eta(hb)) \tag{11}$$

$$Y(ln) - c(ln) = -(c_{ln} + \alpha_{ln} \theta + \sum_{j=1}^{q_{ln}} \delta_{lnj} Q_{lnj} + \eta(ln) - \eta(lb)). \tag{12}$$

The shocks in the cost function, $\eta(s)$, are assumed to be independent across all s. I assume that they are drawn from a Type 1 extreme value distribution, with scale factors specific to each node: $\rho_{\eta n}$ for the initial schooling decision, $\rho_{\eta h}$ for the sector decision among high school graduates, and $\rho_{\eta l}$ for the sector decision among non-graduates. Although accompanied by a number of strong assumptions,[22] this error structure greatly reduces the computational burden of estimating the model as it allows for an analytic expression of the likelihood function and the calculation of standard errors using the information matrix.

In period 1, individuals choose whether or not to go to high school based on current rewards and the continuation value of each choice. In period 2, they choose whether to work and in which sector to work, by comparing the expected net benefits of each choice. Individuals observe the cost shocks $\eta(s)$ before they decide on their next state, but only observe the reward shocks $\epsilon(s)$ after making their choice.

This set-up generates decision rules and transition probabilities (outlined in Appendix section C), which I use to construct a likelihood function. I estimate the model using maximum likelihood, inte-

[22] This implies, for instance, a constant error variance across sector choices within each schooling branch and the independence of irrelevant alternatives.

grating over the ability error term ν using 100 simulations, and setting the discount rate to 0.04.

4.3 Structural Estimation Sample

To estimate this model, I use the MxFLS and generate additional labor market controls from the 1970 to 2000 decennial censuses. I restrict to those 30 and older to exclude late high school graduates and those who have not entered their main career sector. I also restrict to those 50 and younger to exclude early retirees and avoid classifying individuals into a sector they may have switched into later in their careers (in preparation for retirement, for example). It should be noted that this sample is distinct from the one used in the reduced form analysis because thermal inversion data is only available for a relatively young sample (born after 1979), while this model requires information from adults later in life.

I take the schooling, sector, and total annual income for each individual from the most recent survey wave in which they were aged between 30 and 50 and living in Mexico.[23] Other variables I obtain from the MxFLS include age, gender, maternal schooling, paternal schooling, and an urban indicator for the individual's place of residence. To represent the non-stochastic portion of ability θ, I use the individual's standardized Raven's test score from the first test they took.

As mentioned earlier, switching across sectors is ignored by the model. Fortunately, 85% of the individuals who I observe more than once between the ages 30 and 50 never switch between the white-collar and blue-collar sector. More importantly, however, only 5% of those surveyed in all three waves switch more than once.[24] Most individuals appear to be picking a sector and staying in it, or else choosing a sector and eventually ending up there (potentially after dabbling in the other sector first).

Like the sectoral decision, the "no work" decision is also a permanent one in this framework. In order to avoid erroneously placing individuals who are only temporarily out of work in this category, I only include individuals who report having never worked before in this group. Individuals who are currently out of work and therefore missing sector and wage information, but who report having worked before, are dropped from the analysis.

[23] Although the MxFLS tracks migrants, even those that move to the U.S., data from the detailed interviews of these U.S. migrants are not publicly available. As a result, I include migrants in my analysis, but I use their income and sector information from the most recent wave in which they were still in Mexico. Doing this alleviates concerns about comparing income earned in the vastly different labor markets of the U.S. and Mexico.

[24] While the existence of switchers does suggest that an individual's occupational choice is at least partially determined by time-varying shocks or learning, it does not invalidate the important assumption underlying this framework: that individuals can calculate, with reasonable accuracy, the probability that they end up in a particular sector for the majority of their career.

Zone-level labor market variables that serve as exclusion restrictions are calculated from the 1970 to 2000 decennial censuses. For school-aged variables, I assign individuals, by commuting zone, to the value from the census at the beginning of the decade in which they turned 12. For early working age variables, I assign individuals to the census at the beginning of the decade in which they turned 22.[25] As a cost shifter in the white-collar cost equations (Q_{hw} and Q_{lw}), I use the gender-specific proportion of men or women in the white-collar sector in an individual's municipality of residence in their early working years. As a cost shifter in the cost equation for not working (Q_{hn} and Q_{ln}), I use the adult unemployment rate while the individual was working-aged. As a cost shifter in the schooling opportunity cost equation (Q_h), I use gender-specific youth employment rates during an individual's school-aged years. Specifically, I calculate the proportion of boys (for males) or girls (for females) aged 12 to 15 and (separately) aged 16 to 18 who report being currently employed. Appendix Table A2 reports summary statistics for all of the relevant variables described in this section.

5 Results

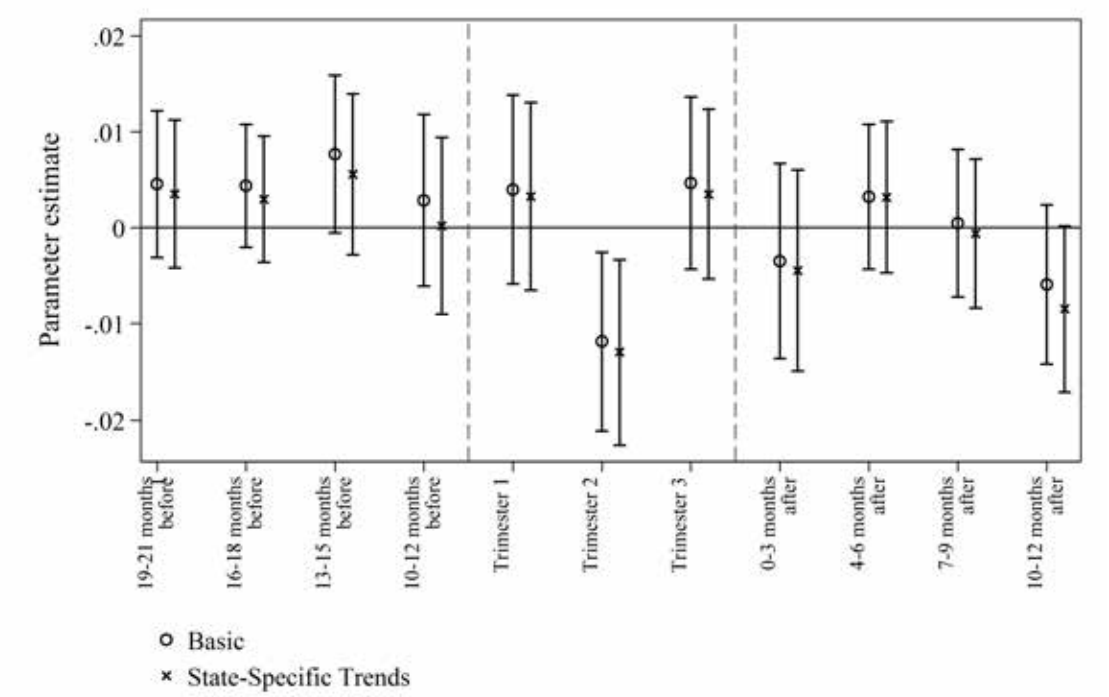
In this section, I begin by discussing the results of my reduced form analysis. After documenting the overall and gender-specific effects of pollution, I then investigate the labor market mechanisms driving the gender differences that I find. Next, I address potential threats to identification. Finally, I discuss the wage parameter estimates from the structural model.

5.1 Main Reduced Form Results

To display my reduced form results, I graphically illustrate the estimated coefficients from equation 3. All corresponding tables are available in the Appendix. Figure 4 reports the estimated biological effects of pollution on Raven's test scores, a measure of cognitive ability. In addition to the coefficients from the baseline specification, I plot the coefficients estimated from a specification that adds state-specific quadratic year trends and state-specific quarter of the year dummies, hereafter referred to as season dummies. Across both specifications, thermal inversions in the second trimester have a significant negative impact on Raven's test scores. In the specification with state-specific trends, I estimate a coefficient of -0.013, which implies that a standard deviation increase in average monthly thermal inversions per trimester (8.2) leads to a 0.106 standard deviation decline in Raven's test scores. I do

[25] Because there is no 1980 census, for individuals whose school aged or working age census was the 1980 census, I use the 1990 census instead.

Figure 4 Effects of Pollution on Raven's Test Scores



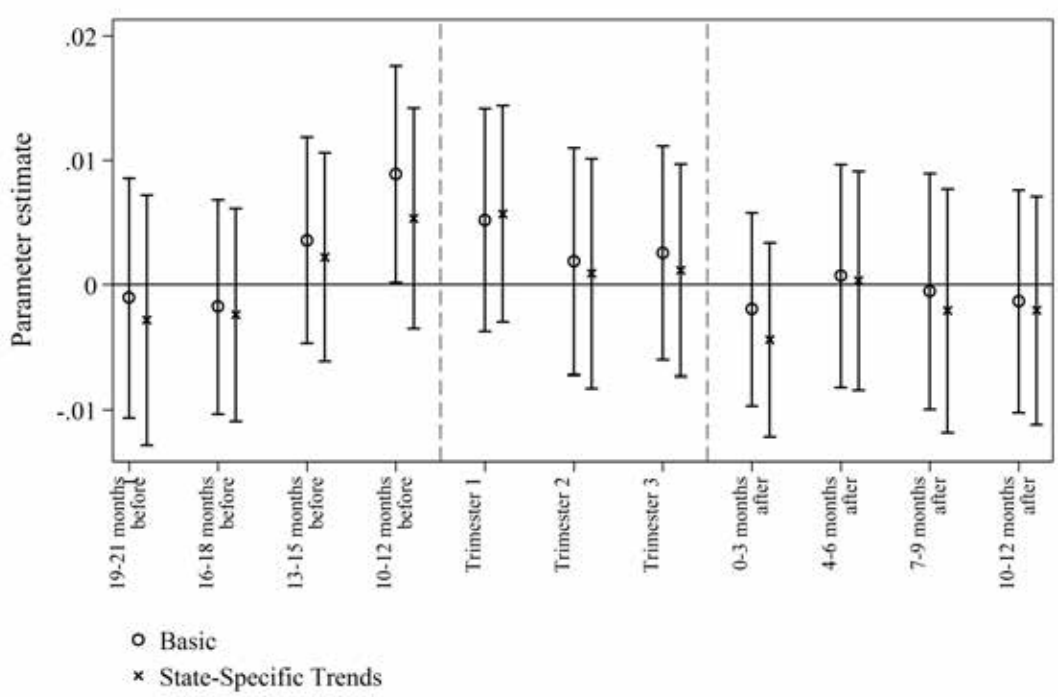
Notes: Intervals represent 90% confidence intervals. "Basic" coefficients are from regressions that control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, gender, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. "State-Specific Trends" include all basic controls, state-by-season fixed effects and state-by-quadratic year trends. See Table A3, columns 1 and 2, for corresponding estimates.

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 3.1, which flags the second trimester as a crucial period for brain development (Otake, 1998; Almond et al., 2009; Black et al., 2014; Schwandt, 2016).

In contrast, Figure 5 shows no evidence of a robust relationship between pollution 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 pollution did not substantially hinder the *physical* development of fetuses and therefore that the negative impact of *in utero* pollution 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 from the state-specific trend specification for males and females on the same graph, reporting only the three trimester coefficients (even though all regressions

Figure 5 Effects of Pollution on Height



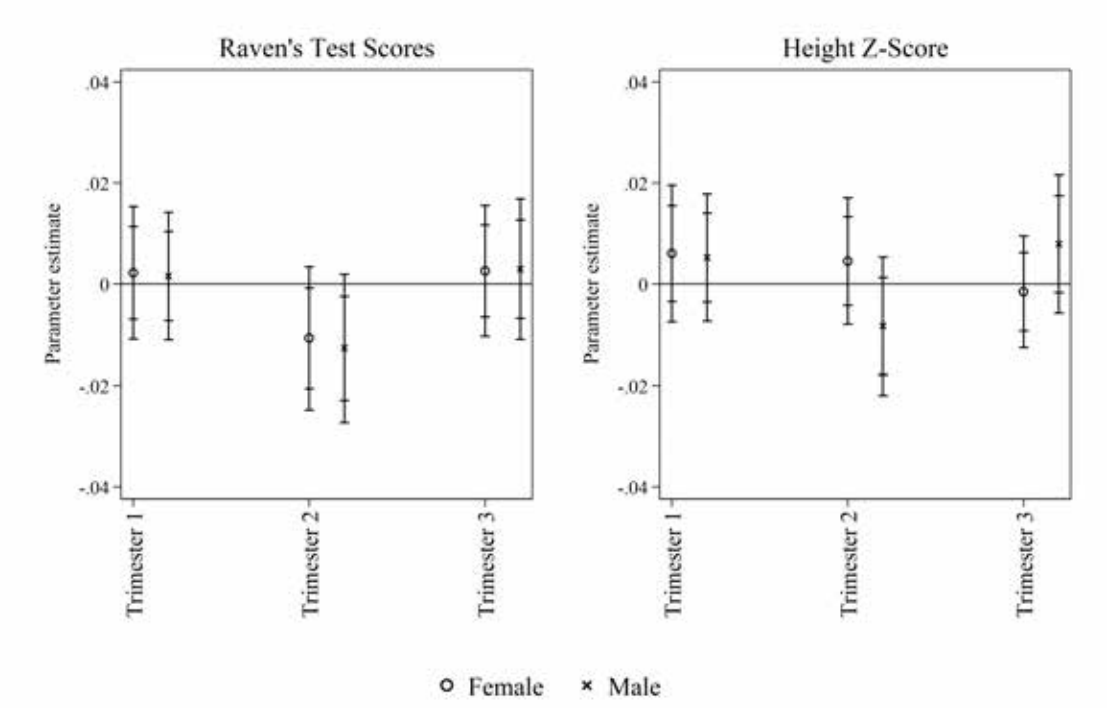
Notes: Intervals represent 90% confidence intervals. "Basic" coefficients are from regressions that control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, gender, mother's education, father's education, cubic functions of average monthly mean, minimum, and maximum 2m temperatures, monthly relative humidity, monthly precipitation, and monthly cloud coverage during each relevant 3-month period. "State-Specific Trends" include all basic controls, state-by-season fixed effects and state-by-quadratic year trends. See Table A3, columns 3 and 4, for corresponding estimates.

control for the remaining three-month periods). In the Appendix, I report these trimester coefficients, along with their differences and associated standard errors. In addition to 90% confidence intervals, I also plot 75% confidence intervals, which can be used for a rough visual detection of differences across groups (significant at the 10% level). The first panel of Figure 6 shows that the second trimester estimates for the effect of pollution on Raven's scores are very similar in magnitude for males and females: -0.0107 for females compared to -0.0127 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 table is that cognition appears to be affected by pollution in similar ways for men and women. For height, in the second panel of Figure 6, there are no significant gender differences.

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 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.[26] The purpose of

[26]See Cunha and Heckman (2007), Cunha and Heckman (2008), and Cunha et al. (2010) for a commonly used dynamic

Figure 6 Effects of Pollution on Health, by Gender



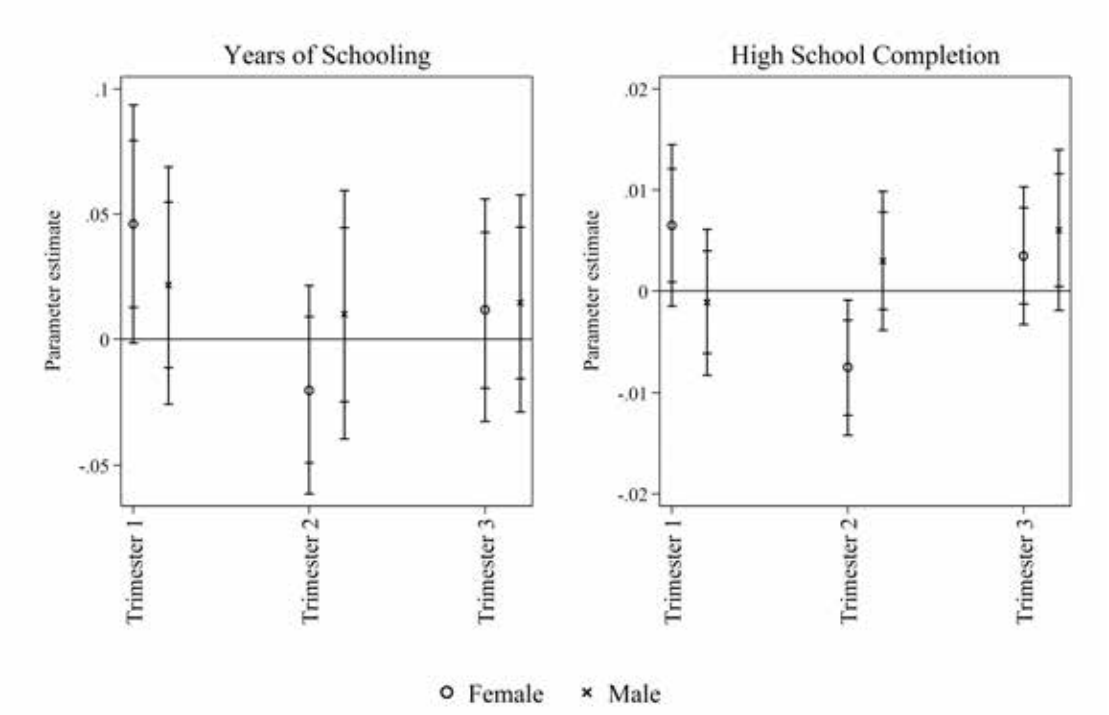
Notes: Separate regressions are conducted for men and women. Intervals represent 90% and 75% confidence intervals. Controls include birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-by-season fixed effects, state-by-quadratic year trends, gender, mother's 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. See Table A4, columns 2 and 4, for corresponding estimates. Although not plotted here, inversions in all other three-month periods are included in these regressions.

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

Having established that *in utero* exposure to pollution 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. For the following schooling regressions, because I am interested in high school completion, I restrict to individuals old enough to have completed high school (those aged 18 and older), but results are robust to using the entire sample. Clear gender differences are apparent in Figure 7. 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

framework for the production function of skill).

Figure 7 Effects of Pollution on Educational Attainment, by Gender



Notes: Separate regressions are conducted for men and women. Intervals represent 90% and 75% confidence intervals. Controls include birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-by-season 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. See Table A5, columns 2 and 4, for corresponding estimates. Although not plotted here, inversions in all other three-month periods are included in these regressions. Sample is restricted to individuals aged 18 and older.

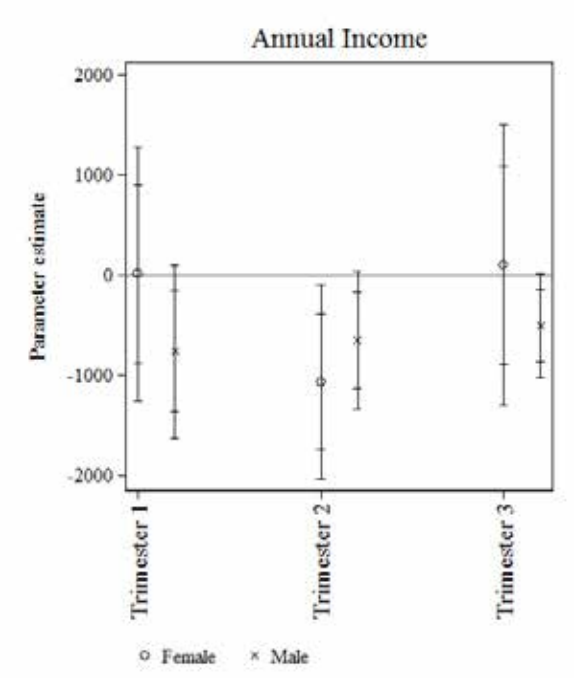
impact on high school completion for women only. The male coefficient, on the other hand, is positive, statistically indistinguishable from zero, and significantly different from the female coefficient.

High school graduation appears to be the only milestone affected by pollution: Appendix Table A7 shows that *in utero* thermal inversions had no significant impact on elementary school or junior high school completion for either gender. This suggests that this cognitive shock primarily affected later-life schooling decisions and had little effect on early parental education decisions.

Figure 8 reports the effects of thermal inversions on income, again by gender, among those that report 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 effect of second trimester pollution 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

8 does not offer clear-cut evidence for stark gender differences. Although it appears that pollution 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).

Figure 8 Effects of Pollution on Income, by Gender



Notes: Separate regressions are conducted for men and women. Intervals represent 90% and 75% confidence intervals. Controls include birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, state-by-season 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. See Table A6, column 2, for corresponding estimates. Although not plotted here, inversions in all other three-month periods are included in these regressions.

Because this is a young sample (aged 15 to 34), the estimated coefficients represent the effect of pollution 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 drastically; the direction and magnitude of the gender differences found here may not be the same as those in lifetime income effects. Moreover, these regressions ignore selection into the sample of full-time workers, although I do not find evidence that thermal inversions affected whether an individual reported work as their main activity (results available upon request).

5.2 Labor Market Mechanisms

According to the model in section 2, gender differences in schooling responses to shocks can arise from gender-specific tendencies to sort into the white-collar sector. In order to directly test this, I take advantage of differences across space and over time in the proportion of men and women in white collar jobs in local labor markets, which I argue are reasonable proxies for p_{jg}.[27] In particular, the gender-specific proportion of white collar employment in the local labor market during a child's critical schooling transition period should be positively related to the expectation that she will end up in a white collar job (p_{jg}). Like Rosenzweig and Zhang (2013), I focus on the local labor market in which a child is residing at age 12. In Mexico, the end of elementary 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.

For the following analysis, I create an indicator equal to 1 if the predicted share of men (for males) or women (for females) working in white collar jobs in the commuting zone in which the individual was residing at age 12 falls in the top quartile of the predicted white-collar proportion distribution. The results in Table 3 use a discrete transformation of proportions predicted by combining municipality-level occupation distributions from the census with national-level industry growth rates from ENIGH, using an industry shift-share strategy similar to Bartik (1991) and others (See Appendix section B for more details). However, the pattern of results is robust to the use of a continuous instead of a discrete measure, as well as simply assigning individuals the relevant value from the census decade in which they turned 12 (Table A8).

I begin this exercise by reporting, in column 1 of Table 3, the trimester coefficients from the fully-interacted specification used to generate the second panel of Figure 7, which demonstrates the significant gender difference in the effect of thermal inversions on high school completion. In column 2, I add inversion-by-p_{jg} interactions to investigate the extent to which this gender difference is being driven by gender-specific labor market opportunities. The negative effect of second trimester inversions on high school completion is concentrated among individuals more likely to go into the white-collar sector:

[27] 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 for p_{jg}. For example, Jensen (2010) finds that 70% of survey respondents in rural India 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 (2012) use current conditions in the marriage market – gender ratios for various education categories – to proxy for marriage market expectations.

the coefficient on the second trimester interaction is negative and significant at the 1% level, while the main effect is positive but not significant. This establishes a clear link between labor market conditions and investment responses to shocks, likely operating through the effect the current labor market has on expectations.[28] More importantly, the gender difference reported in column 1 completely disappears when the labor market interactions are included: it is much smaller in magnitude than the p_{jg} interaction and insignificant. The drastic decrease (and sign change) in the second trimester male interaction from column 1 to column 2 demonstrates that the gender difference in this context is driven by the different labor market conditions facing men and women.

5.3 Threats to Identification

5.3.1 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.[29] 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 my 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 maternal characteristics in the year before birth, which are not available in this data set. For example, thermal inversions are more common in winter, and pregnant mothers

[28]The finding that parental and child expectations can influence child schooling decisions is consistent with evidence from subjective expectations data from urban Mexico (Kaufmann, 2014; Attanasio and Kaufmann, 2014).

[29]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 3 Effects of Pollution on High School Graduation, by White Collar Opportunities

	(1)	(2)
Average monthly inversions…	HS Completion	HS Completion
Trimester 1	0.00648	0.00599
	(0.00485)	(0.00766)
Trimester 2	-0.00757*	0.00704
	(0.00404)	(0.00671)
Trimester 3	0.00347	0.00644
	(0.00414)	(0.00839)
Trimester 1	-0.00760	-0.00619
x 1(Male)	(0.00668)	(0.00872)
Trimester 2	0.0105*	-0.000721
x 1(Male)	(0.00611)	(0.00793)
Trimester 3	0.00255	-0.00148
x 1(Male)	(0.00605)	(0.00849)
Trimester 1		0.000872
x 1(Predicted white collar proportion in top quartile)		(0.00660)
Trimester 2		-0.0177***
x 1(Predicted white collar proportion in top quartile)		(0.00616)
Trimester 3		-0.00350
x 1(Predicted white collar proportion in top quartile)		(0.00737)
N	7353	7214
Dependent variable mean	0.364	0.363
Additional Fixed Effects	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 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. In column 2, the main effect of the white collar variable and the interactions with inversions in all other three month periods are also included. Regressions restrict to individuals aged 18 and older. Predicted white collar proportions calculated using census data and annual growth rates from ENIGH. See Data Appendix for details on the construction of predicted white collar proportions.

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		-0.00180		0.00134
		(0.0177)		(0.00238)
16-18 months before birth		-0.0229		-0.00329
		(0.0194)		(0.00219)
13-15 months before birth		-0.0295		-0.00150
		(0.0184)		(0.00266)
10-12 months before birth		-0.0137		0.00132
		(0.0183)		(0.00256)
DURING PREGNANCY				
Trimester 1		0.00429		-0.00149
		(0.0233)		(0.00269)
Trimester 2	-0.000340	-0.00930	-0.0000635	0.00196
	(0.0175)	(0.0215)	(0.00132)	(0.00248)
Trimester 3		0.0125		0.00237
		(0.0202)		(0.00309)
AFTER BIRTH				
0-2 months after birth		-0.00557		-0.00119
		(0.0178)		(0.00262)
3-5 months after birth		-0.00262		0.000120
		(0.0199)		(0.00281)
6-8 months after birth		0.0121		0.00153
		(0.0170)		(0.00257)
9-11 months after birth		0.0280		-0.00234
		(0.0202)		(0.00256)
N	10322	9770	11104	10496
Mean of dependent variable	6.105	6.170	0.462	0.466
Basic Controls	No	Yes	No	Yes
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
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.

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 can afford 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 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 A1 and A2 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.

5.3.2 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 after 1979 and old enough in at least one survey wave to have been asked about their place of birth, I first 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 Pollution on Cohort Size

	(1)	(2)	(3)	(4)
Average monthly inversions…	Cohort size	Cohort size	Fraction male	Fraction male
BEFORE CONCEPTION				
19-21 months before birth	-0.00351	-0.00482	-0.000354	0.000394
	(0.00329)	(0.00322)	(0.00271)	(0.00269)
16-18 months before birth	-0.00127	-0.00123	0.000777	0.00122
	(0.00320)	(0.00324)	(0.00263)	(0.00275)
13-15 months before birth	0.00514	0.00462	-0.00109	-0.000581
	(0.00323)	(0.00327)	(0.00278)	(0.00285)
10-12 months before birth	0.00369	0.00411	0.00254	0.00368
	(0.00361)	(0.00378)	(0.00259)	(0.00259)
DURING PREGNANCY				
Trimester 1	0.00161	0.00178	-0.00134	-0.000932
	(0.00331)	(0.00344)	(0.00246)	(0.00256)
Trimester 2	0.00216	0.00295	-0.000612	-0.000372
	(0.00357)	(0.00348)	(0.00284)	(0.00277)
Trimester 3	-0.00557	-0.00593	-0.000615	-0.000327
	(0.00467)	(0.00483)	(0.00240)	(0.00233)
AFTER BIRTH				
0-2 months after birth	-0.000247	0.000248	0.000183	0.00142
	(0.00397)	(0.00403)	(0.00244)	(0.00257)
3-5 months after birth	0.000784	0.000110	-0.00167	-0.000926
	(0.00379)	(0.00408)	(0.00267)	(0.00276)
6-8 months after birth	-0.00101	-0.00100	-0.000345	-0.000430
	(0.00345)	(0.00354)	(0.00248)	(0.00261)
9-11 months after birth	-0.00439	-0.00472	-0.00131	-0.00119
	(0.00361)	(0.00365)	(0.00307)	(0.00316)
N (municipality-year-months)	10108	10108	10098	10098
Mean of dependent variable	1.352	1.352	0.482	0.482
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 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.

5.4 Structural Estimates of Wage Function

The above analysis has shown that female schooling decisions are more strongly affected by a cognitive endowment shock than male schooling decisions. This is primarily driven by the higher tendency of women to enter the white-collar sector. Recall that the model in section 2 predicted a larger schooling response among women *if* schooling and ability are more complementary in the white collar than in the blue collar sector. I verify the latter by structurally estimating these sector-specific parameters. Table 6 reports the estimates for the wage parameters from the model described in section 4.2. The parameter estimates for the cost functions can be found in Appendix Table A9.

In Table 6, the first two columns report the coefficient estimates and standard errors for the white-collar wage parameters, the second two for the blue-collar wage function, and the last two report the differences between the two. Average wages are higher in the white-collar sector than in the blue-collar sector. The age patterns differ across sectors as well; the white collar sector offers greater rewards for experience in the older age categories, but the standard errors of these differences are large. Individuals in urban areas earn higher income on average. Conditioning on schooling and ability, men earn significantly higher wages than women in both sectors. Notably, the male advantage is significantly larger in the blue-collar sector than in the white-collar sector, which is consistent with men having a comparative advantage in the more physical blue-collar sector.

Most relevant to the model predictions, however, is the relative magnitude of the sector-specific coefficients on the interaction between high school completion and ability. This term is positive and significant in the white-collar sector, offering evidence for complementarities between ability and educational investments in this sector. In the blue-collar sector, on the other hand, this term is negative but not statistically significant. The difference between the two coefficients is significant at the 1% level. Because sector-specific wage functions separately capture two different types of skill (one that is rewarded in the white-collar sector and one that is rewarded in the blue-collar sector), this result offers a nuanced contribution to the discussion about the production function of skill and whether there are complementarities between cognitive ability accumulated during childhood and schooling investments in adolescence (Cunha and Heckman, 2007; Cunha et al., 2010; Aizer and Cunha, 2012). In short, the existence or strength of complementarities can be heterogenous across different skill types.

These estimates confirm that the reduced form results discussed earlier do indeed support the model predictions from section 2. Because women tend to sort disproportionately into a sector where schooling

Table 6 Wage Function Parameter Estimates

	White Collar		Blue Collar		WC -- BC Difference	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Constant	10.338	(0.117)***	9.829	(0.058)***	0.509	(0.127)***
HS	0.232	(0.121)*	0.200	(0.121)*	0.031	(0.169)
Ability	-0.022	(0.063)	0.161	(0.030)***	-0.183	(0.070)***
HS x Ability	0.231	(0.079)***	-0.071	(0.069)	0.301	(0.103)***
HS: Age 35-40	0.106	(0.103)	0.189	(0.141)	-0.083	(0.175)
HS: Age 41-45	0.144	(0.099)	0.248	(0.148)*	-0.104	(0.178)
HS: Age 46-50	0.677	(0.112)***	0.343	(0.185)*	0.334	(0.216)
No HS: Age 35-40	0.290	(0.140)**	-0.005	(0.058)	0.295	(0.151)*
No HS: Age 41-45	0.245	(0.147)*	-0.013	(0.060)	0.258	(0.159)
No HS: Age 46-50	0.315	(0.169)*	0.120	(0.071)*	0.196	(0.183)
Male	0.371	(0.060)***	0.684	(0.045)***	-0.313	(0.073)***
Urban	0.205	(0.073)***	0.419	(0.042)***	-0.214	(0.082)***
Mother's Education	0.019	(0.005)***	0.008	(0.003)**	0.011	(0.004)**
Father's Education	0.018	(0.005)***	0.005	(0.003)*	0.012	(0.004)***

Notes:
Standard errors are calculated analytically using the information matrix.
* p< 0.1 ** p< 0.05 *** p< 0.01

and ability are more complementary, they exhibit stronger schooling responses to a cognitive endowment shock.

5.5 Policy Simulation

Given that men and women respond differently to cognitive shocks, policies aimed at improving cognitive ability should also have different effects on each gender. The structural approach I take allows me to conduct policy exercises to evaluate this claim. Of particular interest to the literature on early-life circumstances are interventions aimed at improving the skills of the most disadvantaged, starting at very young ages. One of the most well-studied examples of this is the Head Start program in the United States. Initially developed as part of the "War on Poverty," a main goal of Head Start is to enable disadvantaged children to "begin schooling on an equal footing with their more advantaged peers" (Currie, 2001). Another important intervention was the smaller scale yet more intensive intervention conducted in Kingston, Jamaica in the 1980's. This intervention targeted stunted children in poor neighborhoods in Kingston and provided nutritional supplementation and a psychosocial stimulation program (Grantham-McGregor et al., 1991). In an experiment similarly focused on a low-income population, nutritional supplements were offered to children in rural Guatemalan villages. The latter two

programs generated long-term improvements in cognitive ability.

Motivated by these examples, I simulate a policy that brings up the left tail of the distribution by increasing the cognitive ability of those below the 10th percentile to the level of the 10th percentile. I note that this is an ambitious policy: very few interventions have had success in raising IQ in the long-run, and model Head Start programs like Perry preschool are no exception (the IQ gains from such programs have been found to have faded over time). Nevertheless, successful studies like the Jamaican and Guatemalan experiments offer us with some guidance on what can contribute to effective interventions (outside of the formal school system). Because the simulated policy is assumed to bring about cognitive improvements without changing school quality, it should be thought of as a most closely related to these two programs.

I focus on a small percentage of the population for two reasons. First of all, my model is a partial equilibrium model and cannot be used to predict the effects of policy changes that affect large portions of the population and have general equilibrium effects. Secondly, due to budget constraints, policies actually implemented by governments tend to focus on small fractions of the population. Head Start targets children in families living below the poverty line (Aughinbaugh et al., 2001), who make up between 10 and 20 percent of the population.[30] Similarly, two years after it first began, Mexico's *Oportunidades* program (which had a similar goal of improving the human capital of the most disadvantaged, but targeted based on income and focused on educational attainment) reached about 10% of the entire Mexican population (Behrman et al., 2005). The studies conducted in Jamaica and Guatemala were constrained to small sample sizes of a few hundred and a few thousand.

In my sample, raising the cognitive ability of those below the 10th percentile to the level of the 10th percentile is equivalent to an average test score improvement of about 0.4 standard deviations among those affected. This lies in the range of the estimated effect sizes of the two successful studies discussed above: the relatively intensive intervention in Jamaica increased adult cognitive ability by 0.6 standard deviations (Walker et al., 2011), while the nutritional supplementation program in Guatemala increased Raven's test scores by 0.25 standard deviations (Maluccio et al., 2009).

Table 7 summarizes the main results of this exercise, focusing on the sub-sample of individuals falling below the 10th percentile of the Raven's test score distribution. Columns 1 and 2 restrict to men, and columns 3 and 4 focus on women. In columns 5 and 6, I subtract the male values from the female values. For each group, I report the probability of high school graduation, the probability of employment, and

[30] This figure varies across years.

income, prior to the policy. These are predicted values, obtained by calculating 50 simulations of the model using the actual Raven's test scores (and other relevant variables) in the data. I also report the change that takes place as a result of increasing ability to the 10th percentile. Column 7 reports the female to male ratio in the level change (column 4 divided by column 2).

The first row shows that increasing ability leads to an increase in the proportion of individuals who graduate from high school, which is at baseline a mere 5% in this sample of low-ability individuals. As reported in column 6, this increase is 0.7 percentage points (or 23%) larger for women than men, which is is qualitatively consistent with both my reduced form results and conceptual framework.[31] In the second row, I find that the female employment response is over 7 times larger for women than men. Female employment increases by over one percentage point, which is approximately 20% of the increase in female labor force participation that took place in Mexico from 2002 to 2012. This closes the male-female employment gap by almost one and a half percent. The last two rows summarize the resulting changes in average income: first only among those working and then over the entire sample (assigning zeros to the unemployed). Both of these income measures increase for both genders, but the increase in conditional income is larger for men than women, due to the entry of more lower-ability women into the labor force. On the other hand, because of the larger improvements on the extensive margin for women, unconditional average income increases by 46% more for women than men, closing the pre-policy income gap by 0.6%. In short, the fact that improvements in cognitive ability result in different responses for men and women has important implications for how interventions like this one might affect gender gaps in schooling and employment outcomes. This particular intervention could help close the gender gap among low-ability individuals in employment rates, but not in conditional income levels.

6 Conclusion

This study offers evidence that gender differences in investment responses can arise from gender-specific opportunities in the labor market. Long-term cognitive damage caused by pollution exposure *in utero* affects the schooling decisions and income of women, but not of men. This gender difference is largely driven by the different labor market opportunities faced by men and women. In particular, women have

[31] It should be noted that this figure cannot be compared to the reduced form results in Section 5. This policy simulation uses a slightly older sample, restricts to a small sub-sample of individuals, and assumes a shock that hits only a particular part of the distribution.

Table 7 Effects of Simulated Policy on Schooling, Employment, and Income

	Male		Female		Female-Male Difference			
	(1)	(2)	(3)	(4)	(5)	(6)		(7)
	Before policy	Level change	Before policy	Level change	Before policy	Level change (% change)		Female Level Change / Male Level Change
P(High School)	0.0495	0.0031	0.0504	0.0038	0.0009	0.0007	(79.01%)	1.2278
P(Employed)	0.9706	0.0015	0.3067	0.0108	-0.6639	0.0093	(-1.40%)	7.3352
Conditional Income	10.5223	0.0728	10.0555	0.0560	-0.4668	-0.0168	(3.59%)	0.7697
Unconditional Income	10.2133	0.0862	3.0841	0.1261	-7.1292	0.0399	(-0.56%)	1.4623

Notes: All values are calculated using the model to simulate 50 paths for each individual, restricting to those in the bottom 10th percentile. "Before policy" reports the simulated averages using actual Raven's test scores, "Level change" reports the change after increasing Raven's test scores to the 10th percentile. "Conditional Income" is the inverse hyperbolic sine of total annual income among positive income earners, and "Unconditional Income" is the inverse hyperbolic sine of total annual income among all individuals, setting income to zero for the unemployed.

a comparative advantage in white-collar jobs, where I show that schooling and ability exhibit a higher degree of complementarity than in blue-collar jobs. Policy simulations reveal that interventions aimed at improving cognitive ability will have larger effects on female schooling and employment and therefore help to close the gender gap in labor force participation.

These results shed light on the important links between current labor market conditions, future labor market expectations, and investment responses to early-life shocks. 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. I also offer 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). This finding also speaks to a broader literature documenting that labor market conditions, including current and future job opportunities, affect schooling decisions (Jensen, 2010; Atkin, 2016; Shah and Steinberg, 2015).

Finally, these results address an important question that has motivated a number of recent studies: how do early-life shocks interact with events or conditions later in life? Whether these events are policy interventions (Adhvaryu et al., 2015; Rossin-Slater and Wüst, 2015; Gunnsteinsson et al., 2014), economic shocks (Bharadwaj et al., 2014), or simply 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 important implications for future policy and the interpretation of existing results.

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A Appendix Tables

- Table A1 reports ISCO occupation shares, by gender, from the 2010 Mexican census. I group the occupation categories into two groups using the brain-intensive and brawn-intensive classification used by Vogl (2014), who calculates average skill and strength intensities of each occupational category using job requirement scores in the Dictionary of Occupational Titles.

- Table A2 reports summary statistics for all of the relevant variables for the structural estimation described in section 4.2.

- Tables A3 to A6 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 A8 demonstrates the robustness of the labor market mechanism results to the use of other proxies of p_{jg}. The regression in column 2 assigns individuals with the relevant white-collar proportion from the census decade in which they turned 12. Results are consistent with those in Table 3. Column 3 reports the results from using a continuous version of the discrete measure used in Table 3, demeaned so that the main effects can be interpreted as the effects for the average individual. Though more imprecise, these results are consistent with the previous finding that gender-specific labor market opportunities appear to be playing a more important role than gender itself – the male interaction with second trimester inversions is much smaller in magnitude than in column 1.

- Figures A1 and A2 show the robustness of my main results to the inclusion of additional fixed effects.

Table A1 Occupation Distributions by Gender

Occupation, ISCO	Male	Female
White-Collar ("Brains")	**19.76**	**34.85**
Legislators, senior officials and managers	5	4.47
Professionals	7.39	7.88
Technicians and associate professionals	4.08	12.04
Clerks	3.29	10.46
Blue-Collar ("Brawn")	**80.25**	**65.15**
Service workers and shop and market sales	17.62	29.63
Skilled agricultural and fishery workers	12.25	1.7
Crafts and related trades workers	24.23	8.26
Plant and machine operators and assemblers	14.19	5.44
Elementary occupations (domestic workers, laborers, etc)	11.96	20.12

Notes: Brain and brawn categorizations from Vogl (2014). Weighted percentages calculated from adults aged 30 to 50 in the 2010 Mexican census.

Table A2 Summary Statistics for Structural Estimation Sample

Variable Name	Mean	Standard Deviation	N
Individual-Level Variables			
Total annual income (inverse hyperbolic sine)	7.13	5.246	5265
1(Completed high school)	0.25	0.433	5265
1(White collar sector)	0.21	0.407	5265
1(Blue collar sector)	0.45	0.497	5265
1(Not employed)	0.34	0.475	5265
Raven's test score (% correct)	0.52	0.240	5265
Age	38.72	5.795	5265
1(Male)	0.41	0.491	5265
1(Urban)	0.62	0.486	5265
Mother's education	3.35	3.477	5265
Father's education	3.68	3.891	5265
Labor Market Variables			
White collar proportion	0.33	0.170	5265
Unemployment rate	0.02	0.0127	5265
Youth employment rate (ages 12-15)	0.11	0.102	5265
Youth employment rate (ages 16-18)	0.32	0.197	5265

Notes: Sample includes individuals aged 30 to 50 who are either currently employed (with non-missing sector and income information) or reported never having worked before. Individual-level variables are from the Mexican Family Life Survey. Labor market variables are from the 1970 to 2000 censuses and matched to individuals by their commuting zone of residence. White collar proportion is the fraction of adult males (for men) and adult females (for women) working in the white collar sector during individual's early working years. Unemployment rate is the adult unemployment rate during an individual's early working years. Youth employment rate is the proportion of boys (for men) or girls (for women) in the stated age category who report being employed during an individual's school-aged years.

Table A3 Effects of Pollution on Health

	(1)	(2)	(3)	(4)
Average monthly inversions…	Raven's test z-score	Raven's test z-score	Height z-score	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 A4 Effects of Pollution on Health by Gender

	(1)	(2)	(3)	(4)
Average monthly inversions…	Raven's test z-score	Raven's test z-score	Height z-score	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)
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 A5 Effects of Pollution on Schooling by Gender

	(1)	(2)	(3)	(4)
Average monthly inversions…	Years of Schooling	Years of Schooling	HS Completion	HS Completion
FEMALE				
Trimester 1	0.0410	0.0460	0.00517	0.00648
	(0.0289)	(0.0287)	(0.00486)	(0.00482)
Trimester 2	-0.0241	-0.0200	-0.00821**	-0.00757*
	(0.0251)	(0.0250)	(0.00405)	(0.00401)
Trimester 3	0.00532	0.0118	0.00156	0.00347
	(0.0274)	(0.0267)	(0.00413)	(0.00411)
N	3988	3988	3988	3988
Dependent variable mean	10.03	10.03	0.382	0.382
MALE				
Trimester 1	0.0161	0.0216	-0.00141	-0.00112
	(0.0290)	(0.0285)	(0.00434)	(0.00436)
Trimester 2	0.00445	0.0100	0.00150	0.00298
	(0.0284)	(0.0298)	(0.00396)	(0.00415)
Trimester 3	0.0164	0.0145	0.00618	0.00602
	(0.0249)	(0.0261)	(0.00452)	(0.00480)
N	3365	3365	3365	3365
Dependent variable mean	9.866	9.866	0.343	0.343
MALE - FEMALE DIFFERENCE				
Trimester 1	-0.0249	-0.0244	-0.00658	-0.00760
	(0.0416)	(0.0407)	(0.00668)	(0.00668)
Trimester 2	0.0286	0.0300	0.00971	0.0105*
	(0.0400)	(0.0404)	(0.00593)	(0.00611)
Trimester 3	0.0111	0.00276	0.00462	0.00255
	(0.0350)	(0.0356)	(0.00592)	(0.00605)
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 A6 Effects of Pollution on Income by Gender

	(1)	(2)
Average monthly inversions…	Annual income	Annual income
FEMALE		
Trimester 1	-140.1	10.54
	(545.4)	(763.1)
Trimester 2	-1131.4**	-1067.9*
	(570.1)	(585.7)
Trimester 3	-38.51	95.39
	(735.5)	(847.6)
N	946	946
Dependent variable mean	24314.0	24314.0
MALE		
Trimester 1	-404.8	-766.2
	(430.1)	(521.2)
Trimester 2	-465.2	-653.8
	(372.4)	(415.4)
Trimester 3	-225.6	-508.7
	(305.6)	(312.1)
N	1833	1833
Dependent variable mean	31101.5	31101.5
MALE - FEMALE DIFFERENCE		
Trimester 1	-264.7	-776.7
	(649.7)	(783.3)
Trimester 2	666.2	414.1
	(656.4)	(698.4)
Trimester 3	-187.1	-604.1
	(666.6)	(747.9)
Additional Fixed Effects	None	state-by-season, state-by-quadratic-year
Standard errors in parentheses (clustered at municipality level)		
* p<0.1 ** p<0.05*** p<0.01		

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 A7 Effects of Pollution on Early Educational Attainment, by Gender

	(1)	(2)	(3)	(4)
Average monthly inversions…	Elementary School Completion	Elementary School Completion	Junior High School Completion	Junior High School Completion
FEMALE				
Trimester 1	0.00119	0.00165	0.00443	0.00474
	(0.00272)	(0.00268)	(0.00421)	(0.00431)
Trimester 2	0.000538	0.000813	0.000131	0.00103
	(0.00223)	(0.00220)	(0.00410)	(0.00409)
Trimester 3	-0.000728	-0.000798	0.00242	0.00274
	(0.00209)	(0.00204)	(0.00406)	(0.00384)
N	3988	3988	3988	3988
Dependent variable mean	0.944	0.944	0.772	0.772
MALE				
Trimester 1	0.000290	0.000427	-0.00153	-0.000878
	(0.00247)	(0.00260)	(0.00431)	(0.00418)
Trimester 2	-0.000467	-0.00133	0.000975	0.000186
	(0.00284)	(0.00297)	(0.00470)	(0.00485)
Trimester 3	-0.00114	-0.00196	-0.00236	-0.00184
	(0.00281)	(0.00292)	(0.00432)	(0.00447)
N	3365	3365	3365	3365
Dependent variable mean	0.938	0.938	0.753	0.753
MALE - FEMALE DIFFERENCE				
Trimester 1	-0.000900	-0.00122	-0.00596	-0.00561
	(0.00384)	(0.00403)	(0.00572)	(0.00576)
Trimester 2	-0.00101	-0.00214	0.000843	-0.000848
	(0.00368)	(0.00388)	(0.00667)	(0.00646)
Trimester 3	-0.000409	-0.00116	-0.00479	-0.00459
	(0.00353)	(0.00354)	(0.00606)	(0.00599)
Additional Fixed Effects	None	state-by-season, state-by-quadratic-year	None	state-by-season, state-by-quadratic-year

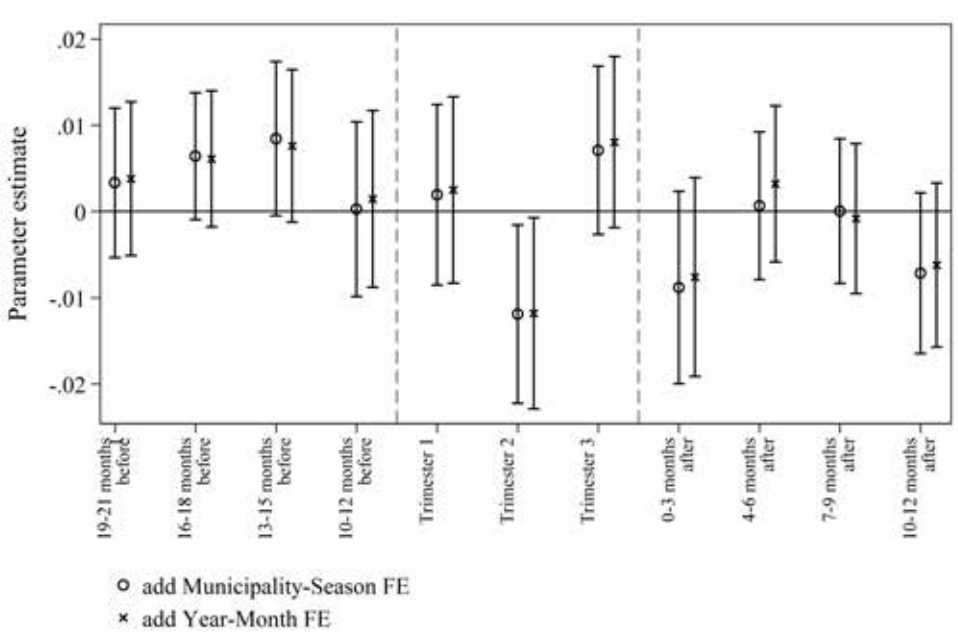
Notes:
Standard errors (clustered at municipality level) in parentheses. * p< 0.1 ** p< 0.05 *** p< 0.01
All regressions control for birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, mother's education, father's education, cubic functions of average monthly 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 A8 Effects of Pollution on High School Graduation, by Alternative White-Collar Variables

	(1)	(2)	(3)
Average monthly inversions…	HS Completion	HS Completion	HS Completion
Trimester 1	0.00648	0.00230	-0.000666
	(0.00485)	(0.00658)	(0.00699)
Trimester 2	-0.00757*	0.00562	-0.00283
	(0.00404)	(0.00648)	(0.00606)
Trimester 3	0.00347	0.00752	0.00367
	(0.00414)	(0.00781)	(0.00698)
Trimester 1	-0.00760	-0.00567	0.00118
x 1(Male)	(0.00668)	(0.00773)	(0.00852)
Trimester 2	0.0105*	0.000246	0.00610
x 1(Male)	(0.00611)	(0.00735)	(0.00774)
Trimester 3	0.00255	-0.00232	0.00141
x 1(Male)	(0.00605)	(0.00769)	(0.00856)
Trimester 1		0.00446	0.0294
x White Collar Variable		(0.00543)	(0.0197)
Trimester 2		-0.0144**	-0.0232
x White Collar Variable		(0.00576)	(0.0196)
Trimester 3		-0.00438	-0.00526
x White Collar Variable		(0.00697)	(0.0197)
N	7353	7317	7214
Dependent variable mean	0.364	0.363	0.363
Additional Fixed Effects		state-by-season, state-by-quadratic-year	
White Collar Variable	None	Discrete, assigned by census	Continuous, predicted

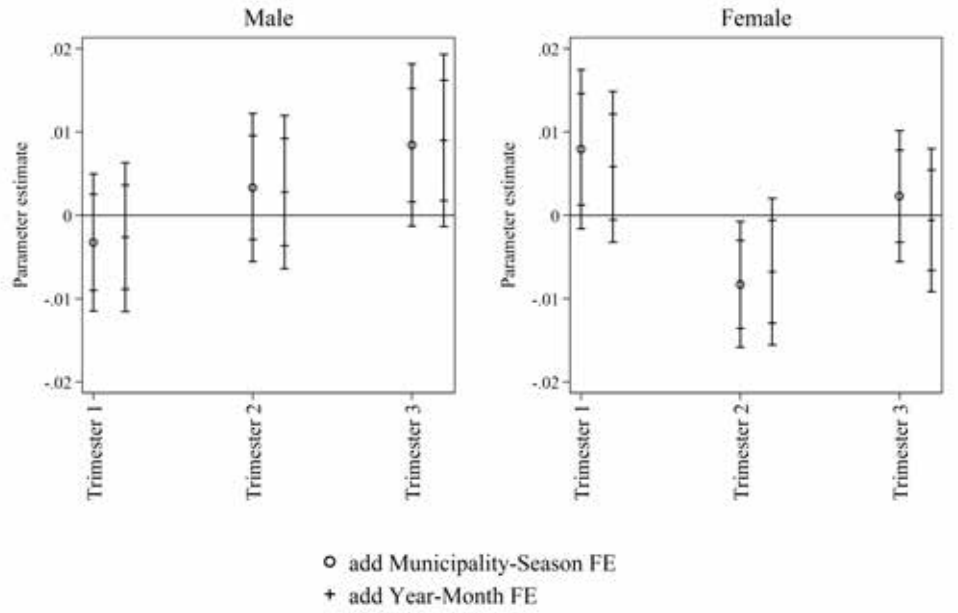
Notes:
Standard errors (clustered at municipality level) in parentheses. * p< 0.1 ** p< 0.05 *** p< 0.01
All regressions control for the following variables and their interactions with a male indicator (as well as the main effect of gender): birth month, birth year, municipality of birth, and survey wave by birth year fixed effects, 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. In columns 2 and 3, the main effect of the white collar variable and the interactions with inversions in all other three month periods are also included. Regressions restrict to individuals aged 18 and older.

Figure A1 Effects of Pollution on Cognitive Ability, with Additional Fixed Effects



Notes: Intervals represent 90% 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 A2 Effects of Pollution on High School Completion by Gender, with Additional Fixed Effects



Notes: Separate regressions are conducted for men and women. Intervals represent 90% and 75% confidence 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. Sample is restricted to individuals aged 18 and older.

B Data Appendix

B.1 Predicting White Collar Proportions

Conceptually, p_g represents the perceived likelihood of an individual entering the white collar sector. If parents or individuals use current conditions to inform this expectation, then this probability should vary with the local labor market opportunities at times when children are making important schooling transitions. I aim to match individuals to the relevant labor market variables in the year they turn 12 years old, in the municipality in which they are living at that age. For the vast majority of the sample, I know exactly where they are living at age 12. If individuals report that they are currently living in the same municipality in which they were living at age 12, I use their current residence. If individuals report that they were living in their municipality of birth when they were 12 years old, I use their municipality of birth. For the remainder of individuals, who make up less than 10% of the sample, I also 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.

For the actual data on local labor market conditions, I use the 1990, 2000, and 2010 Mexican censuses, which span the decades during which individuals in my sample transitioned from elementary to junior high. I use the provided International Standard Classification of Occupations (ISCO) codes to categorize individuals as working in white-collar or blue-collar jobs using the same classification as in Vogl (2014). I then calculate the proportion of men and women in white-collar jobs, separately for each commuting zone. 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).

The census data provides me with gender-specific white-collar proportions for each commuting zone for 1990, 2000 and 2010. However, my empirical test requires knowledge about labor market conditions for each birth cohort at age 12. I use two different methods to assign values to the individuals who turn twelve during intercensal years. The simplest method involves assigning individuals with the relevant value from the census just prior to the decade in which they turned 12. This would be the 2000 census

for those who were born in the years 1988 to 1997, for example. These results are reported in Table A8.

The results discussed in the main body of the paper (Table 3) combine census data with national-level growth rates from ENIGH to predict intercensal years. For each year y, I calculate national-level growth rates of six major industries[32] (subscripted by j) relative to the most recent census decade d. I denote these growth rates g_{yjd}. From the census, in addition to the gender-specific proportions of white collar jobs in each decade (p_{gd}), I also calculate the gender-specific share of brain-intensive jobs in each industry: s_{gjd}. My predicted proportion, $\hat{p}_{gyjd}$, is simply:

$$\hat{p}_{gyjd} = p_{gd} + \sum_{j=1}^{5} s_{gjd} g_{yjd}. \tag{13}$$

[32]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.

C Structural Estimation Details

In this section, I outline the decision rules, transition probabilities, and likelihood function used to estimate the structural model in section 4.2. The last sub-section discusses model fit.

C.1 Agent's Decision Rules

To simplify future notation, I collect all the non-stochastic terms of each state's net rewards into one parameter, so that they can now be written

$$
\begin{aligned}
Y(hw) - c(hw) &= \gamma_{hw} + \sum_{t=0}^{20} \delta^t \epsilon(hw, t) - (\eta(hw) - \eta(hb)) \\
Y(lw) - c(lw) &= \gamma_{lw} + \sum_{t=0}^{20} \delta^t \epsilon(lw, t) - (\eta(lw) - \eta(lb)) \\
Y(hb) - c(hb) &= \gamma_{hb} + \sum_{t=0}^{20} \delta^t \epsilon(hb, t) \\
Y(lb) - c(lb) &= \gamma_{lb} + \sum_{t=0}^{20} \delta^t \epsilon(lb, t) \\
Y(hn) - c(hn) &= \gamma_{hn} - (\eta(hn) - \eta(hb)) \\
Y(ln) - c(ln) &= \gamma_{ln} - (\eta(ln) - \eta(lb)) \\
Y(h) - c(h) &= \gamma_{h} - (\eta(h) - \eta(l)),
\end{aligned}
$$

where

$$
\begin{aligned}
\gamma_{hw} = &\frac{1-\delta^{21}}{1-\delta}\left[\beta_{w0} + \beta_{w1} + (\beta_{w2} + \beta_{w3})\theta + \sum_{j=10}^{k_w} \beta_{wj} X_{wj}\right] + \frac{1-\delta^5}{1-\delta}\sum_{j=4}^{6}(\beta_{wj} + \beta_{w(j+3)})\delta^{5(j-3)+1} \\
&- \left(c_{hw} + \alpha_{hw}\theta + \sum_{j=1}^{q_{hw}} \delta_{hwj} Q_{hwj}\right) \\
\gamma_{lw} = &\frac{1-\delta^{21}}{1-\delta}\left[\beta_{w0} + \beta_{w2}\theta + \sum_{j=10}^{k_w} \beta_{wj} X_{wj}\right] + \frac{1-\delta^5}{1-\delta}\sum_{j=4}^{6}\beta_{wj}\delta^{5(j-7)+1} \\
&- \left(c_{lw} + \alpha_{lw}\theta + \sum_{j=1}^{q_{lw}} \delta_{lwj} Q_{lwj}\right)
\end{aligned}
$$

$$\gamma_{hb} = \frac{1-\delta^{21}}{1-\delta}\left[\beta_{b0} + \beta_{b1} + (\beta_{b2}+\beta_{b3})\theta + \sum_{j=10}^{k_b}\beta_{bj}X_{bj}\right] + \frac{1-\delta^5}{1-\delta}\sum_{j=4}^{6}(\beta_{bj}+\beta_{b(j+3)})\delta^{5(j-3)+1}$$

$$\gamma_{lb} = \frac{1-\delta^{21}}{1-\delta}\left[\beta_{b0} + \beta_{b2}\theta + \sum_{j=10}^{k_b}\beta_{bj}X_{bj}\right] + \frac{1-\delta^5}{1-\delta}\sum_{j=4}^{6}\beta_{bj}\delta^{5(j-7)+1}$$

$$\gamma_{hn} = -(c_{hn} + \alpha_{hn}\theta + \sum_{j=1}^{q_{hn}}\delta_{hnj}Q_{hnj})$$

$$\gamma_{ln} = -(c_{ln} + \alpha_{ln}\theta + \sum_{j=1}^{q_{ln}}\delta_{lnj}Q_{lnj})$$

$$\gamma_{h} = -(c_{h} + \alpha_{h}\theta + \sum_{j=1}^{q_{h}}\delta_{Hj}Q_{hj}).$$

The agent's value function at state s is

$$V(s) = Y(s) + \underbrace{\delta \max_{s' \in S^f(s)} \left\{-c(s') + \delta \mathrm{E}\left[V(s')|I(s)\right]\right\}}_{CV(s)=\text{Continuation Value}}, \tag{14}$$

where $I(s)$ denotes the agent's information set at state s, and $S^f(s)$ denotes the set of feasible states at s. The second term on the right-hand side is the continuation value of state s, $CV(s)$, . This value function determines the agent's decision in each state. I solve for the optimal decision rules at each node, starting with the terminal nodes.

An agent in $s = h$ chooses hw if, given her high school degree, the expected lifetime net rewards from the white collar sector exceed expected lifetime net rewards from the blue collar sector and the expected net rewards from not working, i.e. if

$$\gamma_{hw} - \eta(hw) > \gamma_{hb} - \eta(hb) \text{ and} \tag{15}$$

$$\gamma_{hw} - \eta(hw) > \gamma_{hn} - \eta(hn). \tag{16}$$

An agent chooses hb if

$$\gamma_{hb} - \eta(hb) \geq \gamma_{hw} - \eta(hw) \text{ and} \tag{17}$$

$$\gamma_{hb} - \eta(hb) > \gamma_{hn} - \eta(hn), \tag{18}$$

and chooses hn otherwise.

Similarly, an agent in $s = l$ chooses lw if

$$\gamma_{lw} - \eta(lw) > \gamma_{lb} - \eta(lb) \text{ and} \tag{19}$$

$$\gamma_{lw} - \eta(lw) > \gamma_{ln} - \eta(ln), \tag{20}$$

chooses lb if

$$\gamma_{lb} - \eta(lb) \geq \gamma_{lw} - \eta(lw) \text{ and} \tag{21}$$

$$\gamma_{lb} - \eta(lb) > \gamma_{ln} - \eta(ln), \tag{22}$$

and chooses ln otherwise.

These decision rules also help to solve for the agent's optimal decision in $s = 0$. Here, an agent will choose h if the expected net rewards and continuation value of a high school degree exceeds the expected net rewards plus continuation value of dropping out.

$$\mathrm{E}\left[Y(h) - c(h) + CV(h)|I(0)\right] > \mathrm{E}\left[Y(l) - c(l) + CV(l)|I(0)\right], \tag{23}$$

where

$$\begin{aligned}
\mathrm{E}\left[Y(h) - c(h) + CV(h)|I(0)\right] &= \mathrm{E}\left[Y(h) + CV(h)|I(0)\right] - c(h) \\
&= \mathrm{E}\left[CV(h)|I(0)\right] + \gamma_h - (\eta(h) - \eta(l)) \\
&= \delta \mathrm{E}\left[\max_{s' \in \{hw,\ hb,\ hn\}} \left\{-c(s') + \mathrm{E}\left[V(s')|I(h)\right]\right\}\right] + \gamma_h - (\eta(h) - \eta(l)) \\
&= \delta\rho_{\eta h} \ln(\exp(\frac{\gamma_{hw}}{\rho_{\eta h}}) + \exp(\frac{\gamma_{hb}}{\rho_{\eta h}}) + \exp(\frac{\gamma_{hn}}{\rho_{\eta h}})) + \gamma_h - (\eta(h) - \eta(l))
\end{aligned} \tag{24}$$

where the simplification in the final line is due to the Type 1 extreme value distribution assumption.

Similarly,

$$\begin{aligned}
\mathrm{E}\left[Y(l) - c(l) + CV(l)|I(0)\right] &= \mathrm{E}\left[CV(l)|I(0)\right] \\
&= \delta\rho_{\eta l} \ln(\exp(\frac{\gamma_{lw}}{\rho_{\eta l}}) + \exp(\frac{\gamma_{lb}}{\rho_{\eta l}}) + \exp(\frac{\gamma_{ln}}{\rho_{\eta l}})).
\end{aligned} \tag{25}$$

Combining equations 23, 24, and 25, we can derive a cutoff rule for the agent's first decision. She

will choose h if

$$\begin{aligned}&\rho_{\eta h}\ln(\exp(\frac{\gamma_{hw}}{\rho_{\eta h}})+\exp(\frac{\gamma_{hb}}{\rho_{\eta h}})+\exp(\frac{\gamma_{hn}}{\rho_{\eta h}}))+\gamma_h-\eta(h)\\&>\rho_{\eta l}\ln(\exp(\frac{\gamma_{lw}}{\rho_{\eta l}})+\exp(\frac{\gamma_{lb}}{\rho_{\eta l}})+\exp(\frac{\gamma_{ln}}{\rho_{\eta l}}))-\eta(l)\end{aligned}\tag{26}$$

C.2 Transition Probabilities and Likelihood Function

The individual likelihood contribution of a particular agent is the joint probability of observing that agent's schooling choice, sectoral choice, and (for working individuals) income that is realized in the data.[33] Beginning with the choice probabilities, I define for each agent an indicator function $d(s)$ which equals 1 if the agent visits state s, and calculate the conditional probability of visiting each state in $S^{\mathrm{v}}(s)$, the set of visited states. Collecting all of the observed characteristics in D and structural parameters in a vector ψ, we can use the above cutoff rules to write out these transition probabilities as follows:

$$\begin{aligned}\Pr(d(h)=1|D,\psi,\theta)&=\left[1+\exp\left(-\frac{1}{\rho_{\eta 0}}\left(\rho_{\eta h}\ln(e^{\frac{\gamma_{hw}}{\rho_{\eta h}}}+e^{\frac{\gamma_{hb}}{\rho_{\eta h}}}+e^{\frac{\gamma_{hn}}{\rho_{\eta h}}})+\gamma_h\right.\right.\right.\\&\qquad\left.\left.\left.-\rho_{\eta l}\ln(e^{\frac{\gamma_{lw}}{\rho_{\eta l}}}+e^{\frac{\gamma_{lb}}{\rho_{\eta l}}}+e^{\frac{\gamma_{ln}}{\rho_{\eta l}}})\right)\right)\right]^{-1}\\\Pr(d(l)=1|D,\psi,\theta)&=\left[1+\exp\left(\frac{1}{\rho_{\eta 0}}\left(\rho_{\eta h}\ln(e^{\frac{\gamma_{hw}}{\rho_{\eta h}}}+e^{\frac{\gamma_{hb}}{\rho_{\eta h}}}+e^{\frac{\gamma_{hn}}{\rho_{\eta h}}})+\gamma_h\right.\right.\right.\\&\qquad\left.\left.\left.-\rho_{\eta l}\ln(e^{\frac{\gamma_{lw}}{\rho_{\eta l}}}+e^{\frac{\gamma_{lb}}{\rho_{\eta l}}}+e^{\frac{\gamma_{ln}}{\rho_{\eta l}}})\right)\right)\right]^{-1}\\\Pr(d(hw)=1|D,\psi,\theta)&=\exp(\frac{\gamma_{hw}}{\rho_{\eta h}})\left[\exp(\frac{\gamma_{hw}}{\rho_{\eta h}})+\exp(\frac{\gamma_{hb}}{\rho_{\eta h}})+\exp(\frac{\gamma_{hn}}{\rho_{\eta h}})\right]^{-1}\\\Pr(d(hb)=1|D,\psi,\theta)&=\exp(\frac{\gamma_{hb}}{\rho_{\eta h}})\left[\exp(\frac{\gamma_{hw}}{\rho_{\eta h}})+\exp(\frac{\gamma_{hb}}{\rho_{\eta h}})+\exp(\frac{\gamma_{hn}}{\rho_{\eta h}})\right]^{-1}\\\Pr(d(hn)=1|D,\psi,\theta)&=\exp(\frac{\gamma_{hn}}{\rho_{\eta h}})\left[\exp(\frac{\gamma_{hw}}{\rho_{\eta h}})+\exp(\frac{\gamma_{hb}}{\rho_{\eta h}})+\exp(\frac{\gamma_{hn}}{\rho_{\eta h}})\right]^{-1}\\\Pr(d(lw)=1|D,\psi,\theta)&=\exp(\frac{\gamma_{lw}}{\rho_{\eta l}})\left[\exp(\frac{\gamma_{lw}}{\rho_{\eta l}})+\exp(\frac{\gamma_{lb}}{\rho_{\eta l}})+\exp(\frac{\gamma_{ln}}{\rho_{\eta l}})\right]^{-1}\\\Pr(d(lb)=1|D,\psi,\theta)&=\exp(\frac{\gamma_{lb}}{\rho_{\eta l}})\left[\exp(\frac{\gamma_{lw}}{\rho_{\eta l}})+\exp(\frac{\gamma_{lb}}{\rho_{\eta l}})+\exp(\frac{\gamma_{ln}}{\rho_{\eta l}})\right]^{-1}\\\Pr(d(ln)=1|D,\psi,\theta)&=\exp(\frac{\gamma_{ln}}{\rho_{\eta l}})\left[\exp(\frac{\gamma_{lw}}{\rho_{\eta l}})+\exp(\frac{\gamma_{lb}}{\rho_{\eta l}})+\exp(\frac{\gamma_{ln}}{\rho_{\eta l}})\right]^{-1}\end{aligned}$$

[33] Although the agent observes the idiosyncratic shocks $\eta(s')$ (before deciding on their next state) and $\epsilon(s)$ (after making their decision), the researcher does not.

These transition probabilities are combined with the per-period wage functions (of which we only observe one per working individual) to construct the individual likelihood function for observation i. Recall that t_i is the age of the individual (in the year their income is observed) minus 30. Then, i's contribution to the likelihood function is:

$$\int_{-\infty}^{\infty} \left[\prod_{s \in S} \left\{ \Pr(d_i(s) = 1 | D_i, \theta_i(\nu); \psi) \prod_{t=0}^{20} f(Y_i(s,t) | D, \theta_i(\nu); \psi)^{1(t_i = t)} \right\}^{1(s \in S_i^{\mathrm{y}})} \right] \mathrm{d}F_\nu(\nu), \tag{27}$$

where

$$\begin{aligned}
f(Y(hw,t)|D,\theta;\psi) &= \phi\left(\beta_{w0} + \beta_{w1} + (\beta_{w2} + \beta_{w3})\theta + \sum_{j=4}^{6}(\beta_{wj} + \beta_{w(j+3)})A_{j-3}(t) - Y(hw,t)\right) \\
f(Y(lw,t)|D,\theta;\psi) &= \phi\left(\beta_{w0} + \beta_{w2}\theta + \sum_{j=4}^{6}\beta_{wj}A_{j-7}(t) - Y(lw,t)\right) \\
f(Y(hb,t)|D,\theta;\psi) &= \phi\left(\beta_{b0} + \beta_{b1} + (\beta_{b2} + \beta_{b3})\theta + \sum_{j=4}^{6}(\beta_{bj} + \beta_{b(j+3)})A_{j-3}(t) - Y(hb,t)\right) \\
f(Y(lb,t)|D,\theta;\psi) &= \phi\left(\beta_{b0} + \beta_{b2}\theta + \sum_{j=4}^{6}\beta_{bj}A_{j-7}(t) - Y(lb,t)\right) \\
f(Y(s,t)|D,\theta;\psi) &= 1 \quad \forall s \in \{h,\ l,\ hn,\ ln\}\,.
\end{aligned}$$

θ is equal to the individual's standardized Raven's test score plus a standard normal error term. The discount factor is set to 0.04. I use maximum likelihood to estimate the structural parameters ψ, using 100 simulations to calculate the integral over θ for each individual. The wage parameters are reported in Table 6, and the cost parameters are reported in Table A9.

Table A9 Cost Parameter Estimates

Panel A: Sectoral Choice

	Estimate	Standard Error
White Collar - Blue Collar		
HS: Constant	-1.989	(4.729)
HS: Ability	0.784	(1.364)
HS: White Collar Proportion	1.790	(4.692)
HS: Male	6.015	(4.203)
HS: Urban	-5.751	(2.633)**
No HS: Constant	19.055	(2.560)***
No HS: Ability	-3.591	(1.064)***
No HS: White Collar Proportion	-8.105	(2.721)***
No HS: Male	-4.499	(1.212)***
No HS: Urban	-4.076	(1.287)***
No Work - Blue Collar		
HS: Constant	-157.552	(3.797)***
HS: Ability	0.479	(1.283)
HS: Unemployment	-1.962	(3.443)
HS: Male	28.158	(12.869)**
HS: Urban	-4.276	(2.146)**
No HS: Constant	-144.930	(0.978)***
No HS: Ability	2.026	(0.459)***
No HS: Unemployment	-2.603	(1.091)**
No HS: Male	3.423	(3.292)
No HS: Urban	-4.193	(0.810)***
HS: Scale Parameter	9.708	(3.230)***
No HS: Scale Parameter	2.908	(0.707)***

Panel B: Schooling Choice

	Estimate	Standard Error
Constant	28.024	(11.747)**
Ability	-3.328	(2.934)
Male	-9.436	(4.135)**
Mother's Education	-0.382	(0.472)
Father's Education	-0.367	(0.462)
Youth Employment (12-15)	-2.224	(2.753)
Youth Employment (16-18)	3.363	(3.481)
Scale Parameter	3.063	(3.179)

Notes:
Standard errors are calculated analytically using the information matrix.
* p< 0.1 ** p< 0.05 *** p< 0.01