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Something in the Air: Fetal air pollution exposure and long-run labour outcomes: Evidence from Germany.

by

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Figure 1: Leipzig 1987 (UBA, 2023)

Abstract This study examines the long-run impact of air pollution exposure at the month of birth and during pregnancy on labour outcomes in Germany. I match air pollution levels on a federal-state level to a longitudinal survey sample on individuals born in Germany. The study focuses on individuals born between 1985 to 1992, as this time period relates to consistent economic growth in Germany. The main identification strategy of this study is through sibling fixed effects. Thus, the impact of air pollution at birth on labour outcomes is identified by variation in pollution levels between siblings. Interestingly, the results of this study yield larger and more significant estimates using sibling fixed effects compared to the Ordinary Least Squares (OLS) method. The results show that carbon monoxide (CO) in the month of birth has a significant and adverse impact on real labour income in euros per month, actual work time per week and employment status at age 27. Furthermore, the burden of CO is carried by children of mothers with lower education levels in its entirety, highlighting the importance to minimise air pollution to reduce inequality in society. I also provide evidence that CO at birth has an adverse effect on cognitive ability in young adulthood. Average CO and O3 levels during the whole pregnancy or O3 at the month of birth do not have such a large impact on labour outcomes. These findings contribute to the existing literature by providing some of the first evidence on the long-term effects of CO exposure in-utero for a European country, corroborating the fetal origins hypothesis.

Keywords: Fetal origins hypothesis, Air pollution, Avoidance behavior, Human capital, Sibling comparisons

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I would like to extend an immense thank you to my supervisor Prof. Ana Rodriguez-Gonzalez for her continuous support and encouragement throughout. Her expertise has played a pivotal role in shaping the outcome of this study. Also thank you to Philipp Kaminsky at DIW Berlin and Karin Uhse at the German Environment Agency for assisting me with all of my tiresome questions.

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Glossary

CO Carbon Monoxide.

FE Fixed Effects.

NO Nitric Oxide.

NO2 Nitrogen Dioxide.

O3 Ozone.

OLS Ordinary Least Squares.

PM10 Particulate matter 10 micrometers or less in diameter.

Sibling-FE Sibling Fixed Effects.

TSP Total Suspended Particulates.

WLS Weighted Least Squares.

1 Introduction

There is an overwhelming amount of evidence pointing to the detrimental effects of air pollution exposure in-utero on childhood health (Bateson and Schwartz, 2007; Almond and Currie, 2011). Still, childhood health effects, such as infant mortality are only one of the more acute implications of air pollution. Thus far, long-term effects of air pollution exposure in-utero remain largely unexplored. Some long-term outcomes could have fetal origins, potentially remaining latent for years before manifesting in adulthood (Currie, Zivin, Mullins, & Neidell, 2014). If in fact air pollution exposure in-utero would have adverse effects on long-term human capital accumulation, it would constitute a significant welfare loss to society, and is hence of great importance to research. These welfare losses need to be weighed against the economic benefits of activities generating pollution.

The main hypothesis of this thesis is that air pollution at the month of birth and during pregnancy has an adverse and significant impact on labour outcomes. I merge data on air pollution levels on a federal-state level to a longitudinal survey sample on individuals born in Germany. Germany is specifically chosen for the study due to its high standard of air pollution monitoring and the large quantity of air pollution data available over time unlike any other European country (Builtjes, Loon, Schaap, Teeuwisse, Visschedijk, & Bloos, 2002). Notwithstanding this, the relationship between air pollution exposure in-utero and health outcomes is seldom studied in Germany. There are only two studies to the best of my knowledge, investigating this link: Coneus and Spiess, 2012 looking at several different pollution indicators and Lüchinger, 2014 only looking into the impact of SO2. Notably, there has not been any study before investigating the link between air pollution exposure in-utero to labour outcomes for any European country. Most studies research this relationship in an American context (Isen, Rossin-Slater, & Walker, 2017), creating a gap to bridge with further research into other country settings.

The primary reasons as to why the topic has not been researched to the extent which it necessitates are data scarcity and endogeneity issues. There are two notable channels through which endogeneity may occur: Tiebout sorting and avoidance behaviour. Tiebout sorting refers to the fact that people decide on where to live based on the level of pollution in the area or on other factors strongly related to the level of pollution, whereas avoidance behaviour refers to when parents actively protect their children from high levels of pollution by for instance staying indoors when pollution levels are particularly high (Currie et al., 2014).

The initial empirical strategy of this study controls for federal state, year and month fixed effects in order to control for unobserved heterogeneity that is constant within states over time or across states in a given month or year. In addition the strategy includes controls for mother-characteristics. However, the mother-characteristics controls may not control for all unobserved family characteristics. In contrast, the main identification strategy of this study is through Sibling Fixed Effects (Sibling-FE), accounting for the Tiebout sorting and time-invariant avoidance behaviour of families. Thus, the impact of air pollution at birth on labour outcomes is identified by variation in pollution levels between siblings. Sibling-FE accounts for Tiebout sorting, as long as families do not decide to move between the birth of their children. The identifying assumption in this setting is that the variation in pollution levels across siblings is uncorrelated to other determinants of their future labour market outcomes. A potential violation of this assumption could happen if, for instance, family income increases between the births of the first and second sibling and the family decides to move to a federal state with better schools and lower air pollution (Bharadwaj, Gibson, Zivin, & Neilson, 2017). In such a scenario the estimates would be biased. Notably, in my data mothers move very seldom between sibling births, and movers constitute merely 2,4 percent of the mothers in the sample. I will also carry out a robustness check, confirming the robustness of the results to this endogeneity concern. Interestingly, the results of this study yield larger and more significant estimates using sibling-FE compared to the Ordinary Least Squares (OLS) models, highlighting the importance of accounting for unobserved heterogeneity across families in this setting.

Using these strategies, I investigate the impact of air pollution exposure at birth and during pregnancy on labor market outcomes at age 27. The focus of the thesis will be on real labour income per month at age 27, considered a good proxy for long-term human capital accumulation (Rossi, 2018). Age 27 is chosen as it seems to be a sufficiently old age to analyse considering that most individuals in Germany finish their vocational training or graduate studies in their early to mid-twenties (Destatis, 2023). Also, previous studies have found that it is only in your late twenties that the relation between labour income and life-time income begin to stabilise, (Isen, Rossin-Slater, & Walker, 2017).

Another challenge when estimating the impact of air pollution is the confounding of different pollutants. Many air pollutants are positively and at times strongly correlated, making it difficult to isolate each air pollutant's individual impact. However, considering the epidemiological literature alluding to Carbon Monoxide (CO) being the primary contributor to the harmful effects of air pollution on fetal health, I restrict the analysis to the impact of CO (Longo, 1977). In addition, I include

Ozone (O3) in the analysis, as it is negatively correlated with CO and also has harmful effects on health (Coneus & Spiess, 2012). Presuming that both CO and O3 have adverse effects on long-term outcomes, it is thus necessary to include O3 in the model, as it would otherwise bias the estimate of CO downwards. CO levels are higher in the air during the winter months, whereas O3 levels are higher during the summer months. If O3 would not be included in the model, it would lead to complications disentangling the harmful effects of high CO levels from the beneficial effects of low O3 levels (Bharadwaj et al., 2017).

The analysis focuses on individuals born between 1985 to 1992. This time period relates to consistent economic growth and implementation of pollution abatement policies in Germany. There was no specific event or policy resulting in a large drop in pollution in this time period, but the process was gradual and also volatile during the time, which can be seen in figure 2. For instance, after the German reunification in 1989, the air pollution levels dropped in the former East Germany (Hübner, 2015). This could be attributed to the closure of many old industrial power plants there. Also during this time period Germany introduced various policies and regulations to improve the air quality, for instance the introduction of catalytic converter filters for cars, reducing harmful emissions, such as CO, Nitric Oxide (NO), Nitrogen Dioxide (NO2) and O3 (Hübner, 2015). In essence, the variation of the air pollution stems from variation in pollution over time and within a certain year between federal states, due to factors such as air pollution abatement policies, seasonal variation, and unobserved variations in human activity.

The results show that CO in the month of birth has a significant and adverse impact on real labour income in euros per month, actual work time per week and employment status at age 27. A one standard deviation increase in CO leads to a 21 percent decrease in real labour income, a four hour decrease in actual work time per week and a 10 percent decrease in the likelihood of being employed. Furthermore, the heterogeneity analysis indicates that the burden of CO is carried by children of mothers with lower education levels in its entirety, whereas children of mothers with higher education are able to compensate for the negative effects of CO. I also investigate potential mechanisms, and provide evidence that CO at the month of birth has an adverse effect on cognitive ability, proxied by cognitive test scores in young adulthood. Average CO levels during the whole pregnancy do not have such a large impact, which is consistent with the scientific literature, indicating that CO has more harmful effects towards the end of the pregnancy (Dix-Cooper, Eskenazi, Romero, Balmes, & Smith, 2012). Furthermore, O3 at the month of birth or during pregnancy is not significant in most model specifications, emphasising CO as the main culprit (Longo, 1977). These findings contribute to the existing literature by providing some of the first evidence on the long-term effects of CO exposure in-utero

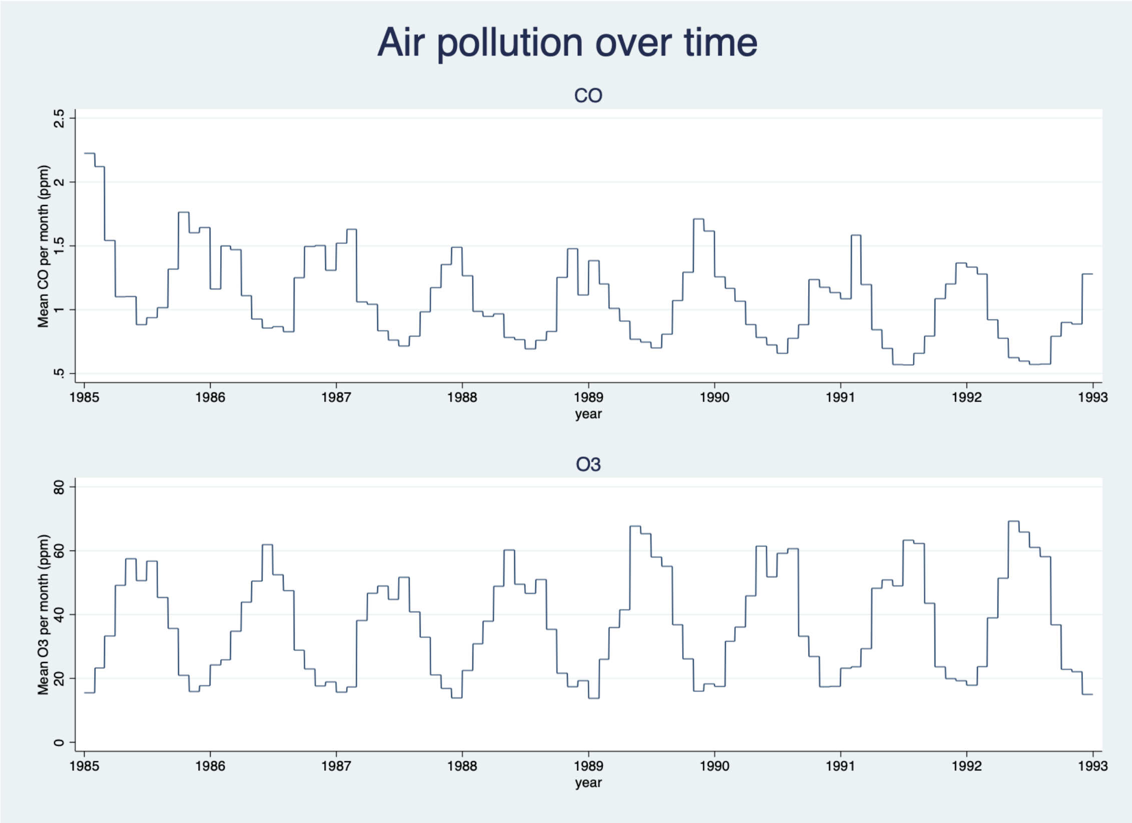

Figure 2: Mean variation in pollution levels across pollution monitors per month in Germany between 1985 to 1992

for a European country. The longitudinal nature of the data allows me to follow individuals over time and study mechanisms of long-term effects such as cognitive development.

The paper is structured as follows. Section 2 outlines the theoretical framework, endogeneity concerns and previous literature in the field. Section 3 elucidates on the scientific reasoning how CO and O3 negatively impacts fetal health. Section 4 describes the data applied and issues with it. Section 5 explains the empirical strategy. Section 6 shows the main results, as well as results from the heterogeneity analysis and robustness checks. Section 7 concludes.

2 Literature

2.1 Theoretical framework

The theoretical foundation of this thesis is adopted from the model by Currie et al., 2014 derived from the fetal origins hypothesis. The fetal origins hypothesis states that fetal conditions may be persistent and have long-term impacts that could lie dormant for years before being activated. In their model, life is divided into three periods: early to late childhood to adulthood, evaluating the impact of pollution as a child on long-run human capital accumulation. They define early childhood as the period from conception to age 5, whereas late childhood refers to the years thereafter until finishing school, and adulthood the years when active in the labour force. The focus of the model is air pollution during the early childhood period, considering the significant amount of evidence pointing to large adverse health effects in-utero due to air pollution (Bateson and Schwartz, 2007; Almond and Currie, 2011).

They assume that early childhood human capital H_E is contingent on the level of pollution exposure P_E and any unobservable family characteristics like genetics that do not vary over time X.

$$H_E = f_E(P_E, X) \tag{1}$$

Late childhood human capital H_L is contingent on the level of pollution during early childhood, and during late childhood. Families invest I_L in their children relative to their child's human capital accumulation in early childhood.

Thus, human capital accumulation in adulthood H_A comprises both early and late childhood human capital accumulation in equation 2. An increase in the level of pollution during early childhood, will lead to ripple effects on adulthood human capital accumulation shown by taking the total derivative of adulthood human capital relative to the level of early childhood pollution exposure in equation 3.

$$H_A = f_A(H_E, H_L) \tag{2}$$

$$\frac{dH_A}{dP_E} = \frac{\partial f_A}{\partial H_E}\frac{\partial H_E}{\partial P_E} + \frac{\partial f_A}{\partial H_L}\frac{\partial H_L}{\partial P_E} \tag{3}$$

There is also evidence suggesting that adverse health outcomes during the early childhood period will have compounded in adulthood (Cunha & Heckman, 2007). In accordance with equation 4, pollution has a larger effect on human capital accumulation during early childhood, as compared to pollution during late childhood, for the same levels of pollution.

$$|\frac{\partial H_E}{\partial P_E}| > |\frac{\partial H_L}{\partial P_L}|, \ \forall P_E = P_L \tag{4}$$

By providing more detailed information in regards to investments, equation 5 is derived:

$$\frac{dH_A}{dP_E} = \frac{\partial f_A}{\partial H_E}\frac{\partial H_E}{\partial P_E} + \frac{\partial f_A}{\partial H_L}(\frac{\partial f_L}{\partial I_L}\frac{\partial I_L}{\partial H_L}\frac{\partial H_L}{\partial P_E}) \tag{5}$$

In equation 5, investments to compensate for early childhood health deficits would mean that $\frac{\partial I_L}{\partial H_L}$ would be negative. On the other hand, in cases where parents would prioritise their children without any health deficits, (and disinvest in the ones with deficits) the term would instead be positive. The question whether parents will invest or disinvest in their children in response to early childhood health and cognitive deficits is yet to arrive at an empirical consensus in the literature (Datar, Kilburn, & Loughran, 2010).

This simplified model encourages even small policy regulation into the protection of fetal health, to prevent the compounded adverse effects to human capital in adulthood. These forms of policies may result in improvements in economic growth and social welfare.

2.1.1 Endogeneity

The previously discussed theoretical framework does not address any endogeneity concerns of pollution exposure. There are two notable channels through which endogeneity may occur: Tiebout sorting and avoidance behaviour. Tiebout sorting refers to the fact that people decide on where to live based on the level of pollution in the area or on other factors strongly related to the level of pollution (Currie et al., 2014). For instance, high-income people are more likely to move to an area with lower pollution levels. There is evidence that lower air pollution levels result in more expensive housing prices (Chay & Greenstone, 2005). Considering this sorting behaviour of people, areas with high levels of pollution may also be linked to other factors influencing health that are unobserved. These unobserved factors would lead to omitted variable bias and consequently confound any results (Currie et al., 2014).

Tiebout sorting may be more difficult to discern on a federal state level, which is the level of aggregation of the data in this study. However, on a federal state level it is still possible to identify Tiebout sorting. The federal states in Germany vary significantly in terms of population density, weather conditions, political identity and culture, making it more likely for people to live in a federal state aligning with their own preferences (Hellfeld, 2021). Whilst, people from better socio-economic backgrounds may prioritise living in a state with lower pollution levels, people from lower socio-economic background may not have this opportunity and stay in federal states where they can easily find a job that may also inadvertently produce more air pollution. However, people from higher socio-economic backgrounds tend also to live in urban areas with more air pollution with better job opportunities, so the direction of the confounding is not clear (Coneus & Spiess, 2012).

Avoidance behaviour refers to when parents actively protect their children from high levels of pollution by for instance staying indoors when pollution levels are particularly high. Avoidance behaviour does not result in omitted variable bias, considering that it is an ex-post decision; the actual pollution level affects behaviour. However, it may affect the interpretation of the estimates. In cases where avoidance behaviour is controlled for in the model, $\frac{\partial H_A}{\partial P_E}$ refers to the biological impact of pollution on human capital accumulation. However, in cases where it is not controlled for, the estimates should be interpreted as a reduced form effect of pollution on human capital accumulation. The estimates comprises both this biological impact as well as the avoidance behaviour, A_B, that may minimise the impact of pollution on health at different degrees, shown in equation 6 (Currie et al., 2014).

$$\frac{dH_A}{dP_E} = \frac{\partial H_A}{\partial P_E} + \frac{\partial H_A}{\partial A_B}\frac{\partial A_B}{\partial P_E} \tag{6}$$

In the next section, empirical research addressing these endogeneity concerns will be discussed. For instance, some researchers have used natural experiments causing a shock to the level of pollution, like the Clean Air Act in the US. And others have used frequent variation in pollution over short time intervals together with area-Fixed Effects (FE), presuming that Tiebout sorting would take place at a slower rate relative to any impact on health outcomes. Finally, other studies have used family fixed effects models, treating the unobserved characteristics shared among siblings as fixed (Currie et al., 2014).

These methods still suffer from some shortcomings. For instance natural experiments like the Clean Air Act affected the level of air pollution directly, but could also affect productivity and competitiveness among firms and result in job losses and in health insurance, having an adverse impact on health. This would result in confounded estimates. Also the longer the time interval estimated is, the more likely it will be that Tiebout sorting confounds the estimates (Currie et al., 2014). A final consideration is that, natural experiments seldom address avoidance behaviour (Sullivan & Wachter, 2009).

2.2 Previous literature

Despite the large scope of literature documenting detrimental effects on infant health, labour outcomes have rarely been studied, and the available evidence comes exclusively from the US. The paper by Isen, Rossin-Slater, and Walker, 2017 investigates the link between population health and earnings later in life through quasi-experimental evidence. In order to study this relationship they use The 1970 Clean Air Act in the US, that regulated the maximum permissible level of Total Suspended Particulates (TSP). Counties exceeding this maximum level were legally required to reduce their TSP levels. These counties were classified as nonattainment counties, whereas counties that did not exceed this level were not required to make any changes to their pollution levels, so-called attainment counties. This regulation created considerable variation in TSP levels across counties. In order to estimate the impact of early-life pollution exposure on labour market outcomes 30 years later, they compare individuals' earnings born just before and after this law was implemented in nonattainment counties, using individuals born in attainment counties as a counterfactual. Despite the fact that being born in a nonattainment county is not randomly assigned, they show that observable characteristics between nonattainment and attainment counties are congruent in trend and level. They conclude first that the law resulted in a 10 percent decrease in TSP levels in nonattainment counties three years after implementation. Second, that this significant decrease in TSP levels led to a 0.7 percent rise in the number of quarters worked annually as well as a 1 percent rise in the mean annual income for individuals impacted by the regulation (Isen, Rossin-Slater, & Walker, 2017).

Bharadwaj et al., 2017 investigate the link between in-utero air pollution exposure and school-grades. They find that fetal exposure to CO and other correlated pollutants, such as Particulate matter 10 micrometers or less in diameter (PM10) has a significant adverse impact on math and language skills, measured using fourth grade test scores in Santiago, Chile, for children born between 1992-2001. They address any endogeneity concerns by using sibling-FE, keeping location fixed. They recognise the strong association between school performance and long-term labour outcomes, and believe a reduction in CO during this period has led to an increase in labour productivity.

One of the most cited papers in the field is Currie, Neidell, and Schmieder, 2009 showing evidence of a negative impact of CO exposure during and after birth on birth weight and infant mortality in New Jersey, in the US. The effect is also amplified by 2-6 times for children born to mothers who smoke, and to mothers of older age (35 and above). For instance they find that a one unit increase of the mean of CO, during specifically the last trimester of pregnancy, leads to an 8 percent decline in birth weight. To carry out their analysis they utilise data on mother's exact residential location from their child's birth certificate and pollution data from air quality monitors within 10 km radius from the mother's location, in New Jersey during the 1990s. Their model is estimated using mother-FE, in order to control for the unobserved attributes of mothers. The mothers in their study tend to be from poorer socioeconomic backgrounds, in alignment with the information on monitors commonly being located in more polluted areas with lower socioeconomic status. This emphasises the importance of controlling for mother-FE. They also show that the effects are smaller and insignificant on health at birth for mothers living 10-20 km away from a monitor or using zip-code FE, due to lower accuracy on residential location and pollution level (Currie, Neidell, & Schmieder, 2009).

Coneus and Spiess, 2012 replicates and elaborates on the study by Currie, Neidell, and Schmieder, 2009 by studying the link between different pollution indicators on infant and toddler health outcomes in Germany 2002-2007. They find that high levels of CO exposure during the last trimester of pregnancy results in a significant decline in birth weight by 289 grams. Not to mention, that even low levels of CO has a significant adverse effect on fetal health outcomes. Furthermore, exposure to high levels of O3 during pregnancy leads to a significant increase in disorders such as bronchitis and respiratory illnesses at the age of 2-3 years old. They utilise data on zip-code area of each household for each year and match each household to a pollution monitoring station within a one kilometer radius away. In their model they control for different mother specific characteristics, as well as family and area FE.

In essence, there is evidence of a detrimental effect of air pollution on infant health, school performance and labour outcomes. However, the studies are primarily focused on the US, and studies are lacking on the impact of air pollution on long-term effects, both in terms of cognitive test results and labour outcomes in Germany or of any European country.

3 Scientific Background

CO, the air pollutant of primary interest in this thesis, is a poisonous gas created through the incomplete process of burning fuels enclosing carbon, for example coal, wood or gasoline. CO is naturally found in the air and our bodies, but has a harmful impact on our bodies when produced in larger quantities by e.g. forest fires, automobiles or malfunctioning heaters. It can access the body through both the skin or through breathing, and hinders the body from delivering oxygen to vital organs. In case of low levels of oxygen, cells will die, which is particularly harmful to the brain and heart. CO levels also fluctuate with the seasons, and people are more prone to breathe in large amounts of it during the winter (Longo, 1977).

CO also hinders the delivery of oxygen to the fetus of a pregnant person. Unlike other air pollutants, its impact on fetuses is two-fold, as it can also get through the placenta and directly enter the baby's blood. There is evidence of a nexus between carbon monoxide poisoning of pregnant people and premature labour, as well as fetal brain damage and death. These effects may vary depending on the amount of CO exposure as well as the timing of exposure during the pregnancy. There is also support for lower pulmonary function due to CO exposure in utero and in early childhood (Longo, 1977). Not to mention, exposure to CO during the third trimester have been found to result in long-term deficits in neuro-psychological aptitude (Dix-Cooper et al., 2012).

O3, on the other hand, is created through the photochemical reaction from other pollutants, namely nitrogen oxides together with volatile organic compounds (VOCs). O3 is a secondary pollutant, meanwhile nitrogen oxides and VOCs are produced by for instance vehicles, industrial power plants and refineries. Photochemical reaction means that O3 is produced through heat and sunlight, and in contrast to air pollutants like CO, is more of an issue during the summer (Coneus & Spiess, 2012). O3 affects lung capacity adversely, destroying the mucuous membranes in the respiratory tract. Children are particularly affected by O3 as they are in need of more oxygen compared to adults (Coneus & Spiess, 2012). Furthermore, there is evidence that O3 exposure and CO exposure in-utero is detrimental to birth weight. A link between low birth weight with other adverse health outcomes in adulthood, such as diabetes and lower IQ score has also been established (Salam, Millstein, Li, Lurmann, Margolis, & Gilliland, 2005).

4 Data

To estimate the impact of air pollution at the month of birth and during pregnancy on various labour outcomes, I merge data-sets connecting individuals' birth information and labour outcomes together with data on environmental factors. The data is in panel format meaning that you can follow individual units over time. Furthermore, the data is based on individuals born in Germany between 1985 to 1992, and the analysis is restricted to analysing their labour outcomes at age 27. It is deemed sufficient to evaluate labour outcomes at age 27, as individuals in Germany usually start their full-time employment after finishing vocational training or a university degree, between their early to mid-twenties (Destatis, 2023). It also allows me to consider a relatively large sample with rich information on pollution at the month of birth.[1]

4.1 Air pollution Indicators and Weather Controls

The air pollution data is collected from the German Environment Agency (Uhse, 2023), and the data on the weather controls, monthly mean temperature and precipitation, is gathered from the German Weather Service (Karsten, 2023). Due to confidentiality reasons of the GSEOP survey data, information on where individuals were born is only obtained on a federal state level and a month and year basis.[2]

[1] The data-set ends at 1992 because the survey year of 2020 is removed, as the coronavirus could have had a significant adverse impact on labour outcomes. This could result in an inaccurate representation of the impact on labour outcomes.

[2] Household location could have been obtained on a zip-code level in case I would have gone to their data centre in Berlin. However, they were fully booked, and only had available time slots in June. Thus, it would perhaps be interesting to carry out the analysis again in the future, but on a zip-code level instead, in order to see if the results would diverge a lot.

Thus, despite the fact that I know the exact address of the air pollution monitors and have daily data on air pollution, the air pollution data needs to also be aggregated on a federal state level per month.

This could pose a problem in case there was not sufficient variation in the pollution data on a federal state level. In order to evaluate whether the air pollution data varies sufficiently on a federal state level, figures 3 and 4 plot average CO and O3 levels at the quarter level by federal state.

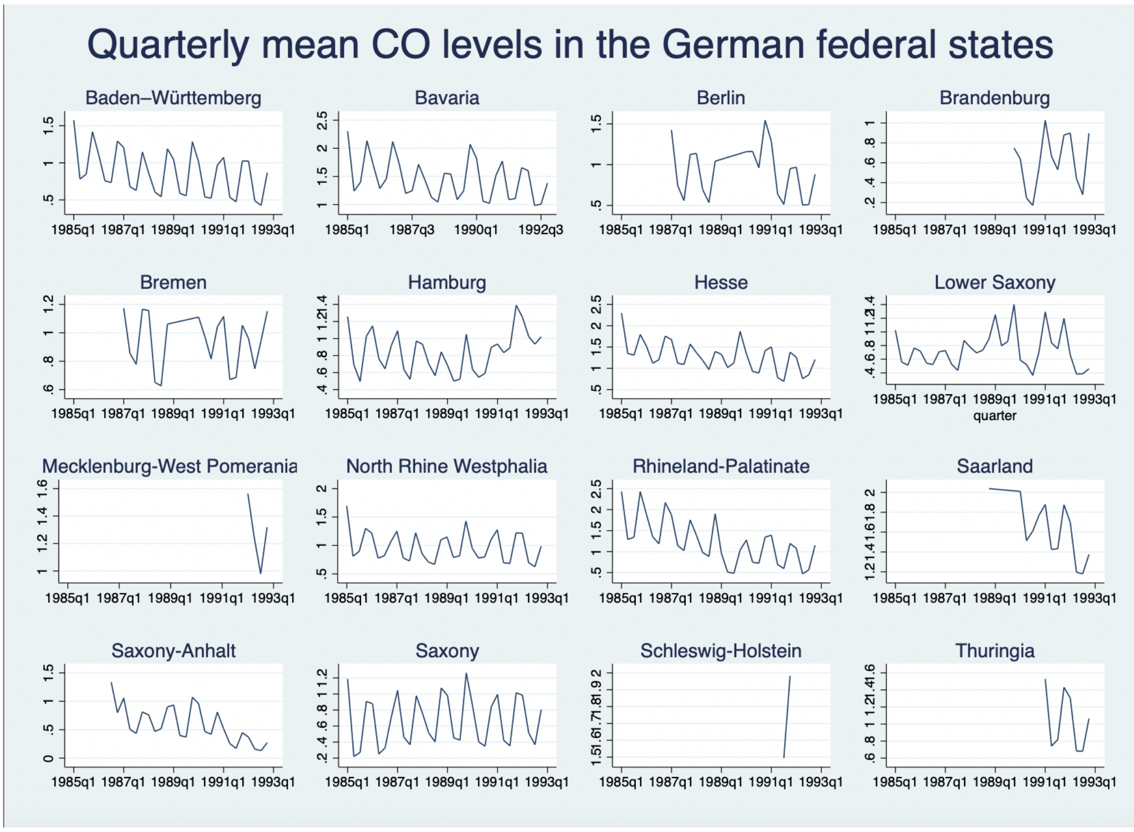

Figure 3: Quarterly Mean CO levels in the German Federal States

From the figures, it is possible to conclude that there is enough variation across individuals born in the same state over time and across individuals born at the same time in different states.

Unfortunately, the data suffers from missing values, which is a common issue with pollution data. Karin Uhse, environmental engineer at the German Environment Agency, explained in an email that during the late 1980s and beginning of 1990s some of the federal states had just started their monitoring of pollution levels and faced some issues with the monitoring procedures. These missing years will affect the accuracy of the analysis. Furthermore, even when the monitoring stations are running at times they malfunction and stop working. No measure has been implemented to address these missing values, as very drastic assumptions would have to be made. The fact that the pollution levels are aggregated by month and state has

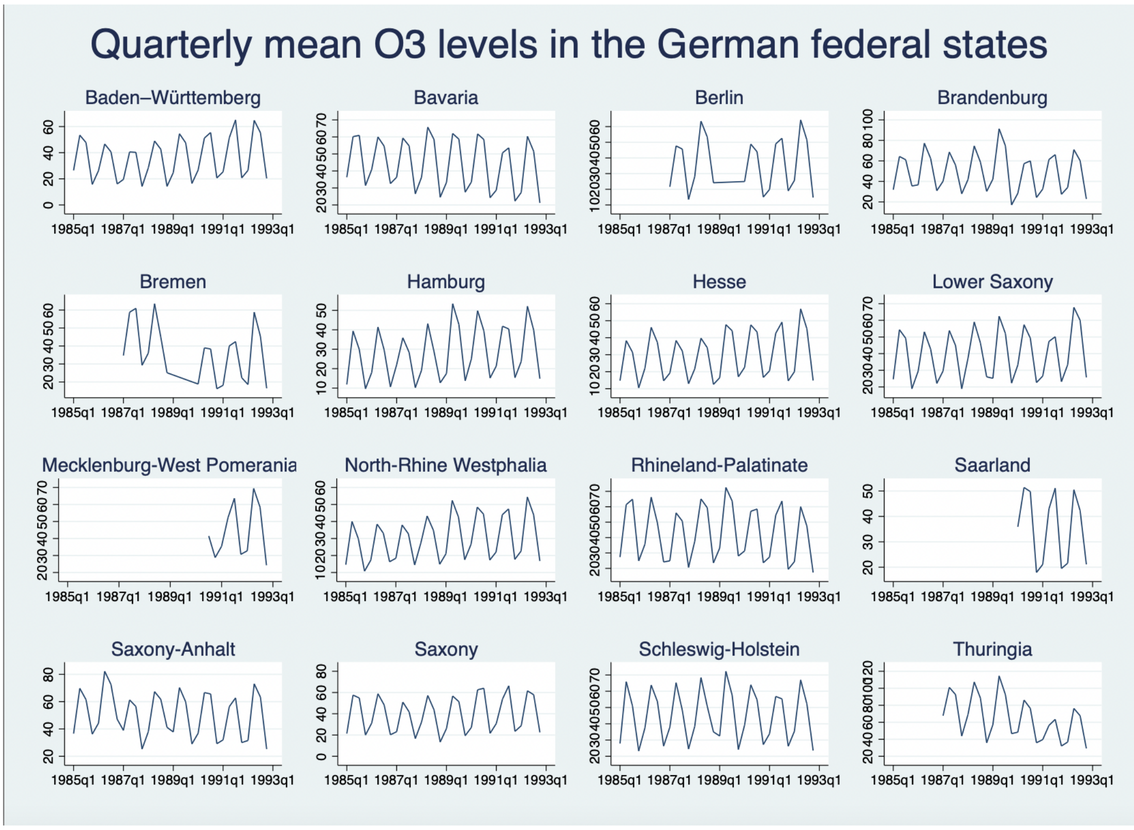

Figure 4: Quarterly Mean O3 levels in the German Federal States

mitigated some of the measurement error issues. It is important to highlight that these missing values may result in an inaccurate representation of the air pollution levels in some federal states, as the missing values are not randomly distributed. This will reduce the sample size and affect the statistical power and validity of the analysis. In the appendix A, tables A.2 and A.1 can be found, showing the active monitoring stations of CO and O3 levels across the federal states in Germany per year, between 1985 to 1992. There is significant variation across federal states and over time in number of monitoring stations. This could result in air pollution measurement errors co-varying with time-varying unobserved characteristics of the dependent variables (Bharadwaj et al., 2017).[3] In section 6 a robustness check is included controlling for the number of active monitoring stations of O3 and CO per year.

[3]The paper by Bharadwaj et al., 2017 carry out their analysis on a balanced as well as an unbalanced monitor panel and find that the estimates from the unbalanced monitor panel result in similar estimates, yet smaller in magnitude, implying a downward bias in the measurement errors.

4.2 GSOEP data

The data on individuals in Germany is gathered from the panel survey called SOEP that started in 1984 by the German Institute for Economic Research (Kaminsky & Napieraj, 2023). It is a longitudinal panel survey that follows a representative sample of households and individuals every year living in Germany. Whenever a new child is born or another person moves into the surveyed household, they will also be included in the survey. Every individual has a unique identification personal number, and also a connected identification number for the mother, allowing the implementation of sibling fixed effects (Siegers, Steinhauer, & König, 2021).

Descriptive statistics for all variables weighted by each individual's sample weight are found in table 1. Furthermore, the descriptive statistics for the unweighted variables are found in table A.3 in the appendix A, as well as table A.4 explaining how the mothers' education levels were classified.

Table 1: Descriptive Statistics weighted by every individual's sampling weight [aw=phrf]

Variable	Obs	Mean	Std. dev.	Min	Max
At age 27:					
Real Labour Income in Euro per month	2,021	1856.810	1124.533	0	12941.500
University Attendance Dummy (1 = attended)	3,186	0.256	0.436	0	1
Amount of education/training in years	2,911	12.815	2.868	7	18
Actual work time per week (h)	1,946	36.986	11.979	1	80
Working experience full time employment in years	3,160	2.658	2.634	0	12
Employment status Dummy (1 = employed)	3,186	0.526	0.499	0	1
At age 18-26:					
Cognitive test: Sum correct number entries in 30 seconds	3,149	11.831	5.232	0	93
Cognitive test: Sum correct number entries in 60 seconds	3,149	24.251	8	0	93
Cognitive test: Sum correct number entries in 90 seconds	3,149	35.943	10.991	0	93
Controls:					
Mother's education (high level)	2,241	0.188	0.391	0	1
Mother's education (medium level)	2,241	0.770	0.421	0	1
Mother's education (low level)	2,241	0.043	0.202	0	1
Female dummy	3,186	0.490	0.500	0	1
Mother's age	2,505	27.329	4.883	14	45

Table 1 continued from previous page

Weather & pollution indicators					
Precipitation (mm) - at birth	3,315	66.797	34.241	7.600	218.400
Precipitation (mm) -during pregnancy	3,360	66.450	14.753	29.940	108.750
Temperature (°C) – at birth	3,315	8.183	6.695	-8.100	20.300
Temperature (°C) – during pregnancy	3,360	8.682	1.529	4.650	11.710
CO (ppm) - at birth	2,791	1.014709	0.446	0.092	2.768
CO (ppm) - during pregnancy	2,885	1.032	0.335	0.197	2.567
O3 (ppm) – at birth	3,109	38.360	19.304	6.166	138.819
O3 (ppm) – during pregnancy	3,192	38.322	10.635	9.305	90.180

4.3 Sampling weights

A limitation with survey data, in comparison to administrative data, is that participation in a survey is rarely completely random. This could result in issues with regression analysis, due to the assumption of random sampling. In case, this self-selection component of survey participation is disregarded, the regression estimates will be biased. A proposed solution to this by the GSOEP database itself is weighting to alter the sample, accounting for the intricate sampling design and attrition, in order to make it more representative of the population of interest. Individuals that have a higher likelihood of participating in the survey will receive a lower weight, whereas individuals with a lower likelihood to participate will receive a higher weight. This weighting factor adjusts for the fact that some people are over-represented and some are under-represented in the sample. The weights are derived by using information on household size, income, education and region, and they are added to each wave of the survey. For instance, households with young household members have a higher likelihood of dropping out from the survey, as well as people with poor internet connection. Furthermore, high-income individuals are also underrepresented in the survey (Siegers, Steinhauer, & König, 2021).

As an illustration, by adding a weight to a regression analysis of the effect of years of education on hourly wage may create an unbiased estimate, accounting for the people who do not get the returns of additional years of education as anticipated. These people have a higher likelihood to drop-out from the survey. Thus the effect of years of education on hourly wage may be much greater compared to without weights. Furthermore, the different weights attached to individuals in the sample may result in the total sample being smaller than without weights (Goebel, Grabka, Liebig, Kroh, Richter, Schröder, & Schupp, 2019).

In terms of descriptive statistics, weights can be applied to an unrepresentative sample of a population to evaluate the mean value of a certain variable for the population of interest, leading to consistent estimates. It is of importance to correct for endogenous sampling for this study, and perhaps also identify any average partial effects. Endogenous sampling refers to the issue when the probability of selection into a survey is related to the dependent variable, despite controlling for certain explanatory variables (Solon, Haider, & Wooldridge, 2015).

Provided that the sampling probability is exogenous, weighting would lead to heteroskedasticity issues. For instance, in case you are using survey data on the US and it includes an over-representation of people from California. By including state fixed effects in your model the model is correctly specified as the error term will no longer be varying with the sampling design. However, by using Weighted Least

Squares (WLS) instead, minimising the sum of squared residuals weighted by the inverse probability of being surveyed, the estimates will still be consistent but not as precise. This is because the standard errors will increase due to the presence of heteroskedasticity. Despite the presence of endogenous sampling, it is recommended to show both weighted and unweighted estimates in order to observe any model misspecifications (Solon, Haider, & Wooldridge, 2015).

Treatment effects are commonly heterogeneous across for instance federal states. Performing WLS does not necessarily mean that consistent estimates of average partial effects are achieved. In case there are heterogeneous treatment effects present in the model, neither OLS or WLS models are able to identify the average partial effects. Average partial effects refer to the change in the expected outcome because of a change in the treatment. They are only able to identify different weighted averages of the heterogeneous effects. In case there may be heterogeneity effects, it is important to model them. If the OLS and WLS results are drastically different, the assumption of homogeneous results may be wrong (Solon, Haider, & Wooldridge, 2015). Thus, in section 6, each model specification is carried out on both a weighted and unweighted sample.

4.4 Missing data

Another limitation of survey data is that it suffers from missing values. When the missing values refer to control variables there is a simple way to address the issue. In this case the control variables for mother characteristics suffer from missing values. It is unfortunate to lose a lot of observations due to missing values, as statistical power will be reduced. It could also result in a less representative sub-sample of the population. Therefore, I imputed missing value dummies for the mothers' education to create more precise estimates. These imputations are harmless, assuming that the missing values are not contingent on the treatment or outcome, if this would be the case, some bias may have been introduced into the estimates (Groenwold, White, Donders, Carpenter, Altman, & Moons, 2012).

5 Empirical strategy

I follow Coneus and Spiess, 2012 and explore the impact of air pollution exposure during the month of birth and during pregnancy. The aim of this study is to estimate the impact of air pollution exposure during pregnancy and at birth on adulthood human capital accumulation in the form of labour outcomes at the age of 27. I also investigate the impact of air pollution during the month of birth on cognitive test results to explore a channel potentially influencing labour outcomes. Due to lack of data availability, it is assumed that every pregnancy is full-term, 40 weeks of gestation. The model used is adapted from Bharadwaj et al., 2017 and Coneus and Spiess, 2012.

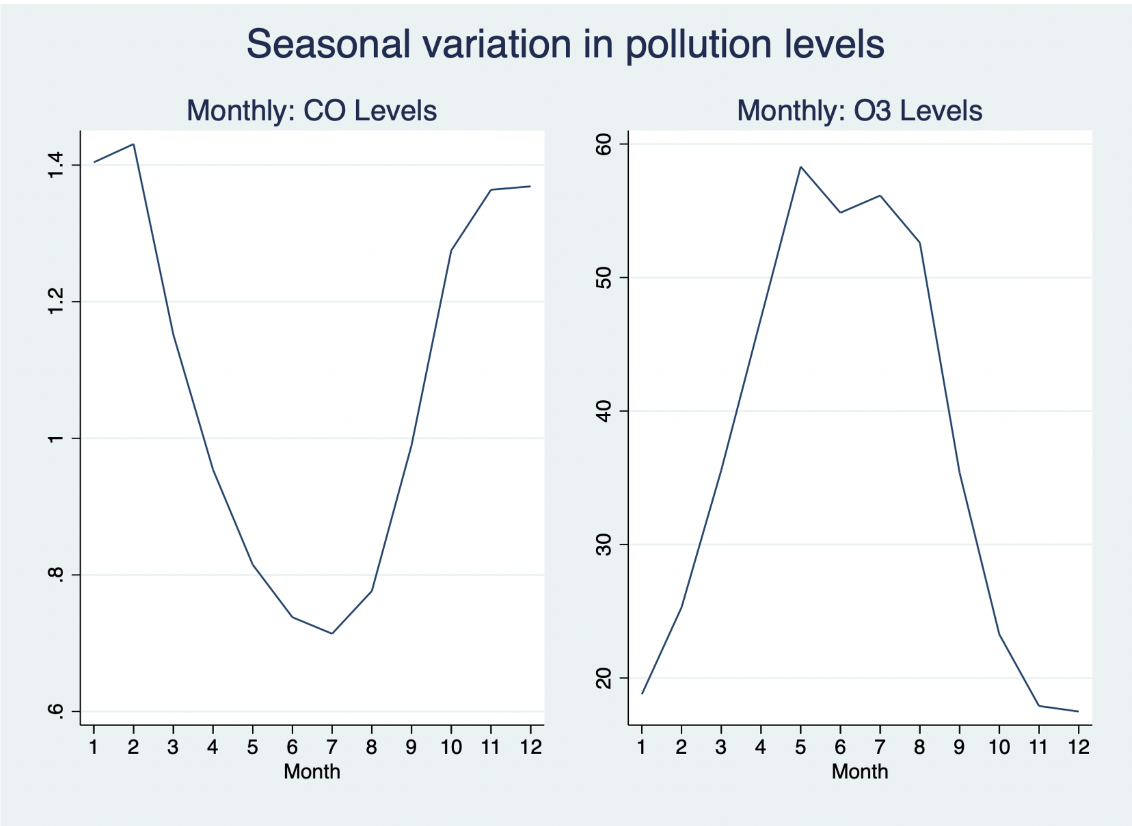

Figure 5: Seasonal variation in pollution levels in Germany

Following the paper by Bharadwaj et al., 2017 month and year dummies will be included in the model, accounting for the seasonality of pollution across the German federal states. Figure 5 shows a strong monthly trend in pollution levels in Germany, where CO levels are higher during the winter month, whilst O3 is higher during the summer. As the pollution levels vary significantly by month, it could mean that other unobserved variables also do vary by month that have an impact on the dependent variable. Hence, it is of importance to control for month fixed effects.[4]

Before carrying out the analysis, I evaluate whether there is sufficient variation in CO levels across Germany when accounting for seasonality. From figure 6 it is possible to conclude that when accounting for seasonality there will still be significant variation in CO-levels.[5] If the figure would be symmetric and centered around zero it would imply that the model is a good fit for the data and the residuals do not vary systematically. However, the figure is skewed to the left and has higher density below zero than above. This may suggest that the residuals vary systematically and that some important predictor variables related to CO is missing. This remaining variation in CO levels navigates this study's identification strategy (Bharadwaj et al., 2017).[6]

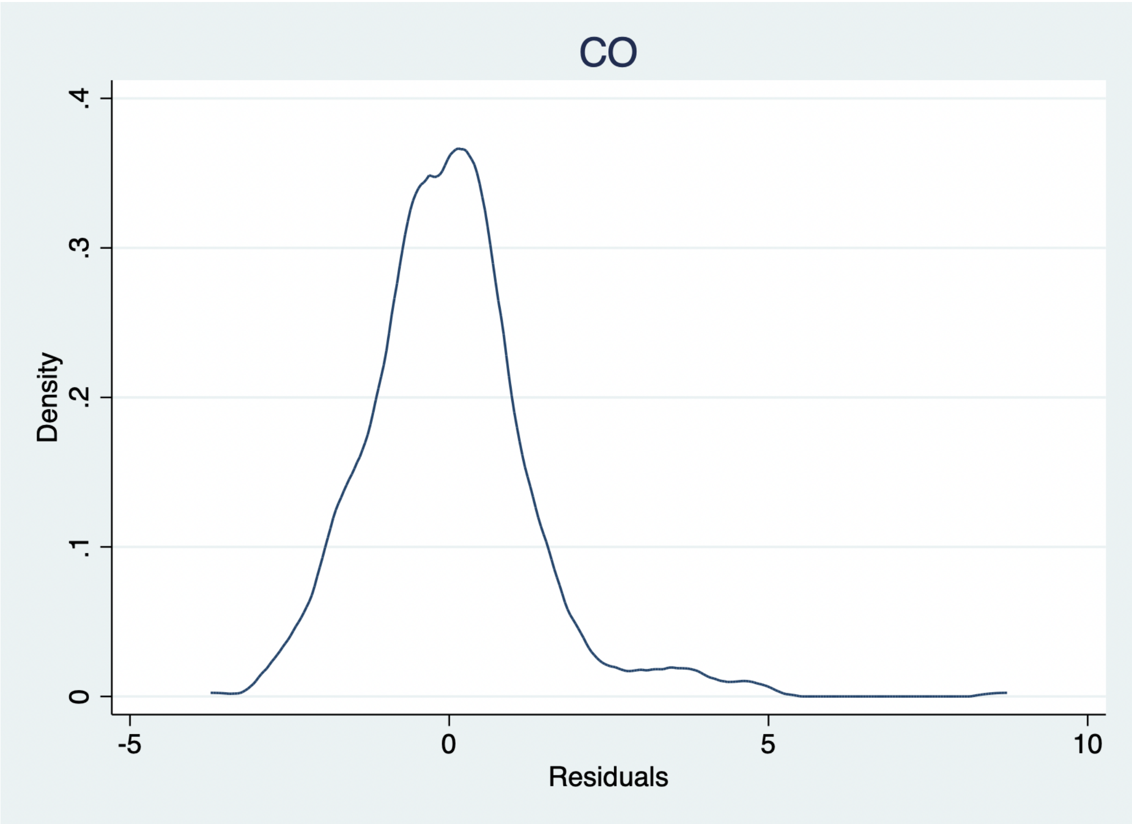

Figure 6: Residualised pollution with year and month dummies

[4]The graphs are made by calculating the mean level of monthly pollution across the federal states between 1985-1992.

[5]The graph is made by regressing mean CO levels in Germany per month and year on year and month dummies. The probability distribution is a kernel density plot with Epanechnikov kernel and MSE-minimising bandwidth with the assumption of a Gaussian distribution function.

[6]Instead of using birth year multiplied by birth month fixed effects, birth year and birth month fixed effects are used separately, in similar fashion as Bharadwaj et al., 2017 and Coneus and Spiess, 2012. Despite, birth year multiplied by birth month fixed effect being more of a conservative approach, the residual variation would not be sufficient.

The simple estimating equation is:

$$Y_{ijrt} = \beta_1 CO_{rt} + \beta_2 O3_{rt} + \theta_t + \rho_r + \gamma W_{rt} + \delta X_{ij} + \epsilon_{ijrt} \tag{7}$$

The dependent variable is Y_{ijrt}, which is the different labour outcomes such as Log of Real Labour Income in Euros per month of individual i, born to mother j, in federal state r, at time t. The term θ_t is a vector of year and month dummies, where the month dummies encompass seasonal effects. The term ρ_r is a federal state fixed effect, accounting for any time-invariant unobserved characteristics varying across federal states, such as cultural or political differences. W_{jt} includes the weather controls: temperature and precipitation calculated as the average of the month of birth or during pregnancy in federal state r. Quadratic polynomials of precipitation and temperature are also added to be able to account for any non-linear effects. For instance, extreme temperature is evidenced to impact fetal health, as well as instigate pollution formation (Deschênes, Greenstone, & Shapiro, 2017). CO_{rt} and $O3_{rt}$ refer to the average level of CO and O3 during pregnancy or month of birth in federal state r. X_{ij} includes mother characteristics in this case education level and a female dummy for the individual i. The identifying assumption is that after controlling for these observed mother characteristics and female dummy, pollution exposure will be independent from the error term ϵ_{ijrt}.

However, this identifying assumption may not hold through avoidance behaviour by the parents. For instance, when pollution levels are high parents may decide to keep their children inside, or they may reduce the adverse pollution effects on health through ex-post investments. These behaviours, as discussed previously in chapter 2, do not bias estimates. They solely affect the inference of the estimates that now represent the net effect of pollution when including this avoidance behaviour.

Adulthood labour outcomes are contingent on investments by parents that vary over time and avoidance behaviour by parents during pregnancy and at birth. These investments by parents are inherently unobserved, but other studies analysing the nexus between air pollution in-utero and long-term human capital accumulation has shown that these investments are primarily to compensate for any health deficits in infancy and are relatively small (Bharadwaj, Eberhard, & Neilson, 2018). These investments will hence be incorporated in the impact of air pollution, expressing the combined impact of air pollution. Presumably parents who are more likely to engage in compensatory investments in their children's health, are also more likely to engage in pollution avoidance behaviour (Bharadwaj et al., 2017). Then instead I identify the impact of air pollution on labour outcomes by variation in pollution levels between siblings born in the same household. In order for this identifying assumption to hold, it is assumed that parents do not consistently discriminate one child over the other by for instance reacting less to pollution level alerts. Furthermore, as discussed in chapter 2 to control for Tiebout sorting, sibling-FE is an efficient method to analyse differences within households. High-income families tend to invest more in their children's health and live in less polluted areas. Furthermore, sibling-FE is a great tool, considering that the mother-characteristics controls suffer from missing values and may not control for all unobserved family characteristics.

The model is a first difference model between siblings, where another sibling is referred to as i' born at time t' in federal state r'.

$$\Delta Y_{ijrt-i'jr't'} = \beta_1 \Delta CO_{rt-r't'} + \beta_2 \Delta O3_{rt-r't'} + \theta_t + \rho_r + \gamma \Delta W_{rt-r't'} + \Delta\epsilon_{ijrt-i'jr't'} \quad (8)$$

5.1 Clustering standard errors

The classical assumption is that the error terms are independently and identically distributed. Clustered standard errors, on the other hand, allow for observations within a certain group to remain correlated in an unobserved way, adjusting for the occurrence of heteroskedasticity and serial correlation. By accounting for this the reliability of the standard errors and the validity of the statistical inference will be improved (Angrist & Pischke, 2009).

In like manner as Bharadwaj et al., 2017 I cluster on household level, but instead of neighbourhood level, I also cluster on federal-state level. However, according to Angrist and Pischke, 2009 a good rule of thumb is to have around 42 clusters in order to get reliable estimates of the standard errors. In this case I only have 16 federal states, and these small clusters on federal-state level could pose a problem, resulting in biased estimates (MacKinnon, Nielsen, & Webb, 2023).

This issue may be resolved by clustering on a combination of household and state level, increasing the number of clusters. In order to evaluate the sensitivity of the results, I will test the results to different clustering methods. Not to mention, when clustering at a combination of household and state level, there may be some bias introduced in the standard errors. Clustering on the state level using a wild cluster restricted bootstrap has been recommended as a way to resolve this issue. Also, robust standard errors can be used as a robustness check (MacKinnon, Nielsen, & Webb, 2023). Furthermore, clustering on a too aggregate level may at times be considered harmful to the precision of the estimates, despite a larger sample size. Especially, in terms of FE models clustering may not be necessary in cases where there is no heterogeneity of treatment effects (Abadie, Athey, Imbens, & Wooldridge, 2017). As a robustness check in section 6, I evaluate the robustness of the results to different standard errors.

6 Results

6.1 Main Results

Table 2 presents negative coefficients for most model specifications for the impact of CO and O3 exposure at the month of birth and during pregnancy. However, only the impact of CO exposure at birth in the sibling FE specification weighted and unweighted is significant. In the weighted specification at birth CO becomes significant at the 1 percent level and almost double the size, as compared to the the unweighted model that is significant at the 10 percent level. As mentioned before in chapter 4.3 this may indicate that there are heterogeneous effects involved. In the weighted sibling FE specification a one standard deviation increase in CO levels leads to a 21 percent decrease in real labour income in euro per month at age 27. It is also possible to see that the sample size decreases in the weighted samples, as is expected. Average pollution levels throughout the entire pregnancy nor O3 at birth have any significant impact on labour income in any specification.

Table 2: CO and O3 exposure at birth and during pregnancy's impact on Log of Real Labour Income

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: At birth:						
CO	0.052	-0.042	0.046	-0.042	-0.125*	-0.209***
	(0.041)	(0.049)	(0.041)	(0.047)	(0.069)	(0.036)
O3	-0.112	-0.025	-0.103	-0.031	-0.443	-0.257
	(0.095)	(0.131)	(0.093)	(0.130)	(0.331)	(0.204)
Observations	937	931	937	931	259	254
R-squared	0.067	0.135	0.088	0.157	0.641	0.745
Model 2: During pregnancy						
CO	0.037	0.017	0.030	0.029	-0.179	-0.182
	(0.032)	(0.063)	(0.029)	(0.058)	(0.138)	(0.167)
O3	-0.024	-0.026	-0.017	-0.032	-0.170	-0.105
	(0.071)	(0.073)	(0.067)	(0.070)	(0.135)	(0.155)
Observations	952	946	952	946	265	260
R-squared	0.063	0.131	0.083	0.152	0.630	0.735
Mother characteristics controls	No	No	Yes	Yes	No	No
State-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	Yes	No	Yes	No	Yes
Sibling FE	No	No	No	No	Yes	Yes

Notes: Standard errors clustered on household and federal state level are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is Log of Real Labour Income in Euro per month at age 27. All regressions from column (1) to (6) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year and month fixed effects. The real labour income per month is expressed in 2010 euros. It is calculated by adjusting the Current Gross Labour Income by the Consumer Price Index (CPI) 2010 for Germany. Data on CPI is gathered from the World Bank Database. The values for CO and O3 are standardised.

Table 3: CO and O3 exposure at birth and during pregnancy's impact on Actual Work Time Per Week

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: At birth						
CO	0.502	-1.163*	0.374	-1.180*	-3.830**	-3.913**
	(0.414)	(0.614)	(0.415)	(0.634)	(1.653)	(1.633)
O3	-1.412	-2.084*	-1.244	-2.164	-5.449	-4.796*
	(1.193)	(1.169)	(1.010)	(1.579)	(4.537)	(2.466)
Observations	931	925	931	925	255	250
R-squared	0.054	0.095	0.089	0.138	0.662	0.792
Model 2: During pregnancy						
CO	0.154	-2.326*	-0.067	-2.183*	-1.265	-4.595*
	(0.640)	(1.126)	(0.550)	(1.027)	(2.301)	(2.479)
O3	-1.272	-1.522	-1.139	-1.639	-2.401	-0.703
	(0.896)	(1.116)	(0.807)	(1.037)	(1.878)	(1.883)
Observations	946	940	946	940	261	256
R-squared	0.054	0.105	0.087	0.147	0.637	0.790
Mean of Y	36	37				
Mother characteristics controls	No	No	Yes	Yes	No	No
State-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	Yes	No	Yes	No	Yes
Sibling FE	No	No	No	No	Yes	Yes

Notes: Standard errors clustered on household and federal state level are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is Actual Work Time Per Week at age 27 (in hours). All regressions from column (1) to (6) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year and month fixed effects. The values for CO and O3 are standardised.

Table 3 could explain the decrease in real labour income. It displays more significant results for several of the weighted model specifications. However, the sibling FE specification shows the most significant results at the 5 percent level for CO exposure at birth for both the weighted and unweighted models. In model (4) at birth with mother-characteristics controls, a one standard deviation increase in CO levels leads to a decrease in actual work time per week by 1 hour. In model (5) and (6), a one standard deviation increase in CO at birth leads to a decrease in actual work time per week by 4 hours. For actual work time per week there seems to not be any heterogeneous effects at birth, as the weighted and unweighted model specifications reveal similar results with sibling FE. The during pregnancy model shows only significant results for the weighted models at the 10 percent level. Moreover, O3 at birth is significant at the 10 percent level in model (6), a one standard deviation increase in O3 at birth leads to a decrease in actual work time per week by 5 hours.

In table 4, the effects of air pollution at the month of birth on other long-run

Table 4: CO and O3 effects on additional labour outcomes.

Variables	Working experience full-time employment		Employment status		University attendance		Years of education/training	
At birth:								
CO	-0.415	-0.564	-0.104**	-0.001	0.059	-0.010	0.129	0.227
	(0.282)	(0.340)	(0.050)	(0.062)	(0.171)	(0.214)	(0.284)	(0.354)
O3	-0.371	-0.694	-0.128	-0.148	0.108	0.126	0.048	-0.175
	(0.549)	(0.407)	(0.113)	(0.129)	(0.459)	(0.357)	(0.560)	(0.533)
Observations	373	370	538	370	334	329	310	308
R-squared	0.699	0.787	0.532	0.705	0.827	0.872	0.789	0.848
Weights	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Standard errors clustered on household and federal state level are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable for each column: (1)-(2) is working experience full-time employment in years, (3)-(4) is employment status (1 = employed), (5)-(6) is university attendance (1 = attended university) and (7)-(8) is years of education/training. All dependent variables refer to at the age of 27. All regressions from column (1) to (8) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year, month and sibling-fixed effects. The values for CO and O3 are standardised.

outcomes are explored using the sibling FE model, my preferred specification. Only employment status in the unweighted model is significant at the 5 percent level. A one standard deviation increase in CO levels leads to a 10 percent decrease in the likelihood of being employed at age 27. The weighted model is not significant and could perhaps be attributed to the sharp reduction in sample size between the unweighted and weighted models. The other models do not show any significance. Notwithstanding this, the coefficients for the working experience full-time model are relatively large in magnitude and negative. It is of importance to discuss the fact that the sample size is fairly small, affecting the statistical power of the analysis.

To summarise, in tables 2 and 3 it is notable that the OLS specifications (1) - (4) seem to understate the magnitude of the coefficients in comparison to the sibling FE models (5) and (6). This could be due to various reasons. To begin with, measurement errors in the OLS models may cause a downward bias in the estimates, whilst in the sibling FE models these may be differenced out. Next, investments by parents could be considered a public good for everyone in the household to use, such as books. Any investments made to compensate for any health or cognitive deficits of one child could inadvertently benefit the other children in the family as well, so-called spillover effects. Thus, the net effect of pollution exposure is perhaps lower in the OLS, as the compensatory investments is included in the net effect, whereas in the sibling FE the impact of the investments is more or less differenced out (Bharadwaj, Eberhard, & Neilson, 2018). As a final point, avoidance behaviour could also play an important role as discussed in chapter 2. The OLS estimates would display the net effect of pollution exposure and avoidance behaviour. In turn, sibling FE would be larger as it would difference out avoidance behaviour by parents that is not varying over time, such as repeated behaviour of avoidance (Currie et al., 2014).

6.2 Heterogeneity of Results

Table 5: CO and O3 effects on Log of Real Labour Income, interacted with mothers' education

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: At birth:						
CO	0.068*	-0.009	0.050	-0.024	-0.212***	-0.311***
	(0.035)	(0.037)	(0.037)	(0.037)	(0.062)	(0.039)
O3	-0.113	-0.032	-0.104	-0.034	-0.432	-0.226
	(0.106)	(0.107)	(0.096)	(0.114)	(0.297)	(0.192)
CO x Mom Higher Education	-0.145**	-0.231*	-0.030	-0.124	0.372***	0.459***
	(0.057)	(0.107)	(0.049)	(0.089)	(0.084)	(0.123)
Observations	937	931	937	931	259	254
R-squared	0.073	0.148	0.088	0.160	0.662	0.764
Mother characteristics controls	No	No	Yes	Yes	No	No
State-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	Yes	No	Yes	No	Yes
Sibling FE	No	No	No	No	Yes	Yes

Notes: Standard errors are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table shows CO and O3 exposure at the month of birth's impact on log of real labour income in euro per month at age 27 and an interaction term for CO levels multiplied by the mother having a higher education level. In the appendix, you can find table A.4 describing how mothers' education is defined. All regressions from column (1) to (6) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year and month fixed effects. The values for CO and O3 are standardised.

Considering that the results from table 2 would suggest heterogeneous effects in the model, it is important to evaluate these through different methods. Table 5 demonstrate how the results differ by mothers' education. By interacting CO with mothers with higher education, it is possible to observe heterogeneous effects. Columns (5) and (6) suggest that children born to mothers with higher education are able to be compensated by more than enough by the detrimental effects of CO pollution at the month of birth. A one standard deviation increase in CO at birth results in a 15 percent increase in real labour income. Thus, the negative effect of CO exposure at birth seem to be borne by children of mothers with lower education levels in its entirety (including mothers with low to medium education level). These results could stem from that mothers with lower education may not have the same capabilities to engage in compensatory investments or avoidance behaviour to make up for their children's poor health, as well as living in areas with more air pollution. Also, health issues such as asthma and stress are more common among families with lower education. These issues could amplify the impact of air pollution (Eggleston, Buckley, Breysse, Wills-Karp, Kleeberger, & Jaakkola, 1999). It is thus difficult to disentangle what factors are driving the results.

Table 6: Max level of CO and O3 effects on Log of Real Labour Income

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: At birth:						
CO	-0.00517	-0.0314	-0.00199	-0.00199	-0.0691	-0.115*
	(0.0239)	(0.0280)	(0.0253)	(0.0253)	(0.0470)	(0.0525)
O3	-0.0581	0.0197	-0.0534	-0.0534	-0.00623	0.0830
	(0.0622)	(0.0478)	(0.0546)	(0.0546)	(0.130)	(0.143)
Observations	937	931	937	937	259	254
R-squared	0.065	0.135	0.086	0.086	0.630	0.737
Mother characteristics controls	No	No	Yes	Yes	No	No
State-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	Yes	No	Yes	No	Yes
Sibling FE	No	No	No	No	Yes	Yes

Notes: Standard errors clustered on household and federal state are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table shows max level of CO and O3 exposure at birth's impact on log of real labour income in euro per month at age 27. All regressions from column (1) to (6) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year and month fixed effects. The values for CO and O3 are standardised.

Furthermore, there is evidence of that the adverse impact of air pollution arises from the more polluted days (Bharadwaj et al., 2017). Thus, I evaluate the impact of maximum CO and O3 levels at the month of birth on log of real labour income per month in table 6, in order to understand if the relationship between air pollution and labour outcomes is actually non-linear. The effects are negative, but only CO remains significant in the weighted sibling FE model, but with a lower magnitude than in table 2. These results do not provide evidence for a non-linear relationship between air pollution and labour outcomes.

6.3 Mechanisms

In order to estimate the different channels that air pollution exposure at birth impacts labour outcomes adversely, it would be interesting to look into both cognitive abilities, proxied by scores on aptitude tests and health at birth, usually proxied by birth weight. This would provide evidence of the theoretical framework discussed in chapter 2.1, that explains the process of amplification of the air pollution effects over time. Unfortunately, for the people born between 1985-1992 there is no collected data on birth weight in the survey or any other conditions at birth. Important to note is that in previous studies, low birth weight only accounts for around 10 percent of the adverse impact on long-term outcomes from air pollution in-utero (Bharadwaj, Eberhard, & Neilson, 2018).

6.3.1 Cognitive test results

Instead of estimating the impact of CO and O3 at birth on various different cognitive tests in young adulthood, it is possible to group these tests together in order to find any generalisable impact on cognitive ability and avoid multiple-hypothesis testing concerns (Schwab, Janzen, Magnan, & Thompson, 2020). There were three different tests performed at ages 18-26 by each individual born between 1985-1992, which entailed summing correct number entries in 30, 60 and 90 seconds. By using the swindex method constructed by Anderson, 2008, it is possible to study these outcomes of interest as an index. The advantage of this method is that it increases statistical power and reduces the risk of rejecting a null hypothesis by mistake. It increases statistical power by cancelling out random errors, independent across the tests. The swindex is generated through the standardisation of the inverse-covariance weighted average of the different cognitive test results. In this manner, test results that are more correlated are attached a lower weight, whereas less correlated ones are attached a higher weight. Furthermore, missing observations are included in the index, yet attached a lower weight (Schwab et al., 2020).

In table 7, the O3 and CO values are negative for all model specifications, and show a much larger magnitude in the sibling FE models compared to the OLS models. In the unweighted model (3) with mother characteristics controls CO is significant at the 10 percent level, whereas in both the unweighted and weighted sibling fixed effects models, CO is significant at the 5 percent and 1 percent level respectively. In the weighted model, a one standard deviation increase in CO at birth leads to a 0.462 standard deviation decrease in test scores. The sample size is relatively large in comparison to previous models and illustrates one channel

Table 7: CO and O3 effects on cognitive tests

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: At birth:						
CO	-0.077	-0.144	-0.079*	-0.137	-0.299**	-0.462***
	(0.044)	(0.120)	(0.044)	(0.115)	(0.136)	(0.169)
O3	-0.097	-0.094	-0.092	-0.061	-0.020	-0.040
	(0.117)	(0.216)	(0.117)	(0.227)	(0.207)	(0.293)
Observations	1,017	1,006	1,017	1,006	623	614
R-squared	0.042	0.169	0.045	0.174	0.559	0.711
Mother characteristics controls	No	No	Yes	Yes	No	No
State-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	Yes	No	Yes	No	Yes
Sibling FE	No	No	No	No	Yes	Yes

Notes: Standard errors clustered on household and federal state are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the indexed score of the test scores: summing correct number entries in 30, 60 and 90 seconds taken between the ages 18-26. All regressions from column (1) to (6) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year and month fixed effects. The values for CO and O3 are standardised.

in which CO exposure at birth could influence labour outcomes, namely through reducing cognitive ability.

6.4 Robustness checks

6.4.1 Standard errors

As discussed in chapter 5.1 it is of value to evaluate the robustness of the results to standard error adjustments. In table 8 and in table 9, I evaluate whether the model specification for real labour income in euro per month is robust to different standard errors. CO remains significant in the weighted model specification using robust standard errors or clustered on household level in table 8. Notably, CO does not remain significant in the unweighted model specification with other standard errors. Furthermore, using a wild bootstrap t-test, clustering standard errors by federal state it is possible to reject the null hypothesis that CO is equal to zero with 95 percent confidence in the weighted model in table 9. However, with the wild bootstrap t-test there is not enough evidence to reject the null hypothesis that CO is equal to 0 with 95 percent confidence in the unweighted model. This means that the weighted model is robust to different model assumptions, whereas the unweighted model is not. Considering, that the weighted model is the more

Table 8: Standard errors adjustments

	Clustered at household level and federal state		Clustered at household level		Robust standard errors	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
At birth:						
CO	-0.125*	-0.209***	-0.125	-0.209**	-0.125	-0.209*
	(0.069)	(0.036)	(0.084)	(0.096)	(0.092)	(0.107)
O3	-0.443	-0.257	-0.443	-0.257	-0.443	-0.257
	(0.331)	(0.204)	(0.282)	(0.273)	(0.297)	(0.306)
Weights	No	Yes	No	Yes	No	Yes
Observations	259	254	259	254	259	254
R-squared	0.643	0.748	0.643	0.748	0.643	0.748

Notes: Standard errors are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table is a robustness check evaluating the robustness of the sibling fixed effects model of CO and O3 exposure at birth's impact on log of real labour income in euros per month to different standard errors. Column 1 is the regression on the dependent variable with standard errors clustered at household and federal-state level, column 2 is the same regression as in column 1, but with weights. Column 3 is the regression on the dependent variable with standard errors clustered at household level, column 4 is the same regression as in column 3, but with weights. Column 5 is the regression on the dependent variable with robust standard errors, column 6 is the same regression as in column 5, but with weights.

Table 9: Wild bootstrap t-test

Wild bootstrap t-test CO = 0		
Variables		
At birth:		
95 percent confidence set	$(-0.3051, 0.01697)$	$(-0.2832, -0.1435)$
Weights	No	Yes

Notes: The table shows the results from a wild bootstrap t-test to test the null hypothesis that CO = 0 for the sibling fixed effects model at birth for log of real labour income in euro per month at age 27, with 999 replications and bootstrap clustering by federal state using Rademacher weights

precise model, accounting for endogenous sampling, the fact that the unweighted model is not robust to different model assumptions is not given too much emphasis.

6.4.2 Additional robustness checks

Table 10: CO and O3 effects on Log of Real Labour Income with monitor controls

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: At birth:						
CO	0.054	-0.039	0.048	-0.040	-0.136*	-0.190***
	(0.040)	(0.048)	(0.040)	(0.046)	(0.065)	(0.037)
O3	-0.125	-0.034	-0.110	-0.036	-0.572	-0.365*
	(0.093)	(0.133)	(0.091)	(0.132)	(0.324)	(0.190)
Observations	937	931	937	931	259	254
R-squared	0.069	0.136	0.089	0.158	0.648	0.752
Mother characteristics controls	No	No	Yes	Yes	No	No
State-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	Yes	No	Yes	No	Yes
Sibling FE	No	No	No	No	Yes	Yes

Notes: Standard errors clustered on household and federal state are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table shows CO and O3 exposure at birth's impact on log of real labour income in Euro per month at age 27, with controls for number of active air pollution monitors per year in each federal state for CO and O3. All regressions from column (1) to (6) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year and month fixed effects. The values for CO and O3 are standardised.

In table 10, controls are added to account for the fact that the number of active monitoring stations of CO and O3 vary over time and across federal states. Comparing the table to table 2, the regression coefficients and the standard errors have remained relatively stable. However, O3 is now significant at the 1 percent level for the weighted sibling-FE specification.

Table 11: CO and O3 effects on Log of Real Labour Income, excluding former East Germany and Berlin

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: At birth:						
CO	0.042	-0.048	0.043	-0.039	-0.157	-0.270**
	(0.056)	(0.068)	(0.056)	(0.066)	(0.099)	(0.088)
O3	-0.147	-0.055	-0.128	-0.053	-0.606	-0.258
	(0.105)	(0.144)	(0.104)	(0.143)	(0.403)	(0.264)
Observations	784	778	784	778	219	214
R-squared	0.066	0.143	0.086	0.163	0.675	0.773
Mother characteristics controls	No	No	Yes	Yes	No	No
State-FE	Yes	Yes	Yes	Yes	Yes	Yes
Year and Month-FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	No	Yes	No	Yes	No	Yes
Sibling FE	No	No	No	No	Yes	Yes

Notes: Standard errors clustered on household and federal state are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table shows CO and O3 exposure at birth's impact on log of real labour income in euro per month at age 27, excluding former East German federal states and Berlin. All regressions from column (1) to (6) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year and month fixed effects. The values for CO and O3 are standardised.

In order to ensure that the fall of the Berlin Wall and the re-unification of Germany is not driving the results, as this would be a time-variant shock influencing both the explanatory variables and the error term, another robustness check is performed in table 11 where the former East German federal states (Mecklenburg-Vorpommern, Brandenburg, Saxony, Saxony-Anhalt and Thuringia) and Berlin are excluded from the analysis. Graphically, from the figures 3 and 4 it has not been possible to identify any significant drop in air pollution levels during this time period. Despite the reduction in sample size, in table 11, CO still remains significant in the weighted model (6) at the 5 percent level and its magnitude is larger than in table 2. The unweighted model specification (5) is no longer significant, but the regression coefficient is negative with a similar magnitude to (5) in table 2. Thus, the exogeneity assumption still seem to hold, and the shock is not confounding the impact of CO at birth on real labour income per month.

Table 12: Regression of CO exposure on second-born child with mover status.

Variables	(1)	(2)
Model 1: At birth:		
Second born child x Mover	-0.001	-0.462
	(0.246)	(0.628)
Observations	464	318
R-squared	0.840	0.878
Mother characteristics controls	No	No
State-FE	Yes	Yes
Year and Month-FE	Yes	Yes
Weights	No	Yes
Sibling FE	Yes	Yes

Notes: Standard errors clustered on household and federal state are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table shows a robustness check: regressing CO exposure at birth on a dummy for being second in the birth order interacted with a dummy for mover status for the mother. All regressions from column (1) to (2) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year, month and sibling fixed effects. The values for CO and O3 are standardised.

It is noteworthy that only 2,4 percent of the mothers in the sample move between sibling births. Still, it is important to explore whether the mothers who do move between sibling births cause any Tiebout sorting issues, resulting in a relation between CO levels and time-variant unobserved factors of labour outcomes. Table 12 regresses CO on the sibling-FE specification with a dummy variable for mothers moving to a different federal state between sibling births interacted with being born second in the birth order. I also restrict the sample to only first-born and second-born siblings, as I want to compare the variation between the two. The regressions test whether families are moving between births to states with lower air pollution exposures. In that case the interaction term would be negative and significant. In the table, the interaction term is not significant in the unweighted nor the weighted specification, and very small in magnitude in the unweighted model. Essentially, mothers do not seem to consistently move to more or less polluted federal states between sibling births.

Table 13: Falsification test: Log of mother's age

	Log of mother's age	
Variables	(1)	(2)
At birth:		
CO	-0.006	-0.004
	(0.018)	(0.027)
O3	-0.013	-0.061
	(0.028)	(0.042)
Weights	No	Yes
Observations	511	355
R-squared	0.750	0.778

Notes: Standard errors are in the parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the log of mother's age. All regressions from column (1) to (2) refer to the sample population born between 1985-1992 and control for precipitation and temperature non-linearly and include federal state, year, month and sibling fixed effects. The values for CO and O3 are standardised.

Table 13 shows results from a falsification test where I regress the predetermined variable Log of mother's age on the sibling FE specification. The coefficients for CO and O3 are both insignificant and very small in magnitude, supporting the validity of the sibling FE strategy.

7 Conclusion

By merging air pollution data to the representative panel survey GSOEP, I have assessed different ways CO and O3 at the month of birth and during pregnancy impact labour outcomes in Germany. Using a sibling-FE model, I find that CO at birth has a significant negative and adverse impact on real labour income in euros per month, and average work time per week as well as employment status at age 27. The decline in real labour income could be partially explained by the decrease in the average work time per week as well as employment status at age 27. The impact of average pollution levels during the whole pregnancy is less pronounced, consistent with the scientific literature, indicating that CO has more harmful effects towards the end of the pregnancy (Dix-Cooper et al., 2012). Furthermore, O3 at birth or during pregnancy is not significant in most model specifications, emphasising CO as the main culprit (Longo, 1977).

I have provided suggestive evidence of one channel of how labour outcomes may be adversely affected by CO exposure at birth through adverse effects on cognition test scores in young adulthood. There are also heterogeneous effects among children of mothers with higher education in comparison to lower education in terms of impact of CO at birth on real labour income per month. Whereas, children of mothers with higher education are compensated by the negative effects of high levels of CO at birth, the adverse effects are borne entirely by children of mothers with lower levels of education.

Due to relying on sibling fixed effects with a small sample size and on such an aggregate level of air pollution, it is difficult to generalise these results, which affects the external validity of the findings. Moreover, FE models cannot completely rule out time-varying unobserved heterogeneity that differs across siblings, potentially confounding influences on human capital accumulation.

For future research, it would be interesting to visit GSOEP'S data centre in Berlin to access more granular household data protected for security reasons. Then, it would be possible to match air pollution monitors to household's location on a zip-code level, increasing the variation in pollution levels. Accordingly, it is expected to observe more significant effects of air pollution on labour outcomes, minimising the noise in the model. Previous literature has shown that gathering pollution levels on a too aggregate level leads to an understatement of the true effect of air pollution on individual health with smaller and insignificant estimates (Currie, Neidell, & Schmieder, 2009). Also, to include controls for air pollution alerts would help to account for time-variant avoidance behaviour. On top of that, it would broaden the scope of understanding when using a composite measure of air pollution like air quality index (AQI), evaluating the general impact of air pollution on labour outcomes.

This study provides fundamental evidence for the necessity to invest in the protection of fetal health for long-term human capital accumulation reasons, by minimising air pollution levels. Considering that air pollution has a differential effect on people depending on mothers' education, these investments could be one of the most vital ones to increase human capital accumulation and decrease inequality in society. Especially, automobiles produce a significant amount of CO, and it is thus of great importance to regulate these harmful emissions (Dix-Cooper et al., 2012).

In essence, the study provides support of the fetal origins hypothesis, but the channels through how these effects occur need to be further explored. An impact of cognition represents only one of the channels. Likewise, the magnitude and effectiveness of compensatory investments and avoidance behaviour by parents is difficult to measure. These investments may constitute a large welfare cost to society, and need to be explored further.

References

Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Wooldridge (Nov. 2017). WHEN SHOULD YOU ADJUST STANDARD ERRORS FOR CLUSTERING?, in: *National Bureau of Economic Research*, vol. C21, no. 24003, pp. 1–79 (cit. on p. 23)

Almond, Douglas and Janet Currie (Summer 2011). Killing Me Softly: The Fetal Origins Hypothesis, in: *Journal of Economic Perspectives*, vol. 25, pp. 153–172 (cit. on pp. 1, 5)

Anderson, Michael L. (Nov. 2008). Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects, in: *Journal of the American Statistical Association*, vol. 103, no. 484, pp. 1481–1495 (cit. on p. 29)

Angrist, Joshua D. and Jörn-Steffen Pischke (2009). Mostly Harmless Econometrics: An Empiricist's Companion, 41 William Street, Princeton, New Jersey: Princeton University Press (cit. on p. 22)

Bateson, Thomas F. and Joel Schwartz (Dec. 2007). Children's Response to Air Pollutants, in: *Journal of Toxicology and Environmental Health, Part A*, vol. 71, pp. 238–243 (cit. on pp. 1, 5)

Bharadwaj, Prashant, Juan Pedro Eberhard, and Christopher A. Neilson (Apr. 2018). Health at Birth, Parental Investments, and Academic Outcomes, in: *Journal of Labour Economics*, vol. 36, no. 2, pp. 1–46 (cit. on pp. 21, 26, 29)

Bharadwaj, Prashant, Matthew Gibson, Joshua Graff Zivin, and Christopher Neilson (Feb. 2017). Gray Matters: Fetal Pollution Exposure and Human Capital Formation, in: *Journal of the Association of Environmental and Resource Economists*, vol. 4, no. 2, pp. 1–38 (cit. on pp. 2, 3, 8, 13, 19–22, 28)

Builtjes, P.J.H., M. van Loon, M. Schaap, S. Teeuwisse, A.J.H Visschedijk, and J.P Bloos (Nov. 2002). The Development of an emission data base over Europe and further contributions of TNO-MEP, in: *Freie Universität Berlin Institut*, (cit. on p. 1)

Chay, Kenneth Y. and Michael Greenstone (2005). Does Air Quality Mattter? Evidence from the Housing Market, in: *Journal of Political Economy*, vol. 113, no. 2, pp. 1–49 (cit. on p. 7)

Coneus, Katja and C. Katharina Spiess (Oct. 2012). Pollution exposure and child health: evidence for infants and toddlers in Germany, in: *Journal of Health Economics*, vol. 31, no. 1, pp. 180–196 (cit. on pp. 1, 3, 7, 9, 10, 19, 20)

Cunha, Flavio and James Heckman (May 2007). The Technology of Skill Formation, in: *American Economic Review*, vol. 97, no. 2, pp. 31–47 (cit. on p. 6)

Currie, Janet, Matthew Neidell, and Johannes F. Schmieder (Feb. 2009). Air pollution and infant health: Lessons from New Jersey, in: *Journal of Health Economics*, vol. 28, pp. 688–703 (cit. on pp. 9, 36)

Currie, Janet, Joshua Graff Zivin, Jamie Mullins, and Matthew Neidell (2014). What Do We Know About Short- and Long-Term Effects of Early-Life Exposure to Pollution?, in: *Annual Review of Resource Economics*, vol. 6, pp. 217–247 (cit. on pp. 1, 2, 5–8, 27)

Datar, Ashlesha, M Rebecca Kilburn, and David S Loughran (Feb. 2010). Endowments and parental investments in infancy and early childhood, in: *Demography*, vol. 47, no. 1, pp. 145–62 (cit. on p. 6)

Deschênes, Olivier, Michael Greenstone, and Joseph S. Shapiro (Oct. 2017). Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program, in: *American Economic Review*, vol. 107, no. 10, pp. 2958–2989 (cit. on p. 21)

Destatis (2023). Labour market - Employment, in: *Statistisches Bundesamt (Destatis)*, vol. https://www.destatis.de/EN/Themes/Labour/Labour-Market/Employment, no. Last checked: 2023-05-19, (cit. on pp. 2, 11)

Dix-Cooper, Linda, Brenda Eskenazi, Carolina Romero, John Balmes, and Kirk R Smith (Mar. 2012). Neurodevelopmental performance among school age children in rural Guatemala is associated with prenatal and postnatal exposure to carbon monoxide, a marker for exposure to woodsmoke, in: *Neurotoxicology*, vol. 33, no. 2, pp. 246–254 (cit. on pp. 3, 10, 35, 36)

Eggleston, P A, T J Buckley, P N Breysse, M Wills-Karp, S R Kleeberger, and J J Jaakkola (June 1999). The environment and asthma in U.S. inner cities., in: *Environmental Health Perspectives*, vol. 107, no. 3, pp. 1–12 (cit. on p. 28)

Goebel, Jan, Markus M. Grabka, Stefan Liebig, Martin Kroh, David Richter, Carsten Schröder, and Jürgen Schupp (2019). The German Socio-Economic Panel (SOEP), in: *Journal of Economics and Statistics*, vol. 239, no. 2, pp. 345–360 (cit. on p. 17)

Groenwold, Rolf H.H., Ian R. White, A. Rogier T. Donders, James R. Carpenter, Douglas G. Altman, and Karel G.M. Moons (Aug. 2012). Missing covariate data in clinical research: when and when not to use the missing-indicator method for analysis, in: *Canadian Medical Association Journal*, vol. 184, no. 11, pp. 1265–1269 (cit. on p. 18)

Hellfeld, Matthias von (2021). German federalism: How does it work?, in: *DW*, (cit. on p. 7)

Hübner, Christian (2015). History of Environmental Policy in Germany, in: *EKLA*, pp. 1–50 (cit. on p. 3)

Isen, Adam, Maya Rossin-Slater, and W. Reed Walker (June 2017). Every breath you take - every dollar you'll make: the long-term consequences of the clean air act of 1970, in: *Journal of Political Economy*, vol. 125, no. 3, pp. 848–896 (cit. on pp. 1, 2, 8)

Kaminsky, Philipp and Janine Napieraj (2023). DIW Berlin. URL: `https://www.diw.de/en/diw_01.c.601584.en/data_access.html` (visited on 06/01/2023) (cit. on p. 14)

Karsten, Friedrich (2023). Deutscher Wetterdienst. URL: `https://opendata.dwd.de/climate_environment/CDC/regional_averages_DE/monthly/` (visited on 06/01/2023) (cit. on p. 11)

Longo, Lawrence D. (Sept. 1977). The biological effects of carbon monoxide on the pregnant woman, fetus, and newborn infant, in: *American Journal of Obstetrics and Gynecology*, vol. 1, no. 1, pp. 69–103 (cit. on pp. 2, 3, 10, 35)

Lüchinger, Simon (Sept. 2014). Air pollution and infant mortality: A natural experiment from power plant desulfurization, in: *Journal of Health Economics*, vol. 37, pp. 219–231 (cit. on p. 1)

MacKinnon, James G., Morten Ørregaard Nielsen, and Matthew D. Webb (Feb. 2023). Cluster-robust inference: A guide to empirical practice, in: *Journal of Econometrics*, vol. 232, no. 2, pp. 272–299 (cit. on p. 22)

Rossi, Federico (Nov. 2018). Human Capital and Macro-Economic Development, in: *World Bank Development*, pp. 1–41 (cit. on p. 2)

Salam, Muhammad T., Joshua Millstein, Yu-Fen Li, Frederick W. Lurmann, Helene G. Margolis, and Frank D. Gilliland (Nov. 2005). Birth Outcomes and Prenatal Exposure to Ozone, Carbon Monoxide, and Particulate Matter: Results from the Children's Health Study, in: *Environmental Health Perspectives*, vol. 113, no. 11, pp. 1638–1644 (cit. on p. 11)

Schwab, Benjamin, Sarah Janzen, Nicholas P. Magnan, and William M. Thompson (2020). Constructing a summary index using the standardized inverse-covariance weighted average of indicators, in: *The Stata Journal*, vol. 20, no. 4, pp. 952–964 (cit. on p. 29)

Siegers, Rainer, Hans Walter Steinhauer, and Johannes König (Dec. 2021). SOEP-Core – 2019: Sampling, Nonresponse, and Weighting in SOEP-Core – 2019: Sampling, SOEP-Core – 2019: Sampling, Nonresponse, and Weighting in Sample P, in: *SOEP Survey Papers*, pp. 1–25 (cit. on pp. 14, 17)

Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge (Spring 2015). What are We Weighting For?, in: *The Journal of Human Resources*, vol. 50, no. 2, pp. 1–17 (cit. on pp. 17, 18)

Sullivan, Daniel and Till von Wachter (Aug. 2009). Job Displacement and Mortality: An Analysis Using Administrative Data, in: *The Quarterly Journal of Economics*, vol. 124, no. 3, pp. 1265–1306 (cit. on p. 8)

UBA (2023). Leipzig 1987, in: *https://www.umweltbundesamt.de/en*, no. Last checked: 2023-03-31, (cit. on pp. i, iii)

Uhse, Karin (2023). Umweltbundesamt. URL: https://www.umweltbundesamt.de/en (visited on 06/01/2023) (cit. on p. 11)

A Appendix

Table A.1: Active monitoring stations of CO levels across the federal states in Germany between 1985-1992

Years	1985	1986	1987	1988	1989	1990	1991	1992
Lower Saxony	5	5	6	5	1	3	1	4
Bavaria	26	27	28	32	32	36	20	37
North Rhine-Westphalia	24	57	59	62	67	69	68	70
Baden-Württemberg	23	27	29	29	34	50	56	58
Saxony	1	2	3	3	3	3	3	9
Hesse	20	20	20	23	23	22	23	24
Thuringia	0	0	0	0	0	0	6	6
Mecklenburg-West Pomerania	0	0	0	0	0	0	0	3
Berlin	0	0	6	6	0	7	7	18
Bremen	0	0	2	2	0	5	4	5
Schleswig-Holstein	0	0	0	0	0	0	2	0
Rhineland-Palatinate	10	11	14	14	2	16	16	20
Saxony-Anhalt	0	1	2	2	2	2	4	6
Saarland	0	0	0	1	0	1	2	2
Brandenburg	0	0	0	0	1	1	4	5
Hamburg	4	8	8	8	8	8	11	12

Table A.2: Active monitoring stations of O3 levels across the federal states in Germany between 1985-1992

Years	1985	1986	1987	1988	1989	1990	1991	1992
Lower Saxony	7	10	14	15	21	17	20	19
Bavaria	8	9	9	11	12	19	23	29
North Rhine-Westphalia	11	19	22	23	27	33	34	36
Baden-Württemberg	18	30	33	33	38	55	62	62
Saxony	2	3	4	4	4	4	7	14
Hesse	14	16	16	21	22	22	25	32
Thuringia	0	0	1	1	1	2	6	7
Mecklenburg-West Pomerania	0	0	0	0	0	1	3	8
Berlin	0	0	6	6	0	8	9	9
Bremen	0	0	2	2	0	5	5	5
Schleswig-Holstein	7	7	6	7	7	9	10	11
Rhineland-Palatinate	6	10	10	10	11	13	15	17
Saxony-Anhalt	2	2	3	3	3	3	5	7
Saarland	0	0	0	0	0	2	2	2
Brandenburg	1	1	1	1	2	2	9	10
Hamburg	1	3	3	3	3	3	3	4

Table A.3: Descriptive statistics unweighted variables

Variable	Obs	Mean	Std. dev.	Min	Max
At age 27:					
Real Annual Labour Income in Euro	2,037	1775.246	1104.108	0	12941.500
University Attendance Dummy (1 = attended)	3,206	0.235	0.424	0	1
Amount of education/training in years	2,923	11.889	3.087	7	18
Actual work time per week (h)	1,962	36.277	12.752	1	80
Working experience full time employment in years	3,179	2.587	2.788	0	12
Employment status Dummy (1 = employed)	5,627	0.277	.4476732	0	1
At age 18-26:					
Cognitive test: Sum correct number entries in 30 seconds	3,524	10.682	5.432	0	93
Cognitive test: Sum correct number entries in 60 seconds	3,524	22.315	8 0.487	0	93
Cognitive test: Sum correct number entries in 90 seconds	3,524	33.325	11.486	0	93
Controls:					
Mother's education (high level)	3,053	0.176	0.381	0	1
Mother's education (medium level)	3,053	0.739	0.439	0	1
Mother's education (low level)	3,053	0.086	0.280	0	1
Female dummy	4,861	0.503	0.500	0	1
Mother's age	3,414	26.743	5.229	14	45

Table A.3 continued from previous page

Weather & pollution indicators					
Precipitation - at birth	3,315	66.797	34.241	7.600	218.400
Precipitation -during pregnancy	3,360	66.450	14.753	29.940	108.750
Temperature – at birth	3,315	8.183	6.695	-8.100	20.300
Temperature – during pregnancy	3,360	8.682	1.529	4.650	11.710
CO - at birth	2,791	1.015	0.446	0.092	2.768
CO - during pregnancy	2,885	1.032	0.335	0.197	2.567
O3 – at birth	3,109	38.360	19.304	6.166	138.819
O3 – during pregnancy	3,192	38.322	10.635	9.305	90.180

Table A.4: Level of education of the mother

Higher Education	Medium Education	Lower Education
Technical High School	Secondary General School	Compulsory Schooling (Abroad)
Upper Secondary School	Intermediate School	No School Degree
	Secondary School (Abroad)	
	Other Degree	