ECONOMIC STATUS, AIR QUALITY, AND CHILD HEALTH: EVIDENCE FROM INVERSION EPISODES

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Abstract

Normally, the temperature decreases with altitude, allowing air pollutants to rise and disperse. During inversion episodes, warmer air at higher altitude traps air pollutants at the ground. By merging vertical temperature profile data from NASA to pollution monitors, and health care records we show that inversions increase PM10 levels by 30% and children's respiratory health problems by 5%. Low-income children are particularly affected, and poor air quality contribute to the steepening income-health gradient over the child's life-cycle. Differences in baseline health seem to be a key mediating factor behind the SES-gap. Inversions reduce parents labor supply by 2.9%.

JEL: I1, J24, J22, Q53

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1 Introduction

It is well documented that adults with low socioeconomic status (SES) have worse health than those with high SES. Case, Lubotsky and Paxson (2002) trace the origins of the SES-health gradient back to childhood, show that the gap is present at birth, and that it becomes more pronounced during the child's life cycle. The gradient steepen primarily due to that children in low-SES households experience health shocks more frequently, and *respiratory diseases* account for much of the SES gap in the arrival rate of chronic health conditions (Currie and Stabile, 2003). Childhood health affects adult health, but may also affect later wellbeing and productivity indirectly via cross-productivity in the accumulation of cognitive and non-cognitive skills (Currie and Stabile, 2003; Heckman, 2007). Yet, despite the key importance for the design of policies intending to reduce inequality in opportunities, the causes of the SES-gradient in child health are still poorly understood.

We examine whether, to what extent, and why poor air quality affects children's respiratory diseases differentially across socioeconomic groups. Extensive evidence has been presented indicating that air pollution affect children's respiratory health. There are also several reasons why air pollution could have a particularly strong impact on health among children in low SES households. For example, children in low-income households have on average worse health to begin with, which may make them more susceptible to damage from air pollution. However, surprisingly little direct evidence exists on differences in the effects of air pollution across SES groups (see review in Table A1), and even less is known about the underlying mechanisms.

We link daily data on health care visits for all Swedish children's during six years to information on parental income and education and local ambient air pollution monitors. Using this uniquely detailed data, we show that temporary changes in air pollution significantly affect children's respiratory health. Specifically, we exploit variation in air quality induced by inversion episodes. On normal days, the temperature decreases with altitude, allowing air pollutants to rise and disperse. During an inversion episode a warmer air layer at higher altitude traps air pollutants close to the ground. In our sample inversions occur on 25 percent of the days, leads to substantially higher pollution levels (e.g. +36 percent PM_{10}, +27 percent NO_2) and to an increase in the health care visits due to respiratory illness (+5 percent). Consistent with air pollution contributing to the income-child health gradient, the impact of inversions on children from high-income households is about 40 percent lower than on children in low-income households. The gradient also seems to widen with child age.

Our study contributes to the literature on the SES-child health gradient by providing direct evidence on the mediating role of air pollution. But we also add to the literature on the effects of air quality on health in several important ways. First, most previous studies assess the health effects of air pollution using overnight hospital admissions and emergency room visits (Moretti and Neidell, 2011; Schenkler and Walker, 2011). These two measures capture the most severe health problems. We also use outpatient data, which allows us to measure health problems that may not be severe enough to warrant overnight hospital admissions. In addition, by using daily information on parental work absence due to care of sick children we are able to assess the impact of poor air quality on health conditions that may not even result in a health care visit. Combined, relative to previous studies, this constitutes a substantial expansion of the coverage of the health outcomes potentially affected.

Second, the possibility to examine effects of air pollution with respect to parental economic conditions has been limited due to the inability to link health records to family income data. US birth records contain information on maternal education which previously have been used to examine SES differences in effects on neonatal health outcomes. However, assessments of differences across family income groups have relied on crude proxies for parental income, which potentially explains the inconsistent results in previous studies (see Appendix Table A1 for a review). Our individual data allow us examine SES difference in the effects of air pollution with respect to both parental income and educational attainments.

A third innovation of the paper is that we exploit a new data source to measure inversion episodes. Inversions are associated with some of the worst and most well-known pollution disasters of the 20th century, including Donora smog 1948 and the London Fog 1952 and the Union Carbide disaster in Bhopal 1984. However, inversions occur frequently (25 percent of days in our sample), and do lead to poorer air quality but rarely to disastrous conditions. We show how data on vertical temperature profiles derived from NASA's AQUA satellite can be used to measure inversion episodes. The AQUA data allows us to measure inversion frequency and strength on a daily basis with high spatial resolution. Previous work have used various ingenious approaches to assess the effects of exogenous changes in pollution levels on health (e.g. Chay and Greenstone, 2003a;2003b; Currie and Niedell, 2005, Lleras-Muney, 2011;

Moretti and Neidell 2011; Schenkler and Walker 2011; Currie and Walker, 2011; Arceo-Gomez, Hannah, Olivia 2012). We contribute by providing an easily implementable method that has the potential to isolate the short-term effects of poor air quality in principle anywhere globally. The vertical temperature profile data is free of charge and is easy to download for specific countries, regions, and cities. This opens up the possibility for comparative studies in widely differing settings using the same empirical strategy (e.g. developed vs. developing countries).

Fourth, the uniquely detailed individual data allow us to examine several of the potentially important mediating mechanisms that could lead to differential effects of temporary changes in air quality across SES-groups. First, as noted above, lower baseline health could make children from poorer backgrounds more vulnerable to damage from poor air quality (SES differences in vulnerability). Second, parents of children in poorer families may be less informed about factors affecting child respiratory health. This could lead to that actions that minimize exposure during high pollution days differs between high and low income families (SES differences in avoidance behavior). Third, if pollution levels influence housing prices, residential sorting may lead to that children in poor families live closer to pollution sources, leading to higher baseline pollution exposure. In the presence of nonlinearities in the effects of air pollution on respiratory health, residential sorting could lead to stronger health effect among children in low-income households for a given increase in air pollution.

Our analysis provides no clear support for nonlinearities being an important mechanism behind the SES differences in the impact of inversions in our setting. Nonparametric estimations suggest a linear relationship between inversion strength and both pollution and respiratory illnesses. Moreover, despite the strong predictive power of inversion on pollution, we show that inversions have no predictive power on pollution *forecast*. Similarly, using data on externally caused injuries we find no support for that children's activity patterns (indoor/outdoor activities) are affected by inversions in general, or differentially across SES groups. Hence, avoidance behavior does not seem to play a key role behind the SES-gap in our setting. However, when comparing the impact of inversions on children with poor baseline health, we find no differences in the effects across children in high- and low-income households. These results suggest that a substantial part of the difference in the effects of temporary changes in air quality may be due to that children in poor households on average have worse baseline health and thereby on average are more affected by poor air quality. Conditional on having poor baseline health, high parental income does not cushion the effect of poor air quality on respiratory illnesses.

Finally, we broaden the picture of the direct costs of air quality on health by using daily data on parental work absence due to care of sick children. Recent studies have documented that contemporaneous air quality affects labor supply among agricultural workers on the intensive margin (Graff Zivin and Neidell, 2012) and in a high pollution settings on the extensive margin (Hanna and Olivia, 2014). We quantifying the contemporaneous effects of poor air quality on all parents labor supply on the extensive margin via the impact on their *children's* health. Each year around 5 million workdays in Sweden are lost due to care of sick children, and the direct costs of child sickness from parental leave compensations (80 percent replacement rate) amounts to around SEK 4 billion yearly. Following inversions the incidence of work absence for care of sick children increases by 2.9 percent.

The rest of the paper is structured as follows. Section 2 reviews the literature on effects of air quality on health,. Section 3 provides an conceptual framework, section 4 describes the data, and section 5 the empirical approach. Section 6 present the results and section 7 summarizes and concludes.

2 Background Regarding the Relationship between Air Quality and Health

There is a vast literature documenting the relationship between air pollution and health. Below we summarize the literature and our contributions.

Epidemiology

Epidemiological studies on the health effects of air pollution have to a large extent relied on cross sectional data and compared the prevalence of hospitalizations due to respiratory illness at different levels of aggregation (e.g. cities) with differing pollution levels at a single point in time, or used aggregated time-series data for e.g. PM10 levels and asthma for a particular city or region over time. Using these approaches, it is difficult to draw causal conclusions about the magnitude of the effects on health.

Cross-sectional studies using individual or aggregated data are likely to confound effects of pollution with effects of unobserved factors that are correlated with pollution levels and respiratory illnesses in the cross section. It is not even clear in which direction omitted variables will tend to bias such estimates; a higher pollution level could capture better employment opportunities and income which, in turn, may mitigate the risk of experiencing respiratory health problems. Alternatively, higher air pollution levels could simply capture effects of unobserved factors such as a generally worse environment, housing standard, parental or child smoking patterns, etc. which, in turn, may result in overstated estimates of the effects of ambient air pollution. Pure time series studies may, on the other hand, not only capture the effect of variations in pollution but also other unobserved factors that co-vary with pollution patterns, for example, weather conditions, seasonal variations in activity patterns etc. As discussed further below, temporal fluctuations in air quality are also, to the extent that they are captured in pollution forecasts, potentially related to defensive investments or avoidance behavior among sensitive populations, such as asthmatics. Such behavioral changes are likely to lead to that the effect of poor air quality is understated.

There are a few exceptions in the epidemiological literature on the effects of air pollution on health that employ a design based approach for inference. Pope, Schwartz and Ransom (1992) examine the effects of variations in PM levels following a temporary shutdown of production in a steel mill. By comparing respiratory related emergency room visits in the valley where the mill was located to the neighboring valley, they find that when PM levels dropped following the plant shut down so did respiratory illnesses.

Economics

Economists have contributed to the literature on effects of air quality on health in several ways during the last decade. Primarily by highlighting potential identification problems and by using increasingly sophisticated empirical strategies designed to address these endogeneity problems.

First, air pollution is not randomly assigned across locations. Chay and Greenstone (2003a) note that air quality is capitalized in house prices. Individuals with a higher income and/or individuals with preferences for clean air may sort into better air quality areas. Thus, exposure to pollution levels is typically endogenous. Failing to account for residential sorting, unobserved determinants of health may bias the estimation of the effect of pollution on health. In the absence of a randomized experiment, this has led to a rise in estimation techniques to isolate the effects on health using exogenous changes in air quality.

For example, Chay and Greenstone (2003a,b) use the implementation of the US Clean Air Act of 1970 and the recession of the early 1980s to exploit the induced temporal and spatial variation in Total Suspended Particulate (TSP) levels. Lleras-Muney (2010) use the allocation of military families across military bases in the US to estimate the effects of air pollution on children's hospitalizations. Other studies exploit seasonal variations in pollution levels within residential areas to address endogenous sorting (e.g. Currie and Neidell (2005); Currie, Hanushek, Kahn, Neidell and Rivkin, 2009). One potential problem with using seasonal variation is the risk of confounding by weather conditions, since weather directly affects health (Deschenes and Moretti, 2009) and pollution levels. Accounting for all possible weather factors influencing both pollution and health is a challenging task. Knittel, Miller and Sanders (2011) show that including higher order terms for temperature and precipitation as well as second-order polynomials for some weather conditions, such as wind speed, humidity, and cloud cover, have a substantial impact on estimates of pollution on infant mortality.

A final problem is that the effect of pollution on health might be highly dependent on behavioral responses. For example, individuals might undertake defensive investments by purchasing preventive pharmaceuticals (Deschenes et al., 2012) or engage in avoidance behavior and reduce their time spent outdoors (Neidell, 2009). Ignoring behavioral responses could generate downward biased estimates.

To account for avoidance behavior, Moretti and Neidell (2011) estimate the health effects of ozone by employing data on daily shipping traffic in the port of Los Angeles as an instrumental variable for ozone levels. The OLS estimates are significant but small, while IV estimates, accounting for behavioral responses, measurement errors and potential confounders are around 4 times higher; indicating an annual cost of $44 million from respiratory related hospitalizations. Schlenker and Walker (2011) instrument air pollution using air traffic congestion in remote major airports to estimate the health impact of air pollution on populations living in the vicinity of 12 airports in California. They find that carbon monoxide (CO) leads to significant increases in hospitalization rates for asthma, respiratory, and heart related emergency room admissions that are an order of magnitude larger than conventional estimates. They do not examine whether the effects of pollution differ across socioeconomic groups.

Studies on the Effects of Inversion Episodes

Many studies have also related inversion episodes to poor air quality. For example, a study by Kukkonen et al. (2005) finds that inversion periods in European cities coincide with levels of particulate matter far above average. Likewise, in January 2004, Utah's Cache Valley experienced an inversion episode that drove particulate concentrations to two times the 24-hour standard used by the US EPA (Malek et al., 2006).

A handful of previous studies have examined the effects of inversion episodes on health. Abdul-Wahab, Bakheit, and Siddiqui (2005) documented an association between the monthly number of inversion days and emergency room visits in Oman. Using weather balloon data, Beard et al. (2012) find that inversion episodes increase emergency room visits in Salt-Lake County. Combining AIRS data and cross-sectional data on 674 asthmatics (on average 55 years old) in Hamilton, Ontario, Canada, Wallace, Nair and Kanaroglou (2010) finds an association between inversion episodes and sputum cell counts (an indicator of airway inflammation).

Methodologically, the closest related previous work is a recent study by Arceo-Gomez, Hanna and Olivia (2013) that examine effects on infant mortality using information on inversions from weather balloon data in one (1) location over Mexico City.[1] Arceo-Gomez et al. exploit the number of inversions over the city per week as an instrument for weekly pollution levels in the municipalities within the city. Their find that a 1 percent increase in PM_{10} over a year leads to a 0.42 percent increase in infant mortality, while a 1 percent increase in CO results in a 0.23 percent increase in infant mortality.

Our study extends and complement Arceo-Gomez et al., in several ways *besides* looking at a different outcome. The two most important additions is that we examine effects across socioeconomic groups, and that the NASA data and the empirical approach we develop easily allows for comparative studies in areas with high (such as Mexico City with a PM10 24-h mean of 67 $\mu g/m^3$), medium (e.g. the United States), or relatively low levels of pollution (e.g. the Swedish cities in our sample, PM10 24-h mean of 20 $\mu g/m^3$) using the same empirical strategy.[2]

[1] This paper was developed independently and without knowledge of the Arceo-Gomez et al. paper. The first-stage results were presented at the ASSA Meetings in Chicago in 2010, Uppsala University (2010), and at SIEPR, Stanford University (2010).

[2] Besides using multiple city measures of inversions which allows us to exploit variation within municipalities, our approach also differ from Arceo-Gomez et al (2013) by focusing on the inversion close to the ground (below 600m) while Arceo-Gomez et al. exploit the occurrence of inversion anywhere in the atmosphere. Our approach increases the power of inversion in predicting ground level pollution levels. Finally, Arceo-Gomez et al. exploits inversions to instrument PM10 and SO2. We do not exploit inversions as an instrument for particular pollution measures since the exclusion restriction is not likely fulfilled as inversions affect all pollutants we can measure (see Table 3).

More generally, the best empirical work on the effects on air quality on health exploit well-defined events that unexpectedly changes air pollution levels. However, since many of the studies make use of setting specific events or factors that change air quality levels, it is not straightforward to compare estimates of the effects of pollution across studies. Our approach opens up for comparative studies across e.g. developing and developed countries using the same empirical approach. A second important contribution is related to the highly detailed outcome data. Previous studies are typically restricted to examining effects on emergency room visits and inpatient records (overnight stay at hospital). Hence, they mainly capture severe health problems. As described further below, our data allows us to also examine effects on much less severe health problems captured in outpatient records, but also health problems that may not even require a health care visit at all, but still may be costly on a societal level.

Moreover, the studies listed above lack data on individual household income, which makes assessments of the contribution of air quality to child health inequality problematic. The data we use allows us to examine the effects across income and education groups, and to assess potential underlying mechanisms behind the SES-gap. We next describe three mechanisms suggested in previous work that could lead to differential effects of across SES-groups.

3 Conceptual Framework

As already noted an important contribution of this study is the possibility to examine the effects across socioeconomic groups in detail. Before we go into the details of the empirical strategy, we start with as simple description of the theoretical pathways that could be important in generating differential effects of poor air quality across socioeconomic groups. Suppose that respiratory illnesses induced by changes in air pollution are capture by the three key factors in:

$$R = f(P, A, H) \tag{1}$$

where respiratory illnesses (R) are a function of ambient air pollution, (P), parental awareness/avoidance behavior (A), and baseline child health (H). P, A, and H can be viewed as functions of parents' income and/or education. In this paper, our three primary objectives are **(i)** to provide causal estimates of the impact of poor air quality on respiratory health, dR/dP, **(ii)** to document to what extent the effects of pollution on child health differ between children in different socioeconomic groups. Recent studies find suggestive evidence that the reduced form effects of air pollution on children's health tend to be larger on children in low socioeconomic status (SES) households. i.e.,

$$\left|\frac{dR}{dP}\right|_{Low\ SES} > \left|\frac{dR}{dP}\right|_{High\ SES}$$

However, conclusive evidence on the mechanisms behind the SES-gap in the effects is still missing. So our third objective is to **(iii)** provide insights on the key underlying mechanisms. To emphasize the different channels highlighted in previous work, assume that Equation (1) can be represented by the linear approximation that allows for interaction effects between P and A, and P and H:

$$R = a_1 + a_2 P + a_3 A + a_4 H + a_5 P^2 + a_6 PA + a_7 PH \quad (2)$$

In Equation (2), respiratory illnesses are portrayed as a function of the three key factors displayed in Equation (1), and capture three mechanisms that could contribute to differences in the marginal effects of air pollution on children across socio-economic groups. First, ambient air pollution affects child respiratory illnesses negatively through an increase in P via $a_2 + a_5$, where a_5 captures potentially nonlinear effects of ambient air pollution levels on child health. Second, A can mitigate the effect of an increase in P through the negative a_6. Finally, the influences of marginal changes in pollution can also be affected by the child's health stock. Children with a higher level of H are assumed to be more resilient to effects of changes in P and hence, $a_7 < 0$.

Equation (2) suggests that children from low SES households can be more affected by changes in ambient air pollution than children from high SES households for three reasons. First, children in low-income households have on average worse health than children in high-income households. Second, parents with high education may be more aware of effects of air quality on child health. Alternatively, parents in high-income households may be more willing to reduce the risk of children's respiratory illnesses since the parental costs of child illness could be higher in terms of lost parental labor earnings. Hence avoidance behavior may be more prevalent in high SES households. Third, residential ambient air pollution levels may affect housing prices. Hence, children from poorer households more often may tend to reside closer to pollution sources, and therefore be exposed to higher levels of pollution (Currie, 2011). Empirically, if we do not observe individual exposure, only ambient pollution levels, children in poorer households may be observed to be more affected by a given increase in pollution if the relationship between air pollution and child health is nonlinear.

Below we provide evidence on the general effect, effects on children from differing socioeconomic backgrounds and also try to shed some light on the importance of the three mechanisms; (i) nonlinearities in effects of air pollution, differences in (ii) avoidance behavior and/or differences in (iii) baseline health across children in high- and low-income households.[3]

4. Data

4.1 Inversion and Pollution data

To measure inversion episodes, we exploit vertical temperature profile data from NASA's Atmospheric Infrared Sounder (AIRS).[4] In 2002, the AIRS instrument was launched onboard the NASA satellite AQUA. The primary mission of AIRS is to improve weather forecasts, and collect a wide range of weather related data twice per day (2 am and 2pm local time). AIRS produce a 3-D map of temperature and water vapors in the atmosphere.

The AIRS data is provided in three different forms. Level 1 data provides the highest resolution (1.5km*1.5km) and is not yet available to researchers outside NASA. Level 2 data (L2) has a spatial resolution of approx. 45km*45km. Level 3 data (L3), which we use, has a spatial resolution of 1°×1° which corresponds to approximately 100km*100km at the relevant latitude. The L3 data is the primary public product and contains only well-validated fields, and reported temperature and water vapor profiles globally. We use L3 data due to the easy access and its readiness for use by researchers. Downloading the L3 data for a selected region is straightforward and NASA have checked it for and corrected data irregularities.

The L3 temperature profile data provide temperatures in 22 layers, defined by average air pressure in the layer. We use the temperatures for the two pressure levels closest to the ground (1000hPa and 925hPa) to identify inversion episodes.[5] The 1000hPa layer temperature corresponds to the surface conditions and 925hPa layer measure conditions at approximately 600m above sea level. We use the temperature differences between these two layers to identify

[3] It is also possible that the extent of parental avoidance behavior depends on the level of P, i.e. that parents in high pollution areas (such as Los Angeles) are more likely to be willing to engage in (potentially costly) avoidance behavior than parents in low pollution areas (such as in our setting). Similarly, parents of children with a lower health stock may also be more willing to engage in avoidance behavior if their child is more likely to be affected by changes in pollution levels.

[4] As part of the activities of NASA's Science Mission Directorate and it is archived and distributed by the Goddard Earth Sciences (GES) Data and Information Services Centre (DISC).

[5] AIRS Level 3 version 5 with spatial box: 55S, 10W, 70N, 24E.

inversion episodes and inversion strength. During normal conditions (inversions), the temperature decreases (increases) with altitude and hence, the temperature difference between the 925hPa and 1000hPa air layer is negative (positive). In our analysis we focus on the night-time inversions since these are more frequent (25 percent of the observations) and stronger predictors of pollution concentrations. The inversion strength is defined as the temperature difference between the two layers with higher positive values corresponding to stronger inversions (see Figure A1 for an illustration).

We also use information on cloud coverage and humidity data from AIRS. Cloud coverage data is a potentially important control variable since the AIRS instruments cannot retrieve temperature profiles if the grid cell is under complete cloud coverage.[6] Humidity has been linked to both air pollution levels and health. Weather data from 119 weather stations provide information on wind and precipitation.[7]

The Swedish Environmental Research Institute, IVL, provides the pollution data. The pollution monitors collect data on either an hourly or a daily basis, and are typically located in the center of the main town of the municipality. 90 out of Sweden's 290 municipalities measured PM_{10} daily during the sampling period. We use the 24-h municipality average PM10 level as our main air quality indicator.[8] Other pollutants are measured with much lower frequency, consistency, and spatial coverage (68 stations measured NO_2, 24 SO_2, 3 NO_x and 3 CO). PM_{10} is moreover highly focused on in policy circles due to the health effects associated with particulate matter exposure.[9] We assigned the temperature profiles of the nearest temperature grid centroid to each pollution monitor (see Figure A2). We then link the inversion data to the pollution monitor data by assigning each pollution monitor to its closest AIRS grid centroid point located over land.

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[6] In our sample, on average 13.5 percent (i.e. around 4 days per month) of the AIRS observations are missing due to full cloud coverage. The share of missing temperature profile days per month: Jan (.196) Feb (.160) March (.111) April (.093) May (.095) June (.113) July (.132) Aug (.107) Sept(.119) Oct (.149) Nov (.171) Dec (.178).

[7] For each monitor we first calculated daily means and then assigned the inverse distance weighted mean of the six nearest weather stations to each vertical temperature profile grid point, replacing missing values with the monthly mean.

[8] For the minority of municipalities having more than one monitor we calculated an average daily municipality pollution level.

[9] PM is a general term used for particles where the major components are sulfate, nitrates, ammonia, sodium chloride, carbon, mineral dust and water. The particles are identified according to their aerodynamic diameter, as either PM_{10} (with a diameter of 10 micrometers or less) or $PM_{2.5}$ (with a diameter smaller than 2.5 µm). By definition, PM_{10} thereby includes both 'coarse particles' and the finer $PM_{2.5}$ particles. Sweden follows the air quality standards set by the EU-directive 2008/50/EG. For PM_{10} there are limit values for short-term (24 hours) and long-term (annually) exposure. However, the consequent inability to identify a threshold below which adverse health effects are not observed implies that any limit value may leave some residual risk when exposed to PM. This has led the World Health Organization (WHO) to recommend more stringent air quality guidelines (WHO, 2006).

4.2 Child Data

From Statistics Sweden (SCB) we acquired data on all children living in Sweden during the observation period. The individual data include information on background characteristics, such as year and month of birth, place of residence (250m by 250m grid), parents' income and education.

The individual identifiers allow us to merge the SCB data to the health care records from the Swedish National Board of Health and Welfare (Socialstyrelsen). We acquired inpatient and outpatient data covering all children living in Sweden in the age span of 0-18 years.[10] The inpatient data contains information on all visits to the health care providers that result in an overnight stay at hospitals. The outpatient data cover health care visits when the patient does not stay overnight. Both data sources include information on the exact date of admission, type of diagnosis and municipality of residence. Socialstyrelsen provided aggregated diagnoses codes (based on ICD codes) using the Clinical Classification Software (CCS) developed by the Agency for Healthcare Research and Quality (AHRQ). We calculated a daily incidence rate of health care visits with respiratory illness as the main diagnosis. The rate is constructed by dividing the total daily number of health care visits in each municipality by the total number of children who resides in the municipality, multiplied by 10,000. This rate is our main outcome variable, and is referred to as respiratory illness rate henceforth. In the analysis we also consider the impact on respiratory sub-diagnoses (e.g. asthma, bronchitis), constructed in a similar fashion. Using the municipality of residence we link the health data to the inversion and pollution data.

4.3 Summary statistics: Health, Weather and Pollution

Table A2 provides summary statistics on the municipality level of the inversion, weather, health and pollution variables. Panel A shows information on the rate of health care visits broken down by age and cause of visit. Respiratory illness admissions decreases with age, and asthma related admissions are the most common sub-diagnosis. Around 10 percent of children in Sweden are ever diagnosed with asthma. Panel B provide descriptive statistics for the key covariates used in our analysis. The average PM10 level is 21 $\mu g/m^3$ in our sample and inversion episodes occur on

[10] Young children are among the most susceptible to effects of air pollution (ALA, 2001; Kim et al., 2004). Compared to adults, children have higher breathing rates and therefore a higher intake of air pollutants per unit of body weight. Since children's lungs and immune system are not fully developed, exposure to air pollution opens up for the possibility of different responses than seen in adults. Furthermore, they also spend more time outdoors than adults when concentrations from air pollution are generally higher, thereby adding to their potential exposure. Since as much as 80 percent of alveoli are formed postnatally and the lung continues to develop throughout adolescence, exposure to air pollutants poses a serious risk to this population group (Schwartz, 2004).

25 percent of the days. The average temperature differences between the two air layers is -1.35°C (i.e. temperature decrease with altitude). For the 90 municipalities measuring PM_{10} during our observation period (September 2002 to September 2007), there are 34,175 valid vertical temperature profiles (non-missing temperature readings in both layers). Out of these, 8,608 night-time inversions were identified.

Descriptive statistics for the key variables conditional on inversion status are provided in Table 1. On average, the PM10 level is around 60 percent higher and the respiratory illness rate is about 5 percent higher during inversions. However, inversions are most frequent during the first (55 percent) and second (24 percent) quarter of the year. For the third and fourth quarter, the corresponding frequencies are 6 percent and 15 percent, respectively. Hence, the raw averages do not solely reflect the influence of inversions on pollution and respiratory illness, but also the seasonality in inversions, pollution and respiratory health.

Figure A3 provides average PM_{10} levels by calendar month and inversion status. PM_{10} levels are highest in the spring. The seasonal pattern is partly caused by residential and commercial heating, but road wear caused by the use of studded tires during March and April (typically snow free months) also contribute. Following inversions PM_{10} levels are substantially higher during nearly all months of the year. Figure A4 show the correlation between inversions and PM_{10} across the days of the week.

Since not only pollution but also unobserved factors that affect respiratory health problems (e.g. time spent outdoors) may vary with the day of the week/season of the year, the descriptive above highlight the importance of flexibly accounting for season of the year, day of week, and weather conditions in the empirical analysis.

5 Empirical specification

We assess the impact of inversions on air quality using the following baseline specification estimated on municipality-day level data:

$$\mathrm{Pollution}_{\mathrm{md}} = \gamma_0 + \gamma_1 \mathrm{INVERSION}_{\mathrm{md}} + \delta' \mathrm{w}_{\mathrm{md}} + \mu_{\mathrm{d}} + \theta_{\mathrm{m}} + \vartheta_{\mathrm{md}} \qquad (3)$$

Where pollution is one of the measured pollutants (PM_{10}, NO_2, NO_X, CO, SO_2) in municipality m, on day d. $\mathrm{INVERSION}_{\mathrm{md}}$ is a binary dummy variables taking the value 1 if the temperature differences between the air layers is positive (i.e. temperature increases with altitude).

Our baseline specification for the health outcomes is,

$$\text{Respiratory Illness Rate}_{\text{md}} = \beta_0 + \beta_1 \text{INVERSION}_{\text{md}} + \delta' \text{w}_{\text{md}} + \mu_{\text{d}} + \theta_{\text{m}} + \varepsilon_{\text{md}} \quad (4)$$

where the Respiratory Illness Rate_{md}, as specified above, is our primary outcome variable. In equation (2) and equation (3), w_{md} is a vector of weather controls, including precipitation, wind, humidity, cloud cover, and their squared counterparts, together with daily and nightly temperature polynomials to account for a potential nonlinear relationship between temperature, pollution levels, and the respiratory illnesses rate, and δ is the corresponding parameter vector. μ_{d} is year-by-month specific effects and day-of-week effects that non-parametrically take year-by-calendar month and weekday variations in pollution/respiratory health into account. θ_{m} are municipality-specific effects, which are accounts for time-invariant differences between municipalities that affect pollution concentrations and respiratory illnesses (e.g. demographic characteristics, industry composition, geographic conditions, etc.). We also include time-varying variables such as the average age of the children in the municipality and the share of mothers with college degrees as additional controls. In all estimations we cluster the standard errors at the municipality level, to account for arbitrary correlated errors within the municipality across time.

We also provide estimates using a generalized additive model (Hastie and Tibshirani, 1986):

$$\text{Y}_{\text{md}} = \beta_0 + \text{f}_1(\text{Inversion Strength}_{\text{md}}) + \text{f}_2(\mathbf{w}_{\text{md}}) + \varepsilon_{\text{md}} \,. \quad (5)$$

Where Y_{md} is the PM10 level or the Respiratory illness rate, and $\mathbf{w}_{\text{md}}$ is a vector of weather and calendar month controls. $\text{f}_i(.)$ is estimated (by backfitting) using local linear regression smoother with a narrow bandwidth. The estimates from this parsimonious but highly flexible specification, that non-parametrically takes daily weather conditions and seasonal patterns into account, provides evidence on whether the baseline linear specification of equation (3) and (4) provides a reasonable approximation of the relationship between inversions, pollution and health.

6. Results

6.1 Main Results

We first present results from the nonparametric specification of Equation 5. Figure 1 provides separate GAM estimates of how inversion affect the PM10 level (grey line) and respiratory illness rate (black line) using a narrow bandwidth local linear regression smoother. The abscissa displays the inversion strength, i.e. the temperature difference between the two air layers. A negative inversion strength value corresponds to non-inversion days and positive values inversion days. The kernel density estimate (dashed) shows the distribution of observations with respect to inversion strength. Around 25 percent of the days in the sample are inversion days. The left(right)-hand side *y*-axis measures the PM_{10} level (the respiratory illness rate).

Figure 1 shows that, conditional on weather conditions and season of the year, neither PM_{10} or respiratory illness are strongly related to the differences between the two air layers during non-inversion days (i.e. when inversion strength is negative). However, during inversions (i.e. inversion strength is positive) both PM_{10} levels and respiratory illness increases almost linearly with the strength of the inversion. This first set of results summarizes the main results of the paper. As shown below, even after adding a large set of additional controls, the estimated effects never deviate substantially from that which can be inferred from this parsimonious, but highly flexible specification.

Table 2 provides the estimates of the effects of inversion on pollution using our baseline specification. Clearly, conditional on wide range of weather conditions, municipality and time effects, inversion are strongly linked to worse air quality. On average, inversions leads to 36 percent higher PM_{10}, 27 percent higher NO_2, 16 percent higher $NO_{x,}$ 23 percent higher SO_2, and 12 percent higher CO levels.

Table 3 provides the effects on respiratory illness in the full sample using equation (4). Column (1) shows that inversion increases the respiratory illness rate among children aged 0-18 by 4.9 percent. Columns (2) and (3) add child age and maternal education controls, respectively. Adding these controls do not change the estimated effect. Column (4) drops the local weather station control variables (wind and precipitation). This does not change the results, highlighting that a similar analysis could be conducted even when local weather station data is not available. Finally, column (5) restricts the sample to children residing within 2 km of a pollution monitor. This effectively limits the sample to children living in urban areas close to the main city center of the municipality, since this is where the pollution monitors are located. This restriction homogenizes the sample, but hardly change the estimated impact at all.

6.2 Some Additional Specification Checks

The baseline model provide estimates of the contemporaneous effects of changes in air quality on respiratory illnesses. A potential concern with this daily specification is that inversion episodes simply may displace the timing of respiratory illnesses forward. Such a short-term forward shift in the timing of health effects would imply that while we may see an increase in health effects on inversion days, while the respiratory illness rate may fall and be fully compensated for over the following days. To assess this concern, we follow Schlenker and Walker (2011) and provide estimates from a distributed lag model that check how current and lagged inversion episodes over the past five days affect the current respiratory illnesses rate. If inversions simply displace the timing of a health care visit then we would expect to find that the cumulative effect is *smaller* than the effect of current inversions only (i.e. $\sum_{k=0}^{5} \beta_{t-k}^{full} < \beta_0^{baseline}$).

Table A3 in Appendix A report the estimates from the distributed lag model. Column (1) reiterate the baseline model estimates for comparison, column (2) report the lagged effects and the total cumulative effect of inversion over the last five days and today. Column (3) report the estimate when regressing the respiratory illness rate on day *t* on the share of days with inversion over the past five days. Both the cumulative impact and the average impact from inversions over the past five days are *larger* than the baseline effects. These results highlights first of all that displacement effects are not likely a major concern in our setting. Second, both day *t* and *t-1* inversions significantly affect day *t* respiratory illness rates; while the other lagged coefficients are smaller and insignificant. This suggests that inversions today and yesterday affect current respiratory illness rates. For simplicity, in the remainder of the analysis we stick to the more parsimonious baseline (contemporaneous effect) specification.

Our estimates may also be compromised if emissions are an important determinant of air temperature and thereby inversions. However, first, it seems unlikely that local anthropogenic emissions have a strongly differential impact on temperature in the two layers. Second even if so, our estimates would likely be downward biased since local emissions likely primarily heat the ground level air layer, *reducing* the occurrence of inversion. Third, we provide a test of the severity of this concern by exploiting the well-known variation pollution levels over the weekdays. In the final two columns of Table A3 we exploit the sharp decreases in pollution levels on weekends (column 4), and show that inversions are not more or less frequent during weekends (column 5) despite the sharp drop in pollution levels during weekends. This exercise provides evidence that pollution levels do not cause inversions.

6.3 Heterogeneity: by respiratory diagnosis and child age

So far, all respiratory illnesses have been lumped together, but it is possible that the effect of air pollution varies across type of illness. In Table A4, columns (2) to (5), we split the respiratory illness diagnosis data into Asthma, Pneumonia, Bronchitis, and Other respiratory conditions. The first three conditions are likely to be exacerbated from current exposure as opposed to conditions such as Emphysema where the effect of exposure is mainly cumulative over a longer time. Therefore, we expect to find the largest effects for the first three conditions. This pattern is also largely confirmed, with the largest effect for Asthma, Bronchitis and Pneumonia, (6 percent), and substantially lower but still significant for the other respiratory conditions (3 percent).

Columns (6) and (7) provide separate estimates for pre-school children (0-6) and school age children (7-18). Note that the mean respiratory illness rate is higher for children in the age span 0-6 years. The estimates are positive and significant for both age groups, but relative to the mean respiratory illness, the largest increase of respiratory related hospital admissions occur for the older age group.

6.4 Examining the Effects across Socioeconomic Groups

Table 4 report estimates by socio-economic status. The table presents separate estimates for children in high-, medium-, and low-income households. We also report separate estimates for the children who have/do not have a mother with at least some post-high school education. Before turning to the impact of inversion, note that the mean respiratory illness rate is marginally higher in the high education group compared to the low education group, but substantially higher in the low-income group compared to the high income group. These mean differences highlights that SES differences in respiratory health are present in Sweden, at least with respect to parental income.

Column (1) reports the baseline model estimates in the sample of children for whom we observer maternal education. Interestingly, we do not find any differences in the effects between children in low and high education households (columns 2 and 3). However, the estimated impact monotonically decreases with parental income. Relative to the respective mean respiratory illness rate in the groups, the effects of inversion on children in low income households are about 50 percent larger than in medium income households and around 70 percent larger than on children in high income households. These results clearly suggest that parental income play an important role in mediating the effects of air quality on children's health. Figure 2 summarizes the results in Table 4.

Figure 3 summarizes the results of appendix Table A5, and shows the point estimates for the low-, medium-, and high-income group by child age. The difference in the effects of inversions across income groups seems to widen with child age. Relative to the mean respiratory illness rate, the effects increases from around 5.6 (4.0) to 8.3 (8.9) percent in low (medium) income households for preschool and school age children respectively. For high-income households the point estimates hardly change at all with child's age (3.47 to 3.56 percent). However, note that the estimates are not statistically distinguishable from each other.

In summary, the impact of inversions on respiratory illness decreases with parental income and poor air quality also seem to contribute to the widening of income-child health gradient with child age. The absence of differential effects with respect to maternal education contrasts with Currie and Stabile (2002) who find an increasing gradient for both income and education in Canada. However, it is consistent with Case et al. (2002) who find an increasing gradient over the child's life cycle with respect to households income, but not parental education.

6.5 The underlying mechanisms behind the SES-differences

The clear differences in the effects with respect to education and income provides some clues about the likely potential reasons behind the gap in effects across income groups. In particular, to the extent that highly educated parents are more informed about risk factors or are better at processing such information, the absence of differential effects with respect to maternal education suggests that information differences across households is not a key factor. Below we discuss and provide further evidence for the potentially important underlying mechanisms highlighted above.

(i) Differential Effects of Inversions in High and Low Income Neighborhoods

An important difference between rich and poor households could be that residential segregation leads to differences in average levels of pollution exposure. Hence, a potentially important mechanism behind the SES-gap could be that children from poorer households are exposed to higher pollution levels than children from wealthier households.

Such residential sorting could imply that the observed SES differences stems from nonlinearities. If a higher share of the poor children lives in neighborhoods where the pollution level is close to a threshold after which the relationship between pollution and respiratory illnesses steepens, then the reduced form effects of inversions could have a stronger effect on poor than rich kids. However, this explanation squares poorly with the results from the non-parametric estimates in Figure 1 that give no indication of strong nonlinearities.

Alternatively, it is possible that inversions have differential impact on pollution levels in rich and poor neighborhoods. If so, even in the absence of nonlinearities, inversions could yield larger effects on poor than rich kids. To assess this mechanism directly one would ideally like to have access to residential location specific pollution monitors. With such data we could test whether inversions generates similar or differential increases in pollution levels across rich and poor neighborhoods. We do not have access to such data, however we do get some insights about the potential role of differential changes in pollution levels experienced by low and high income children by comparing the column (3) and (5) in Table 3 above. The pollution monitors are located in the center of the municipalities, while the children in the estimation sample used in column (3) lives anywhere in the municipality. Hence, if inversions have dramatically different effects on pollution levels in the center of the urban areas (where the monitors are located and pollution levels can be expected to be highest) than in other areas we would also expect to see sharp differences in the estimated impact in the full sample (col. 3) and estimate on the children living within 2km of the pollution monitor. However, the estimates are virtually identical. We also estimated separate models for children living less/more than 500m from a freeway. If children living close to this major sources of pollution where sharply differentially affected by inversions than children living further from freeways, it could suggest that inversions influences pollution more in areas with high levels of pollution. However, again the estimated impacts of inversions on children in these two groups were almost identical.[11]

We interpret these results as unsupportive of the hypotheses that the SES-differences are driven by nonlinearities or by strongly differential effects of inversions on pollution levels in rich and poor neighborhoods.

(ii) Avoidance Behavior

However, SES differences in exposure could emerge for other reasons than residential sorting. Previous studies from high pollution settings have suggested that so called avoidance behavior may affect estimates of air pollution on health (Neidell, 2003; Moretti and Neidell, 2011). If individuals observe inversions and change their behavior in order to minimize exposure, our baseline estimates will likely understate the effects of poor air quality. Moreover, information differences about inversions across high and low SES households could potentially explain the observed differences in the impact of inversions across SES-groups.

Our prior is that the general public is not perfectly informed about inversions, and is not able to predict inversions or how inversions affect pollution levels. Neither information on inversion, nor inversion strength, are published in Swedish media or by local authorities. Vertical temperature profiles are not available on a large scale, nor is the data from the four Swedish ground level sounders.[12]

Ideally, we would like to test avoidance behavior using individual child pollution monitors. Since we do not have access to such data, to assess the potential role of avoidance behavior, we first test whether inversions influence pollution predictions. Daily pollution predictions are only available in the Stockholm region. SLB, which produce the pollution predictions, provided us with their PM10 predictions during the observation period. The predictions for day (d) are produced in the afternoon the day before (d-1), and are distributed to local media, and published on SLBs webpage. The predictions are mainly based on current (day d-1) pollution levels, but also weather predictions and other observable factors (including e.g. road surface conditions etc.). However, no direct measure or prediction of inversion episodes is

[11] Results are not reported here but are available upon request.
[12] Access to SMHI's and the Swedish military's in weather balloon stations that measure vertical temperature profiles on a daily basis is under way according to SMHI but is not available at present (2013-11-04) .

used in the analysis.[13] SLB report the expected PM10 level for the following day as Low, Moderate, Pretty High, and High.

Table A6 show that conditional on previous day pollution levels, which is the main predictor of pollution levels for the following day, and other weather conditions, inversions have no significant effect on the pollution prediction. This suggests that publicly provided pollution forecasts is not likely to generate differences in avoidance behavior across SES-groups.

Yet, even though professional forecasters do not seem take inversions into account, likely due to lack of data, it is possible that sensitive populations may have strong enough incentives to gather private information on inversion episodes since it is a strong predictor of air quality. In some heavily polluted areas around the world, inversions can sometimes be observed with the naked eye. In Sweden, this is generally not the case due to relatively low pollution levels and low humidity. Moreover, recall that we examine the effects of nighttime inversion. Even if individuals do understand the meteorological relationship in general, it seems unlikely that they are able to correctly identify inversion episodes and inversion strength at 2 am. We therefore believe that the risk of (SES-differences) in inversion observance is minimized.

However, we also try to test this assumption indirectly. Any test of the extent and prevalence of avoidance behavior relies on proxies (Graff-Zevin and Neidell, 2013). Previous studies have used visits to outdoor facilities (e.g the zoo or sport event) (Neidell, 2009; Moretti and Neidell, 2011) to proxy for avoidance behavior. We make use of child injury data. The idea is that if inversions are associated with substantial changes not only in pollution levels but also in e.g. children's (outdoor/indoor) activity patterns, we may detect that the share of injuries occurring indoors also change. To test this we first use the Injury Database, that include detailed information on all health care visits related to externally caused injuries over the observation period in nine regional hospitals.[14] The National Board of Health and Welfare provided us with counts of injuries due to external causes by location at the time of injury (indoors/outdoors) and the date of injury. Using these data we created a hospital-day of injury dataset to which we linked the weather and inversion data by geocoding the locations of the hospitals.

Table A7 provide estimates of the baseline model using the share of indoor injuries as the outcome variable, replacing the municipality fixed effects with hospital fixed effects. The table

[13] Personal communication with Michael Norman at SLB-analys, who provides the pollution prognosis for Stockholm, September 6 2013.
[14] Arvika sjukhus, Bollnäs sjukhus, Hudiksvalls sjukhus, Karlstads sjukhus, Ljusdals sjukhus, Norrlands (Umeå) Universitetssjukhus, Skaraborgs sjukhus, Söderhamns sjukhus, and Torsby sjukhus.

shows that the share of injuries occurring indoors are not significantly influenced by inversions in the full sample (children aged 0-18), the preschool, or school kids sample. However, note that rain and wind that are strong predictors of the share of injuries occurring indoors. Since we expect that these weather conditions should increase time spent indoors, this supports the validity of the share of injuries occurring indoors as a measure of indoor activities.

With our full sample health care data we can also construct health care visit rate for injuries due to external causes. With this much larger but less detailed data on injuries we can assess whether externally caused injuries changes with inversion episodes, and whether the effects differ by family income. Table A8 provides the results from the main specification (Equation 4) for the full sample, and the low, medium, and high parental income groups respectively. There are no significant effects of inversions on the rate of injuries due to external causes. For the highest income group the point estimate is slightly larger than for the other groups, but none of the estimated coefficients are statistically distinguishable from each other or from zero.

In summary, pollution forecasters do not take inversion into account, and inversions do not seem to affect children's time spent indoors. Jointly these findings suggest that inversions shift pollution levels, but parental responses are held fixed. Hence, avoidance behavior is not likely to be a major contributor to the observed differences in the impact of inversions on respiratory health in our setting. These results also provide support for the validity of our research design, since health conditions (injuries with external causes) that we do not expect to be directly affected by poor air quality are shown not to be significantly affected by inversions.

(iii) Differences in Health

A final potentially important mechanism that we are able to assess using the data at hand is the role of differences in baseline health. Children from poorer backgrounds have worse health in general (Currie et al., 2010). If children with poorer health are more susceptible to pollution shocks, the SES gap in the effects of pollution could in part be explained by differences in children's baseline health across rich and poor households.

To assess the relevance of the hypothesis we make use of data on health at birth. Neonatal health data is useful since it is a strong predictor of subsequent health in childhood and beyond, but also because this measure has been collected in a similar manner for all cohorts and is available for virtually all children in our sample. Specifically, we construct an index of initial health using the first principal component of gestational week at birth and birth weight. The children are then split into a good and poor health status group if they are above or below the median of the initial health index.

Table A9 provide the baseline specification results for the full sample of children for whom we observe health at birth (column 1), and after splitting the sample into children with "good" and "poor" health in columns (2) and (3). Relative to the mean respiratory illness rate, which is much higher in the low income group than in the high income group, the estimates impact of inversions are around 30 percent larger on children in poor health than on those in good health. Columns 4 through 9 show estimates after splitting the sample further by income of the parents. Columns 3 through 6 show that for children with *good* health, the impact of inversions on respiratory health are much larger for those with low (6.4 percent) and medium (5.5 percent) income than for those with high income parents (1.3 percent). The final columns in Table A9 show that this huge income gap in the effects decreases substantially if comparing children with *poor* health, for whom the estimated impact across income groups are virtually identical (6.4, 5.8, and 6.0 percent respectively). Figure 4 provides the results of Table A9 graphically.

Two things stand out from this analysis. First, children in poor health are similarly affected by inversions *irrespective* of their parents' income. Poor children are much more likely to be born low-birth weight and prematurely than children in high income households, and the mean respiratory illness is around 40 percent lower among high income compared to the low income children. Hence, differences in *baseline health conditions* across the income groups may play an important role in explaining the *average* SES-differences of inversion on respiratory health. A second interesting pattern, as also reflected in Figure 3, is that the main differences in our setting seems to be between high income groups and the two other income groups. These results suggest that environmental policies may benefit not only health among the poorest but also significantly improve respiratory health in the middle class and among children in high income households with poor baseline health. Children in good health in high-income households are not significantly affected by air quality changes following inversions.

Summary of the results for the underlying mechanisms

In summary, out of the mechanisms suggested to explain differential effects of ambient air quality on children's health, differences in initial health across households with differing economic conditions seems to be key in explaining the differential impact of air quality on respiratory illnesses. Our results have little to say about the mechanism leading to worse baseline health. It is possible that high levels of pollution cause lower birth weight and shorter gestation, which we use to build our health index. Our results do suggest that the poor air quality during the child's life cycle seems to exacerbate health differences associated with worse neonatal health. Moreover, it is important to keep in mind the low pollution setting. In high pollution settings with strong information differences across SES groups, avoidance behavior likely plays a more important role in generating differences in the effects of air pollution across SES groups.

Finally, an additional mechanism could be that parents with more resources may have greater opportunities for, or receive higher returns (e.g. by reducing the lost income due to work absence during children's illness spells) from, medical defensive investments. A higher level of defensive investments may reduce the need for visits to health care facilities in connection with high pollution days. If so, this could also contribute to parts of the SES-gap in the effect on health care visits. There is little evidence of the importance of defensive investments with respect to air quality, but Deschenes et al. (2012) document that when ozone levels decrease, so does medication expenditure in the US. To our knowledge, there are no studies examining whether defensive investments related to respiratory illnesses differ (for children) across SES-groups.

Difference in defensive medical investments is difficult to completely rule out as an additional explanatory factor, given the lack of data on daily medical consumption. However, in Sweden all children have health insurance, and during the observation period medical expenses of children (under age 18) are all fully subsidized if the sum of expenses of *all* children in the same family exceeds SEK 2200 (USD 320) for 12 months after the date when the threshold is exceeded. Health care visits are free of charge for children under age 19. Hence in our setting, while possible, it seems less likely that differences in defensive investments constitute a major contributing factor to the SES gap in the effects of air quality on health. Future studies with access to data on daily medical consumption and parental income, may be able to assess this additional mechanism directly.

6.6 Additional results: The Effects on Parents Labor Supply

This section provides evidence on the impact on parental labor supply using data from the Swedish National Insurance Board on benefit compensation for labor income lost due to care of sick children. With this data we constructed indicators for whether a child was home due to illness and in the care of a parent. Parents are eligible for benefits for taking care of a sick child aged less than 12 years, and may claim benefit compensation for up to 120 days per year. The replacement rate is 80 percent of lost earnings, up to monthly wage celling of SEK 37,000 (~ USD 5,000 during the sample period). The benefit compensation data contain information in the start and end date of a *parental* work absence spell for each specific child and the benefits the parent received for that spell. Most parental work absence spells due to care of a sick child are short (1-2 days).

Using this data we constructed a *child* sick spells. Since mothers (fathers) on average take out regular parental leave for 13.5 (3.5) months during the first two years, we restrict the sample to children aged between 2 and 11 years old. Spells that end on a Friday and continue on the following Monday are treated as a single spell, since parents only are eligible to compensation for lost work time. Since many parents alternate staying home (mothers take out approx. 64 percent of the days), the average child spell length is 2.9 days, and 95 percent are shorter than eight days.

We construct three municipality-day outcome variables using the child sick spell data. The number of child sick spells that started on a specific date divided by the number of children in the municipality (comparable to the respiratory illness rate), the average duration of the spells that started on a specific date, and the total benefits the parents received for a spell starting on a specific date.

Table 5 provides the estimated impact of inversion on these outcomes. Column (1) show that the sick-child incidence rate increases by 2.9 percent following inversions. Column (2) that the total municipality spell length increased by 2.4 percent. Inversions also increase the total benefit compensation by 2.5 percent. Each year around 5 million workdays are lost due to care of sick children, and the direct costs of child sickness from parental leave compensations amounts to around SEK 4 billion yearly (~USD 550 million). Moreover, women take care of the sick child for nearly two out of three days. To the extent that parental leave due to care of sick children influences career opportunities and/or wage-earnings profiles, poor air quality may affect labor supply of parents via its impact on children's health, and potentially also inequality in the labor market. Of course, the care of sick child data is also interesting as a complement to the health care records, since it is captures health conditions that not necessarily lead to health care visits.

7 Conclusions

Few studies have been able to directly assess the impact of air pollution across income groups. We examine the effects of air quality across SES groups in a low pollution setting with universal health insurance, heavily subsidized health care and medicine expenses for children. Yet, we find stark differences in the impact of poor air quality. We find that inversions sharply decreases air quality and increases health care visits due to respiratory illnesses. The impact of inversions is around 40 percent lower on children in high-income families than on low income families, and we also find suggestive evidence that the income-child gap in the effects increases with child age.

Importantly we also examine potential mediating mechanisms behind the SES gap. We show that among children with poor baseline health, higher parental income does not seem to be able to cushion the impact of poor air quality. Hence, since children in lower income households have higher baseline level of health problems, one important mechanism behind the differences in the effects of poor air quality across income groups seem to be that children in low income households are more vulnerable due to an on average already lower health stock. Since pollution exposure early in life has also been shown to influence long-term outcomes (cognitive ability, educational attainments, earnings, crime) (Nilsson, 2009; Sanders, 2012; Grönqvist, Nilsson, and Robling, 2014; Isen et al, 2014), it seems that environmental policies could also play an important role in reducing inequalities in economic outcomes. More research on long term effects of early life air pollution exposure and the interaction with parental income is of clear policy interest.

NASA provides the inversion data on a daily and global scale, and is easy to access and download. The empirical approach we develop opens up the opportunity for comparative studies across e.g. developed and developing countries using the same empirical strategy. Moreover, despite the strong predictive power of inversion on pollution, we show that inversions have no predictive power on pollution forecast. This suggests that the forecasters in our setting do not take inversion into account when predicting pollution levels for the following day, potentially due to the lack of reliable inversion data. Hence, forecasters may potentially be able to produced more precise pollution forecasts by exploiting the NASA inversion data, and which if effectively disseminated may decrease the health costs associated with poor air quality at a low cost by allowing sensitive population to more efficiently engage in defensive medical investments.

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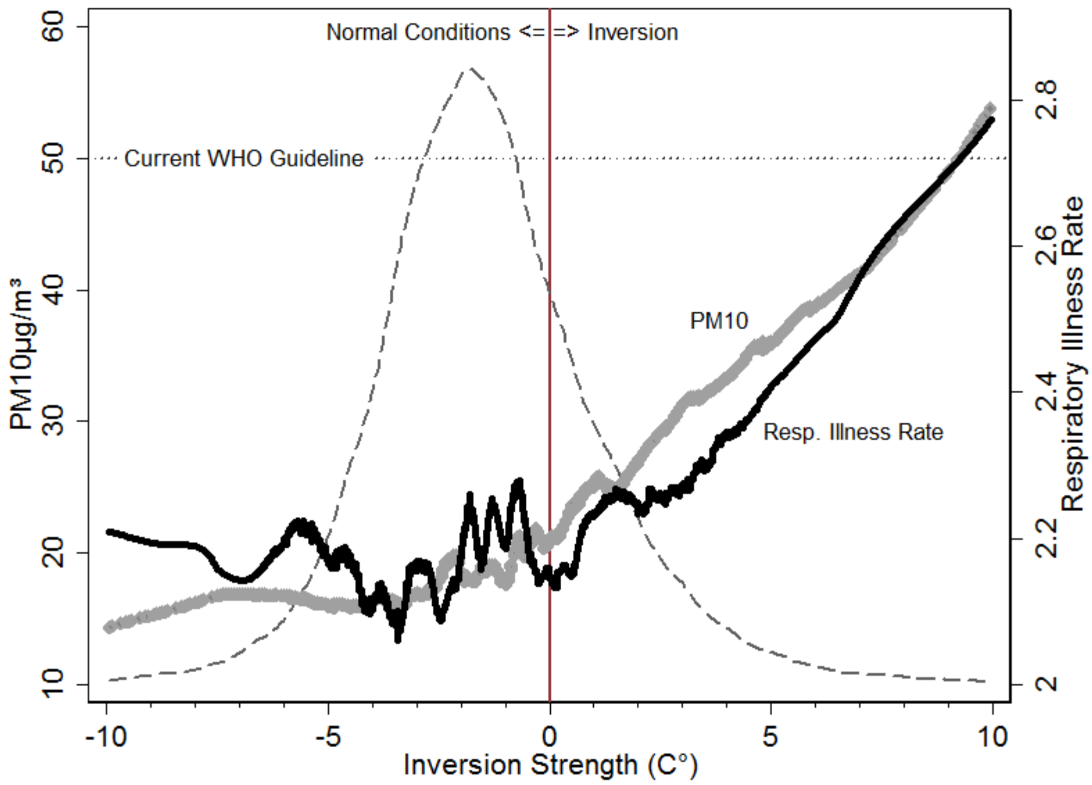

Figure 1: The Effects of Inversions on Pollution and the Respiratory Illness Rate

Note: Generalized additive model estimates (equation (5)) of respiratory health care visits per 10,000 children (black) and PM10 level (gray) on inversion strength using a local linear smoother (bandwidth 0.07 for PM10 and 0.1 for respiratory illness rate), controlling for calendar month and an extensive set of weather variables (see the text for details). Kernel density estimate of distribution of observation wrt inversion strength (dashed), and current WHO 24-h PM10 μg/m^3 guideline for reference (dotted).

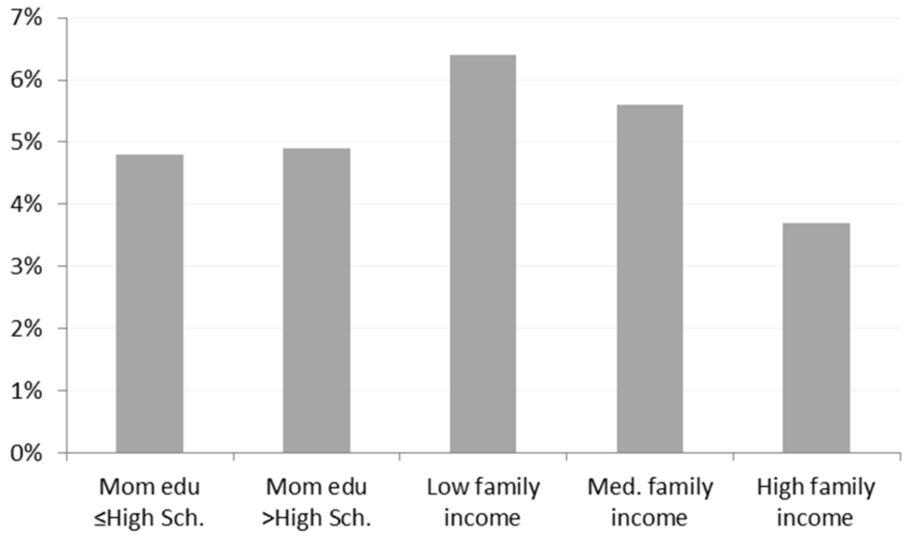

Figure 2: The Estimated Impact of Inversions by Parental Income and Education

Note: the figure shows the estimated impact relative to the mean respiratory Illness by parental income group and maternal education. See text and table 6 for details and full results.

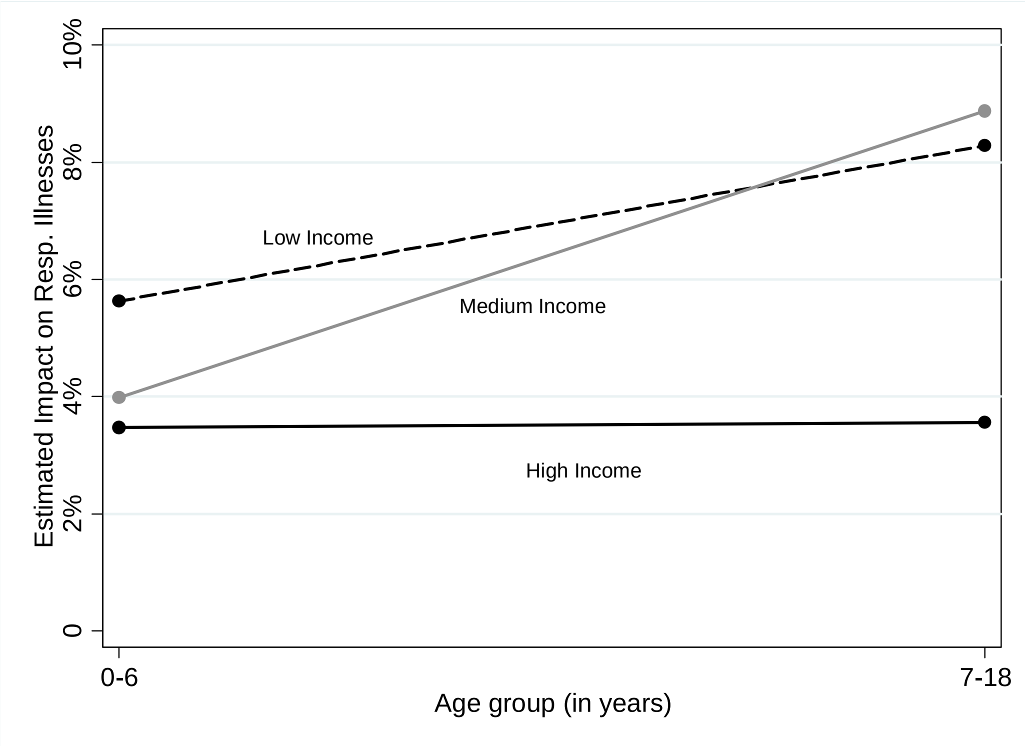

Figure 3: Effects of Inversions by Parental Income and Child Age

Note: The Figure shows the point estimated effects by child age groups and parental income. See Appendix Table A3 for full results

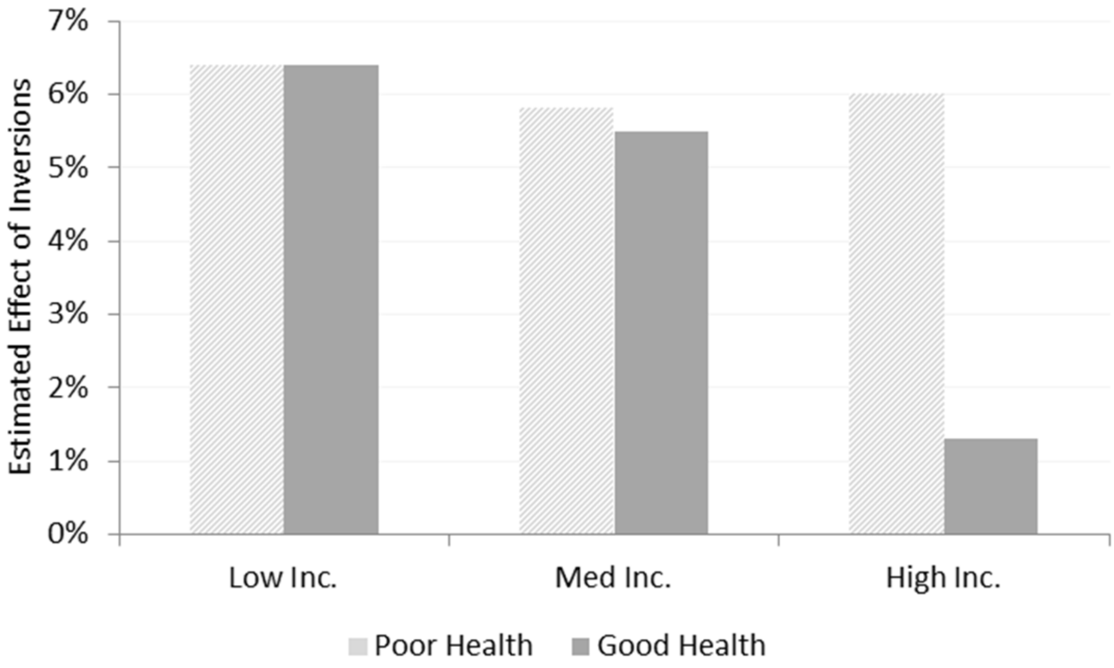

Figure 4: The Estimated Impact of Inversions by Income and Health
Note: the figure shows the estimated impact relative to the mean respiratory Illness by parental income group and child health status. See text and table 9 for details and full results.

Table 1: *Descriptive statistics for key variables by inversion status*

Normal Days *N*=25,567	Mean	Standard Deviation
Rate of health care visits per 10,000 children:		
Any respiratory illness	2.14	2.51
PM_{10} (μm/m^3)	18.06	13.09
Temperature (˚Kelvin) *Daytime (ground level)*	277.80	8.90
Temperature (˚Kelvin) *Nighttime (ground level)*	276.06	7.48
Precipitation (mm) *(N=24,862)*	0.63	1.24
Wind speed (m/s) *(N=24,862)*	3.48	1.79
Daily Cloud cover ratio	0.47	0.27
Nightly Cloud cover ratio	0.49	0.26
Inversion Days *N*=8,608		
Rate of health care visits per 10,000 children:		
Any respiratory illness	2.24	2.68
PM_{10} (μm/m^3)	28.82	25.08
Temperature (˚Kelvin) *Daytime (ground level)*	276.87	10.40
Temperature (˚Kelvin) *Nighttime (ground level)*	272.01	8.68
Precipitation (mm) *(N=8,217)*	0.15	0.59
Windspeed (m/s) *(N=8,217)*	2.61	1.46
Daily Cloud cover ratio	0.33	0.27
Nightly Cloud cover ratio	0.32	0.26

Notes:

Table 2: The Effects of Inversions on Air Quality

	(1)	(2)	(3)	(4)	(5)
Air Quality Measure:	PM10	NO2	NOx	SO2	CO
Inversion	8.129***	4.351***	11.63**	0.528***	0.0607**
	(0.881)	(0.577)	(1.533)	(0.158)	(0.0116)
Muncipality Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year by Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day of Week Fixed Effects	Yes	Yes	Yes	Yes	Yes
Daily Weather Controls	Yes	Yes	Yes	Yes	Yes
Observations	39,781	40,234	12,514	15,749	7,930
R-squared	0.308	0.379	0.148	0.239	0.176
Number of Municipalities	90	68	3	24	3
Mean Pollution Level	22.38	22.57	72.17	2.580	0.499
% Effect	36%	27%	16%	23%	12%

Notes: The table show estimates of inversion episodes on 24-h pollution levels using equation (3). ***/** denotes statistical significance at the 1%/5% level respectively. Standard errors are clustered at the municipality level.

Table 3: Effects of Inversions on the Respiratory Illnesses Rate

	(1)	(2)	(3)	(4)	(5)
Specification:	Baseline specification:	Baseline specification: + age	Full Baseline Specification: + age + maternal education	Full Baseline specification: without weather station data	Full Baseline Specification: Residence within 2km of a pollution monitor
Inversion	0.106***	0.107***	0.107***	0.107***	0.104***
	(0.0276)	(0.0275)	(0.0274)	(0.0254)	(0.0281)
Other Controls	No	Yes	Yes	Yes	Yes
SMHI weather	Yes	Yes	Yes	No	Yes
NASA weather	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year by Month FE	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes
Mean dep. var.	2.164	2.164	2.164	2.164	2.215
Observations	34,156	34,156	34,156	34,156	34,156
# of cluster	90	90	90	90	90
% Effect	4.9%	4.9%	4.9%	4.9%	4.7%

Notes: The table show the effects of inversion on the respiratory illness rate using equation (4). Column (1) controls for weather conditions (from SMHI), year-by-month, day of week, and municipality fixed effects. Column (2) adds the average age of children in the municipality-year as a control. Column (3) adds average maternal education in the municipality as a control variable. Column (4) drops the local weather station data from SMHI, showing that this is not crucial and the analysis can be implemented using only the NASA weather data. Column (5) drop all children residing more than 2km from the pollution monitors. This effectively restricts the sample to children living in urban areas close to the major city in the municipality. The percent effect is (Inversion coefficient)/(mean of dependent variable) ***/** denotes statistical significance at the 1%/5% level respectively. Standard errors are clustered at the municipality level

Table 4: Effects across SES-groups

Outcome Variable:	Respiratory related health care admissions per 10,000 children					
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline specification for the sample where mothers' education data are observed	Mother's Education ≤ High School	Mother's Education > High School	Low income families	Medium income families	High income families
Inversion	0.108***	0.108***	0.107***	0.185***	0.133**	0.0596
	(0.0287)	(0.0326)	(0.0293)	(0.0230)	(0.0539)	(0.0436)
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year by Month Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week Effects	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,156	34,156	34,156	34,156	34,156	34,156
# of cluster	90	90	90	90	90	90
Mean resp. illness	2.235	2.266	2.186	2.895	2.358	1.621
% Effect	4.8	4.8	4.9	6.4	5.6	3.7

Notes:) ***/** denotes statistical significance at the 1% /5% level respectively. Standard errors are clustered at the municipality level. Column (1) reiterate the baseline specification results for the sample for whom we observed parental income and maternal education. Column (2) reports estimates after splitting the sample into those with mothers with less than or equal to high school education. Column (3) report estimates for those with mothers with more than high school education. Column (3 to 5) split the data by total parental yearly income divided into tertiles. The percent effect is (Inversion coefficient)/(mean of dependent variable

Table 5: Effects on Parents Labor Supply

	(1)	(2)	(3)
Dependent Variable:	Child Sick Spell Incidence Rate (per 10,000 Children)	Summed duration of Spells starting on Day *t*	Average Compensation for Taking Care for Sick Children (SEK x 10000)
Inversion	1.549**	3.089*	1,963*
	(0.638)	(1.583)	(1,048)
Weather controls	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes
Time & Municipality FE	Yes	Yes	Yes
Number of clusters	90	90	90
# observations	34,156	34,156	34,156
Mean Dependent var.	53.46	129.2	77248
%Effect	2.9%	2.4%	2.5%

Notes: The percent effect is (inversion coefficient)/(mean of the dependent variable). “Sick spell Incidence rate” is the number of new spells starting on day *t* divided by the total number of children age 2-11 in the municipality multiplied by 10,000. “Summed duration” is the summed length of the spells in days for spells that start on day *t* , divided by the total number of children age 2-11, times 10,000. “Care for Sick Child Benefits” is the total amount in SEK that the parents received from the social insurance to compensate for lost labor income for taking care of their sick child for spells that started on day *t* divided by the total number of children in the municipality, multiplied by 10000 for readability. Each column represent a separate estimation ***/**/* denotes statistical significance at the 1% /5% /10% level respectively. Standard errors clustered at the municipality level.

For Online Publication

APPENDIX A

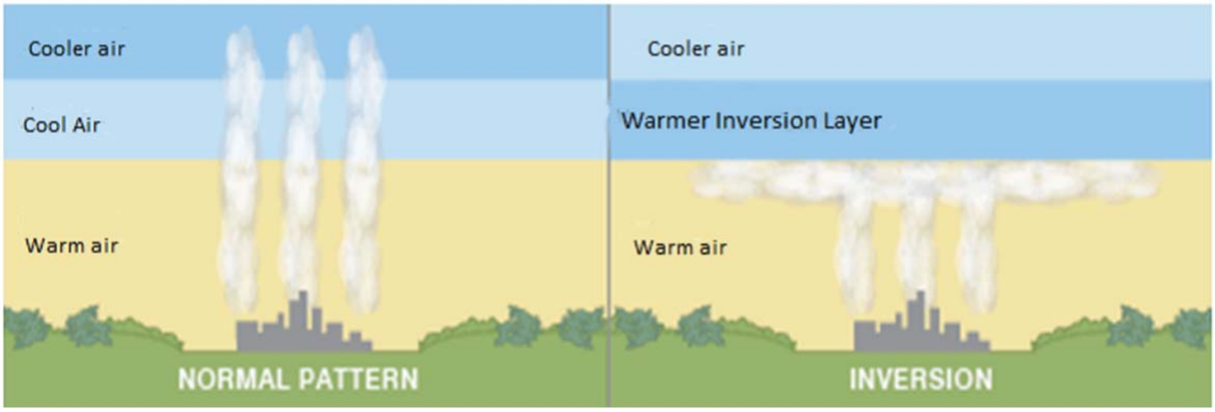

Figure A1: Illustration of Effect of an Inversion Episode

Notes: Figure X provides an illustration of the identification strategy. The left hand side of the figure show normal conditions, and the right hand side shows the inversion days. We measures health in children in the urban areas using health care records, pollution levels in 90 municipalities, and measures vertical temperature profiles using the NASA AQUA satellite data.

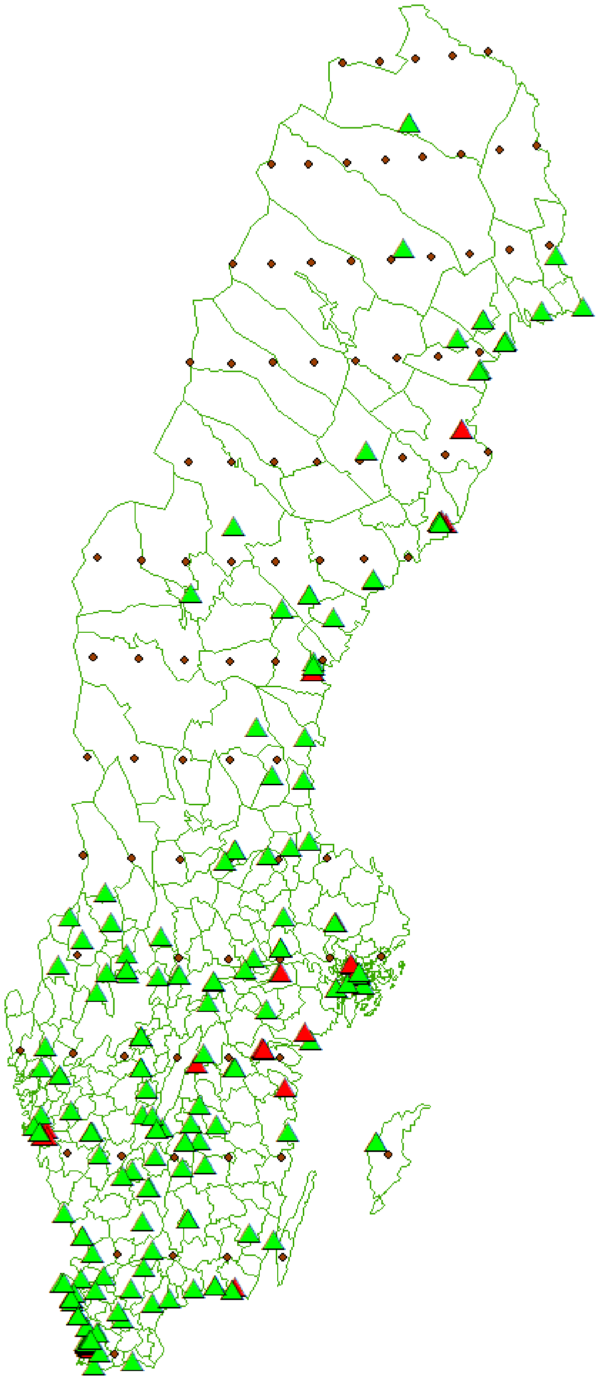

Figure A2: Municipalities, Temperature Grid Centroids (⋄) and Air Quality Monitors (Δ).

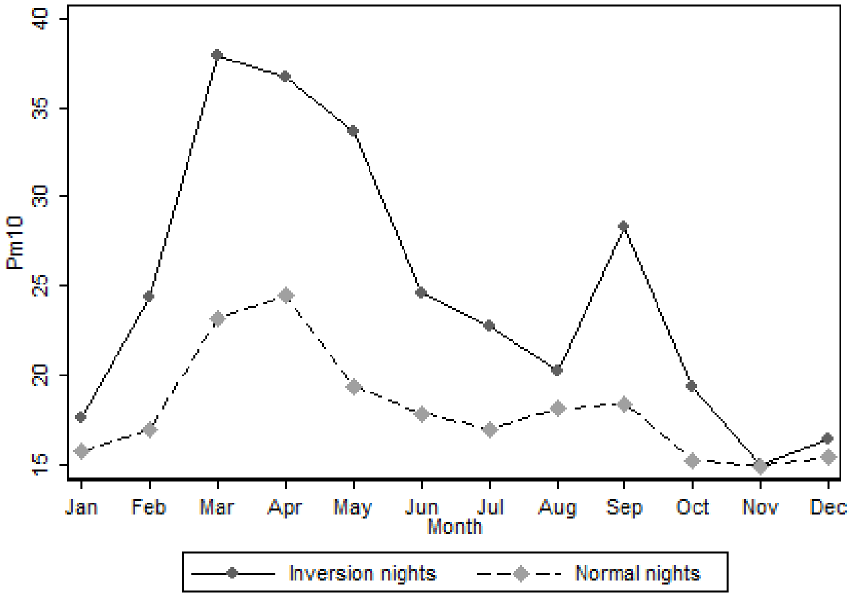

Figure A3: Seasonal comparison of 24h-mean PM_{10} levels during normal and inversion episodes

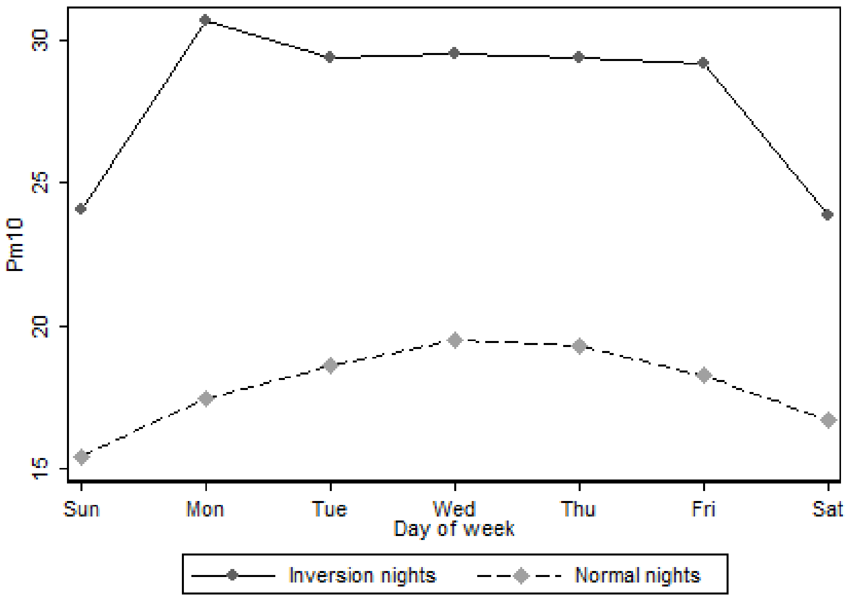

Figure A4: Comparison of 24h-mean PM_{10} levels during normal and inversion episodes

Table A1 Effects of Air Pollution Across SES groups.

	Outcomes	SES Measure:	Assessing SES differences?	Any SES differences?
Schlenker and Walker (2011)	Respiratory disease Heart disease	none	No	-
Arceo-Gomez, Hanna, & Oliva (2014)	Infant mortality	none	No	-
Bharadwaj et al. (2014)	Grade 4 GPA	none	No	
Isen, Rossin-Slater, Walker (2014)	Labor market outcomes	County averages	No	-
Currie and Neidell (2005)	Infant Mortality	Zip code average	No	-
Currie and Walker (2011)	Infant health	Maternal education	No (but larger effects for African Americans)	-
Sanders and Stoeckers (2011)	Sex-ratio (indicator of spontaneous abortions)	Maternal Education (High school)	Yes	Yes
Currie, Neidell, & Schmieder (2009)	Infant health	Individual mom education, census tract income (split sample)	Yes	No
Knittel, Miller, and Sanders (2011)	Infant Mortality	Public insurance was used at delivery, maternal education	Yes	Mixed Results: Medicaid eligible => slightly smaller effects Mom high school drop out => larger effect)
Nilsson (2009)	Labor market outcomes, Cognitive ability, Grade 9 GPA	Direct measure of parental income, education	Yes	Yes, larger effects for low SES groups
Grönqvist, Nilsson, Robling (2014)	Crime convictions (age 15-23)	Direct measure of parental income, education	Yes	Yes, larger effects for low SES groups

Table A2: *Summary statistics*

	Mean	Standard deviation
A. Dependent variables		
Rate of respiratory related hospital visits per 10,000 children		
Any respiratory illness	2.16	2.55
Age 0-5	4.45	5.77
Age 6-10	1.47	3.40
Age 13-18	1.03	2.19
Asthma	1.68	2.55
Pneumonia	0.56	1.52
Bronchitis	0.78	1.88
Other respiratory illness	1.82	2.51
External causes	2.44	2.33
B. Independent variables		
PM_{10} (µm/m^3)	20.77	17.57
Temperature (ْKelvin) *Daytime (ground level)*	277.57	9.31
Temperature (ْKelvin) *Nighttime (ground level)*	275.04	7.99
Precipitation (mm) *(N=33,079)*	0.51	1.14
Windspeed (m/s) *(N=33,079)*	3.26	1.75
Daily Cloud cover ratio	0.43	0.28
Nightly Cloud cover ratio	0.45	0.27
Share of Inversion days	0.25	0.43
Inversion strength	-1.35	2.80
Number of Observations	34,156	

Table A3 Specification Checks

Specification	(1)	(2)	(3)	(4)	(5)
Outcome variable:	Respiratory Illness Rate			PM10	Inversion
Inversion (d)	.1154***	.0781***			
	(.0232)	(.0249)			
Inversion (d-1)		.0927***			
		(.0286)			
Inversion (d-2)		.0389			
		(.0270)			
Inversion (d-3)		-.0126			
		(.0293)			
Inversion (d-4)		.0090			
		(.0366)			
Inversion (d-5)		.0399			
		(.0343)			
Share inversion days (*d* to *d*-5)			.2501***		
			(.0641)		
Weekend Dummy				-4.754***	0.0042
				(0.993)	(0.003)
Cumulative Effect ($\sum_{k=0}^{5} \beta_{d-k}$)		.2462***			
		(.066)			
Observations	10979	10979	10979	34,156	34,156
Mean of Outcome Variable:	2.1	2.1	2.1	20.8	0.25

Notes: Column (1) report estimates for the estimation sample used in the cumulative effect analysis (column 2). In the distributed lag model we control for the lagged weather variables for each day. Column (3) report the estimated impact on current respiratory illness rate from the average number of days with inversion over the current and past 5 days. Column (4) show the drop in PM10 levels on weekends, while column (5) show that the sharp drop in pollution levels on weekends do not influence inversions. ***/**/* denotes statistical significance at the 1% /5% /10% level respectively

Table A4: Effects on Sub-diagnosis and by Child age

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	Respiratory Illnesses	Asthma	Bronchitis	Pneumonia	Other respiratory	Pre-School Kids	School-age Kids
Inversion	0.107***	0.0588***	0.0121**	0.00704**	0.0293**	0.166***	0.0736***
	(0.0274)	(0.0170)	(0.00591)	(0.00286)	(0.0125)	(0.0519)	(0.0172)
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,156	34,156	34,156	34,156	34,156	34,156	34,156
# of cluster	90	90	90	90	90	90	90
Mean outcome	2.181	0.914	0.189	0.114	0.964	4.053	1.154
% Effect	4.9%	6.4%	6.4%	6.1%	3.0%	4.1%	6.4%

Notes: The percent effect is (Inversion coefficient)/(mean of dependent variable) ***/** denotes statistical significance at the 1% /5% level respectively. Standard errors are clustered at the municipality level. The pre-school age group covers children aged 0-6 and school kids are children 7-18. Column (1) reports estimates for the baseline outcome, and column (2-5) report estimates for sub-diagnoses of the respiratory illness category.

Table A5: Effects of Inversions by Child Age and Parental Income

Sample:	All families		Low income families		Med income families		High income families	
	0-6 years	7-18 years	0-6 years	7-18 years	0-6 years	7-18 years	0-6 years	7-18 years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inversions	0.179***	0.0745***	0.277***	0.106***	0.159	0.113***	0.104	0.0417
	(0.0551)	(0.0180)	(0.0487)	(0.0229)	(0.102)	(0.0306)	(0.0775)	(0.0361)
Observations	34,156	34,156	34,156	34,156	34,156	34,156	34,156	34,156
Number of cluster	90	90	90	90	90	90	90	90
Mean resp. illness	3.977	1.142	4.920	1.280	3.992	1.273	3.000	1.170
% Effect	4.5%	6.5%	5.6%	8.3%	3.9%	8.9%	3.5%	3.6%

Notes: The table report separate estimates by income group and child age used to construct Figure 5.

Table A6: Does Inversions Affect Pollution Forecasts in Stockholm?

	(1)	(2)	(3)	(4)
Outcome variable:	PM10 predicted to be **High** on day *t*	PM10 predicted to be **High** on day *t*	PM10 predicted to be **pretty High or High** on day *t*	PM10 predicted to be **pretty High or High** on day *t*
Inversion	.0127	.0197	.0319	.0255
	(.0270)	(.0246)	(.0299)	(.0282)
Lagged (*d*-1) PM10 level	.0063***	.0048***	.0074***	.0061***
	(.0006)	(.0006)	(.0007)	(.0008)
Daily Weather controls	Yes	Yes	Yes	Yes
Year by Month Effects	No	Yes	No	Yes
Day of Week Effects	No	Yes	No	Yes
Muncipality Fixed Effects	No	No	No	No
Observations	1401	1401	1401	1401
R-squared	0.35	0.46	0.38	0.47
Mean of dep. variable	0.11	0.11	0.16	0.16

Notes: The table show estimates on if inversion affect pollution level forecasts in Stockholm. The IVL produce forecasts in the afternoon for the following day, and report the expected PM10 level in the following way: 1=”Low”,2=”Moderate”, 3= “Pretty High”, 4= “High”. The outcome variable in columns 1 & 2 is equal to 1 if IVL predicted that pollution would be “High”. In Columns 3-4 the outcome variable is equal to 1 if pollution would be Pretty High or High IVL ***/**/* denotes statistical significance at the 1% /5% /10% level respectively.

Table A7: Does inversions affect children's indoor/outdoor activities?

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Share of Injuries Occurring Indoors	Share of Injuries Occurring Indoors	Share of Injuries Occurring Indoors	Share of Injuries Occurring Indoors	Share of Injuries Occurring Indoors	Share of Injuries Occurring Indoors
Age Groups:	All Kids	All Kids	Pre-school Kids	Pre-school Kids	School-Age Kids	School-Age Kids
Inversion	0.0080	-0.0049	0.0142	0.0074	0.0004	-0.0138
	(0.0065)	(0.0094)	(0.0077)	(0.0087)	(0.0078)	(0.0100)
Wind speed (m/s)	0.0161***	0.0033	0.0163***	0.0127***	0.0127**	0.0003
	(0.0035)	(0.0034)	(0.0042)	(0.0021)	(0.0041)	(0.0036)
Precipitation (mm)	0.0115***	0.0143***	0.0101***	0.0147***	0.0113***	0.0126***
	(0.0021)	(0.0026)	(0.0018)	(0.0026)	(0.0024)	(0.0032)
Year by Month Effects	No	Yes	No	Yes	No	Yes
Day of Week Effects	No	Yes	No	Yes	No	Yes
Hospital FE	No	Yes	No	Yes	No	Yes
Daily Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,560	5,560	3,876	3,876	5,333	5,333
R-squared	0.192	0.266	0.158	0.193	0.190	0.270
Mean of Dependent var.	0.419	0.419	0.609	0.609	0.359	0.359

Notes: The table presents estimates of the effects of inversion on the share of indoor injuries that require health care visits as a proxy for avoidance behavior as described in the text. Each column represent a separate estimation. For comparison, the estimated effects of precipitation (mm) and wind speed (m/s) are also reported. ***/**/* denotes statistical significance at the 1%/5%/10% level respectively. Standard errors are clustered at the hospital level and are reported in parenthesis.

Table A8: Does inversions affect children's activities?

Dependent Variable:	Injuries with External Causes per 10,000 children			
	(1)	(2)	(3)	(4)
	Full sample	Low income families	Medium income families	High income families
Inversion	0.0173	0.000804	0.00009	0.0452
	(0.0327)	(0.0415)	(0.0383)	(0.0431)
Weather Controls	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Year by Month Effects	Yes	Yes	Yes	Yes
Day of Week Effects	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Observations	34,156	34,156	34,156	34,156
# of cluster	90	90	90	90
Mean resp. illness	2.342	2.301	2.254	2.495
% Effect	0.7%	0.04%	0.004%	1.8%

Notes: ***/**/* denotes statistical significance at the 1% /5% /10% level respectively. Each column represent a separate estimation

Table A9: Effects by Health Status and Parental Income

	Full Health Index Sample			Good Initial Health			Poor Initial Health		
Dependent Variable	Respiratory Illness Rate	Respiratory Illness Rate	Respiratory Illness Rate	Respiratory Illness Rate	Respiratory Illness Rate	Respiratory Illness Rate	Respiratory Illness Rate	Respiratory Illness Rate	Respiratory Illness Rate
Sub-sample:	All	Good Health	Poor Health	Low income families	Medium income families	High income families	Low income families	Medium income families	High income families
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Inversion	0.122***	0.0974***	0.147***	0.173***	0.122***	0.0197	0.196***	0.145*	0.104
	(0.0334)	(0.0285)	(0.0465)	(0.0493)	(0.0442)	(0.0284)	(0.0400)	(0.0837)	(0.0759)
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by Month Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,156	34,156	34,156	34,156	34,156	34,156	34,156	34,156	34,156
# of cluster	90	90	90	90	90	90	90	90	90
Mean outcome	2.322	2.169	2.480	2.716	2.231	1.526	3.061	2.492	1.729
Effect RF	5.3%	4.5%	5.9%	6.4%	5.5%	1.3%	6.4%	5.8%	6.0%

Notes: ***/**/* denotes statistical significance at the 1% /5% /10% level respectively. Each column represent a separate estimation