Coal Smoke and Mortality in an Early Industrial Economy*

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Abstract

Air pollution was severe in the industrial cities of the 19th century, yet studies of health during this period often overlook the role of pollution. This study fills in the gap in existing knowledge by providing estimates of the effect of industrial pollution from coal use on mortality in Britain in 1851-1860. To overcome the lack of direct pollution measures during this period, we infer local industrial coal use levels by combining data on the industrial structure of 581 districts with information on industry coal use intensity. To improve identification, we focus on infant mortality and estimate the effect of coal use on mortality in upwind relative to downwind districts. Our results indicate that a one standard deviation increase in coal use raised infant mortality by 6.7-8.0%. Moreover, we find evidence that local industrial coal use can explain roughly one-third of the urban mortality penalty in 19th century Britain.
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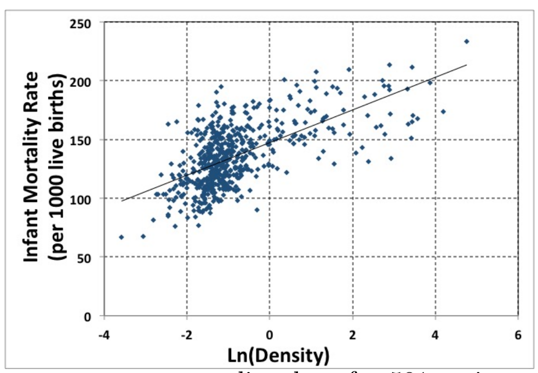
1 Introduction

Cities were incredibly unhealthy places to live during the 19th century. To illustrate this point, Figure 1 plots the relationship between district-level infant mortality rates and population density in 19th Century England and Wales. The strong positive relationship between these two variables indicates that a one log point increase in population density is associated with about 12.5 more deaths per 1000 births.[1]

The strong positive relationship between population density and mortality, often referred to as the urban mortality penalty, is a common feature of industrial nations during this period (e.g., Cain & Hong (2009); Kesztenbaum & Rosenthal (2011)). The literature offers two main explanations for these patterns. The first emphasizes the role of infectious diseases, particularly those associated with unclean water and improper sewage disposal.[2] Others have suggested that poor nutrition may have also been important.[3] One explanation that is curiously absent from this literature, however, is the role of air pollution.

Figure 1: The urban mortality penalty for infants, 1851-1860



Notes: This figures compares mortality data for 581 registration district covering all of England & Wales from 1851-1860, digitized by Woods (1997) from reports produced by the Registrar General's office to district population density in 1851 based on data from the 1851 Census of Population.

[1] We also observed a strong positive relationship between population density and deaths across all age groups (see Figure 4 in the Appendix), but our analysis will focus primarily on infants because the effects of pollution are easier to identify in this group and infants accounted for a large fraction of total deaths during this period. There is also substantial evidence that infants are strongly affected by pollution exposure (Currie (2013)).

[2] See, e.g., Troesken (2002), Cutler & Miller (2005), Ferrie & Troesken (2008), (Kesztenbaum & Rosenthal, 2011, 2012), Alsan & Goldin (2014), Antman (2016).

[3] See McKeown (1976), Fogel (2004), and Fogel & Costa (1997).

The health consequences of air pollution during the 19th century have been largely ignored despite contemporary reports that make it clear that pollution – particularly air pollution from the burning of coal – was a severe problem in the 19th century. As an example, Mr. Leigh, a local health official in Manchester, described how,[4]

> *Coal smoke forms a continual dark and dense canopy over the town, and causes a murkiness in the streets from which they are never free...The constant inhalation of these black particles...must be highly irritating to the lungs...*

Why has the literature largely ignored the impact of pollution on health in the 19th and early 20th century? The main explanation is that direct pollution measures are almost entirely unavailable during this period, which makes it difficult to assess quantitatively the impact of pollution on health.[5] The goal of this study is to bridge this gap in our current understanding by providing broad-based quantitative estimates of the impact of one important type of pollution – industrial air pollution from coal burning – on mortality in Britain in the middle of the 19th century. To our knowledge this is the first quantitative assessment of the contribution of air pollution to generating the urban mortality penalty during this period.

An important contribution of this study is to introduce an approach that allows us to infer local industrial pollution levels in the absence of direct pollution measures, which are not systematically available before the mid-20th century. To do so, we combine data describing the industrial structure of 581 districts covering all of England & Wales with information on industry coal use per worker. Together, these two pieces of information allow us to estimate the spatial distribution of industrial coal use in 1851-1860, the earliest decade for which all of the necessary data are available. These estimates are then paired with mortality data in order to analyze the impact of coal use on health.

[4] Quoted from *The Times*, May 17, 1866, p. 11.

[5] While there is a larger qualitative literature on this topic (e.g., Mosley (2001), Thorsheim (2006), and Brimblecombe (1987)), estimates of the relationship between pollution and mortality largely begin in the middle of the 20th century (e.g., Barreca *et al.* (2014), Clay *et al.* (2016), and Clay *et al.* (2015)). A number of studies investigate the health impacts of particular pollution events in the 20th century (Townsend (1950), Logan (1953), Greenburg *et al.* (1962), Ball (2015)). One 19th century exception to this literature is Troesken & Clay (2011), who study the evolution of mortality following large fog events. Relative to previous work, our study offers a new identification approach and provides evidence for an earlier period and a broader set of locations.

Comparing these local industrial coal use measures to infant mortality patterns reveals a strong positive relationship. Our baseline estimates suggest that a one standard deviation (s.d.) increase in log coal use raised infant mortality by 10.7-13.7 deaths per 1,000 live births, or about 8-10%. Moreover, we show that accounting for industrial coal use explains roughly one third of the urban mortality penalty for infants. However, we may worry that these simple cross-sectional results are subject to bias from omitted variables or population sorting.

To address these concerns, we exploit variation in wind patterns to identify how coal use in one area affects mortality in neighboring downwind and upwind districts. Using wind patterns allows us to focus directly on the role of air pollution associated with industrial coal use, while also dealing with concerns about omitted variables or reverse causality. Also, to help address the possibility that less healthy populations were sorting into areas downwind of major pollution centers, we include a set of control variables reflecting the disease environment of these locations. By controlling for mortality due to causes of death that reflect poverty, poor sanitation, and crowded living conditions, we argue that we are able to separate the impact of sorting from the direct effect of pollution exposure.[6]

These results indicate that increasing industrial coal use in upwind districts by one standard deviation raised infant mortality rates in downwind districts by 2.3-3.0 deaths per 1,000 live births. This is equivalent to a 1.7-2.2% difference in the infant mortality rate. We also provide evidence that the mortality effects of coal use were stronger in hilly areas, where air pollution was likely to be trapped in more densely inhabited valleys, which provides an alternative check on our results.

We also show how results generated by comparing upwind and downwind districts can be used to evaluate the magnitude of bias present when comparing coal use to mortality *within* a district. To do so, we start by generating predicted pollution diffusion plumes using modern pollution modeling data.[7] We feed into the software parameters typical of a 19th century industrial smokestack as well as modern meteorological data for four regions of England & Wales. The model then generates estimates of how pollution concentrations generated by a given amount of coal use

[6] This approach is similar to the route taken in several recent papers, such as Galiani *et al.* (2005) and Alsan & Goldin (2014).

[7] Specifically, we follow Heblich *et al.* (2016) in using the ADMS-5 software provided by Cambridge Environmental Research Consultants. More information about this software is available at `http://www.cerc.co.uk/environmental-software/ADMS-model.html`.

in a source district falls as we move into upwind or downwind districts. Relying on this model, we can then scale up our estimates of the effect of coal use in upwind vs. downwind districts in order to predict the impact of the same amount of coal use on mortality within the source district. This exercise predicts that a one s.d. increase in local industrial coal use will raise infant mortality by 8.12-10.82 deaths per 1,000 live births, or 6.0-8.0%, in the source district. These values are just below the estimates obtained in naive regressions comparing local industrial coal use directly to infant mortality, which suggests that any bias in our baseline estimates is likely to be small.

Finally, we apply the same approach study the relationship between local industrial coal use and mortality across all age categories. These results suggest that most of the effects of coal use were concentrated among children under five, though there is also evidence that coal use led to smaller mortality increases among adults.

In terms of life expectancy, the estimated impact of coal use on infant mortality alone implies that a one s.d. increase in local industrial coal use lowered life expectancy at birth by 0.33-0.56 years or 0.86-1.44%. If instead we look at the impact on all children under five, the same increase in coal use is associated with a decrease in life expectancy at birth of 0.84-1.58 years or 2.19-4.11%. Thus, our estimates suggest that industrial pollution had an important role in influencing mortality in 19th century Britain. These results complement the existing pollution literature by quantifying the health effects of pollution in an environment characterized by high levels of pollution without access to modern medical services.[8]

The results in this paper shed new light on the magnitude of the impact of pollution in early industrializing economies and open the door to further studies on the long-run impacts of local pollution. A growing literature has shown that historical environmental conditions can play an important role in shaping economic development.[9] By documenting the importance of historical air pollution, our paper provides a foundation for further work assessing the economic and developmental consequences

[8]Seminal examples highlighting substantial health impacts of pollution, even at the relatively low concentrations observed in modern developed countries, include Chay & Greenstone (2003) and Currie & Neidell (2005). For recent reviews see Graff Zivin & Neidell (2013) and Currie (2013).

[9]One example is Bleakley (2007), which showed that hookworm eradication in the American south in the early 20th century had important effects on human capital development. Beach *et al.* (2016) show that the use of water purification technologies to reduce typhoid had similar benefits for human capital. Another example is provided by Almond (2006), which documents the long-term effects of the 1918 influenza pandemic. Similarly Isen *et al.* (Forthcoming) use pollution reduction caused by the 1970 Clean Air Act to show that early-life pollution exposure can affect adult income.

of coal-based pollution. In this vein, Heblich *et al.* (2016) document the sorting response to pollution *within* 19th century British cities and show that these sorting patterns persist today. They identify industrial pollution sources within cities by locating chimneys on historical maps and then interact those locations with wind patterns to identify variation in pollution levels across neighborhoods. Using this, they show that locations downwind of polluting factories had a greater share of residents that were low-skilled workers in 1881 than other parts of the city and that these areas continue to have higher poverty levels today. Another recent study, Hanlon (2016), provides evidence that local industrial coal use had a substantial negative effect on long-run city growth in Britain in the 19th and early 20th centuries. By documenting the mortality impact of coal-based pollution, this paper provides support for both of these studies, while their results show that the pollution effects that we document continue to influence modern conditions.

The next section provides background information on the empirical setting. Section 3 introduces the data. The analysis is presented in Section 4. In Section 5 we relate our findings to modern studies on the relationship between air pollution and health. Section 6 concludes.

2 Empirical Setting

In England, air pollution was a problem reaching back at least to the 17th century, when Evelyn published his Fumifugium (1661) decrying the smoke of London. Most of this pollution was generated by the burning of coal, the main source of power in Britain during the 19th century. Consequently, this problem became much more acute in the 19th century as industrialization took off and steam-driven factories expanded across the country.

In 1854, an estimated 58 million tons of coal were consumed in England & Wales with industry accounting for 65% of coal consumption.[10] The intensity of coal use, however, varied enormously across sectors, a pattern we document below. Together, variation in coal use intensity across industries along with industry agglomeration patterns, led to substantial variation in industrial coal use across locations.

[10]Data from Mitchell (1984) and Mitchell (1988). The 65% figure covers the industries included in our coal use measure, which span manufacturing and mining. See figure in Appendix A.1.3.

The way that coal was used by industry in the 19th century resulted in particularly high levels of pollution exposure. Coal was often burned inefficiently, resulting in incomplete combustion, which released additional particulates into the air.[11] Also, prior to electrification, coal had to be burned on-site at factories, which tended to be in urban areas where they could be reached on foot by large numbers of workers. This resulted in high levels of pollution exposure.

The severity of the air pollution problem, particularly in the industrial cities of 19th century Britain, was not lost on contemporary observers, as the quote from Mr. Leigh in the introduction shows. His report is typical of descriptions of air pollution during in this period.[12] Though contemporaries did not fully understand the health effects of air pollution exposure in the 19th century, they did associate pollution with negative health effects, particularly respiratory diseases. Beyond the health effects, coal smoke in the industrial cities was so intense that light-colored clothes went out of fashion and the lack of visibility could cause traffic accidents.

Today, we know that burning coal releases soot and other particulate matter that can increase mortality. As noted by the US Environmental Protection Agency, the release of small particulate matter (less than 10 micrometers in diameter) is especially dangerous as the matter can get deep inside of a person's lungs or even their bloodstream.[13] Consistent with this, several studies have documented a link between exposure to particulate matter and increased risk for respiratory and cardiovascular disease.[14] The coal combustion process also releases a variety of other chemicals, such

[11]For example, the 1871 Coal Commission report (p. 135) describes the inefficient stoking of coal-powered boilers, stating that, "The careless and wasteful manner of stoking in most of the coal-producing districts is not only a source of vast waste, but of extreme annoyance to all the surrounding neighborhood. Coal is piled upon the fire without any discretion, producing dense volumes of the blackest smoke, which is so much fuel actually thrown away; nor is the waste the worst part of it; vegetation is destroyed, or seriously injured, for miles, and that which acts so seriously on the plant cannot fail to be injurious to man."

[12]See Thorsheim (2006) for many more examples.

[13]See `https://www.epa.gov/pm-pollution`.

[14]See Pope *et al.* (2009) on the relationship between air pollution and life expectancy. On the relationship between air pollution and infant health, see Chay & Greenstone (2003), Currie & Neidell (2005), Currie *et al.* (2009), Knittel *et al.* (2016), and Arceo *et al.* (2016). Rückerl *et al.* (2011) provides an excellent review of the epidemiological literature on the effects of short and long-term exposure to air pollution. Currie (2013) provides a review of studies examining the impact of pollution on mortality within the economics literature. As for the underlying mechanism of these effects, recent research indicates that the channel is due to the proinflamatory effects of particulates as well as their activation of stress-signaling pathways (see discussion in Brunekreef & Holgate (2002)).

as sulfur dioxide, carbon dioxide, and nitrogen oxides, and metallic pollution such as mercury, lead and cadmium. These pollutants are associated with a wide variety of negative health effects, particularly on the respiratory and cardiovascular systems.[15]

Despite high levels of pollution, regulation was in its infancy in the middle of the 19th century. While the idea of regulating pollution emerged in the 1860s, with provisions for the reduction of excess smoke included in the Sanitary Act of 1866 and the Public Health Act of 1875, historical sources suggest that these measures had limited effectiveness until the beginning of the 20th century (Thorsheim (2006), Fouquet (2012)). Pollution regulation faced an uphill battle against the influence of local industrialists and the strong *laissez faire* ideology that dominated British policy-making during this period.

In the absence of regulation, those who could afford to protected themselves from pollution by sorting into neighborhoods that were upwind of pollution sources, as documented by Heblich *et al.* (2016). However, while sorting took place across neighborhoods within cities, the ability of most people to avoid pollution by sorting across cities was constrained by the high cost of commuting during this period and the need for many different types of workers to be present in cities.[16] Given this, and the fact that our analysis is conducted at the district level (which is generally larger than cities), we expect sorting to have only a modest effect on the relationship between coal use and mortality in our study.

3 Data and Measurement

In this section we describe the main data sets used in the analysis (i.e. data on mortality patterns and the spatial distribution of industrial coal use). A discussion of ancillary data is available in Appendix A.2.3.

[15]See, e.g., Rückerl *et al.* (2011) for a review of these effects.

[16]Consistent with this, Hanlon (2016) finds that the urban wage premium associated with increased local industrial coal use, using data from 1905, was quite small. Further, in their analysis of mobility in England and Wales between 1851 and 1881, Long & Ferrie (2003) and Long & Ferrie (2013) find that fewer than 27 percent of migrants crossed county borders. The mean migration distance was only 35 miles, while 25 percent of all moves were less than 5 miles. These results, combined with the fact that the average registration district radius was just over 5.5 miles suggests that most sorting likely occurred within rather than across districts.

3.1 Mortality data

To track mortality rates, this study draws on the detailed data available from the Registrar General's reports.[17] The Registrar's data were collected by an extensive system aimed at registering every birth, marriage, and death in England and Wales. Of the data collected by the Registrar's office, those on mortality are considered to be the most accurate and comprehensive, the "shining star of the Victorian civil registration" (Woods (2000)). For every death, registration with the local official (the "Registrar") was required within five days before the body could be legally disposed of. The Registrar was required to document the gender, age, and occupation of the deceased, together with the cause of death.

The data we use come from the decennial supplement and provide mortality patterns averaged across 1851-1860. Decadal averages are desirable in this setting because the presence of epidemic diseases can introduce substantial noise into annual mortality rates. The data are available at the district level for over 600 districts covering all of England & Wales. To obtain consistency, we combine a small number of districts that experienced border changes between 1851 and 1860. In addition, we treat London as a single "super-district" for our analysis by collapsing the many small districts within the traditional borders of London.[18] As a result of these adjustments, our main analysis covers 581 districts.

Our analysis draws on both the age and cause-of-death tabulations in the mortality data. While the age-tabulated data provide the foundation of our analysis, we also use the cause-of-death data to generate control variables that help address concerns about the sorting of poorer or less healthy populations into more polluted areas. Our reliance on the cause-of-death data raises the natural concern that deaths may have been inaccurately categorized during this period. While there is clearly some scope for measurement error related to the cause-of-death data, the Registrar General's office put a substantial amount of effort into standardizing classification. This included sending circulars to all Registrars and medical professionals, constructing a

[17]These data were digitized by Woods (1997) and were obtained through the UK Data Archive.

[18]Because many of the London districts were small, workers often lived and worked in different districts, which undermines our ability to infer local industrial coal use from occupation data for these small districts. Also, because these districts were so small, much of the coal use in one area likely impacted residents in other nearby areas. Working with a single London district avoids these issues and results in a district that is more similar to other districts in the data in terms of area. In the appendix we show that our results are robust to excluding London from the analysis.

standardized set of disease nosologies, and providing Registrars and medical professionals with standardized blank cause-of-death certificates. Despite these efforts, it is likely that substantial measurement error remains in the reported cause-of-death statistics. Thus, care is required when using the cause-of-death information.

To construct the cause-of-death controls used in this study, we look for diseases satisfying three criteria. First, they should not be among the causes-of-death typically associated with air pollution exposure. This eliminates, for example, diseases that primarily affect the respiratory system.[19] Second, the diseases should be related to patterns of poverty and poor living conditions. Third, these causes of death should have clearly identifiable symptoms that would have been well known in the 19th century. These diseases should be more accurately reported than other cause-of-death categories.

Based on these criteria, we construct two control variables based on the cause-of-death data, one based on deaths among infants and a second based on adult deaths. These controls, which we label "Child NPR mortality" and "Adult NPR mortality" (as in "not pollution related"), include deaths from a set of major infectious diseases: cholera, diarrhea, dysentery and other digestive disorders, diphtheria, smallpox, scarlet fever and typhus. These were all important infectious diseases, all have clearly identifiable symptoms which we review in more detail in Appendix A.2.1, and all were associated with poverty and poor living conditions.

To eliminate the potential concern that polluting industries may have had more on-the-job accidents, which could influence adult mortality rates, we exclude deaths from accidents or violence from all of our analysis.[20]

When calculating infant mortality rates we use data on births from the Registrar General's report as our denominator. When we study mortality across all age categories, the population denominators used to generate our mortality rates are based on average population figures calculated by the Registrar's office using the Census of Population for 1851 and 1861. We may be concerned that these values may not do

[19] For example, we exclude infectious diseases that affected the respiratory system, such as measles and whooping cough, where the effects could have been exacerbated by air pollution exposure. We also exclude tuberculosis, an important infectious disease, both because it was primarily a disease of the respiratory system and also because it was not well diagnosed during this period.

[20] Note, however, that our results will still capture the impact of on-the-job pollution exposure, which will show up in causes of death other than accidents and violence. This reflects a potentially important channel through which pollution increases mortality that we want to capture.

a good job of capturing district population if there are flows into and out of districts in between the census years. To check this, in the appendix we present additional results using only deaths between 1851 and 1853 with population levels from the 1851 census used to calculate mortality rates. Analysis on this narrower window, where inaccurate denominators should pose less of an issue, produces similar results.

3.2 Measuring local industrial coal use

To measure local industrial coal use, we start with data describing the industrial composition of each registration district in England & Wales, which we digitized from the 1851 Census of Population. In this Census, every resident was asked to list their occupation, but the occupational categories that were gathered are more similar to industry than what we think of as occupation today. Examples include cotton textile worker, iron founder, and boot and shoe maker. One reason for focusing on the 1851-1860 decade is that this is the earliest decade for which reliable district-level occupation data are reported.[21] Following Hanlon & Miscio (2014), we collapse these data into 26 industry categories covering nearly the entire private sector economy, including manufacturing, construction, services, and transportation.[22] These collapsed occupation data can then be easily matched to data describing the coal use intensity of each industry. The second necessary piece of information for measuring local industrial coal use is an estimate of coal use per worker in each industry. We collected these data from the first Census of Manufacturers, which was taken in 1907. Because these data come from several decades after the decade of interest, we conduct several checks, discussed below, to assess whether they allow us to accurately estimate local industrial coal use levels in the 1850s.

Coal use per worker varied enormously across industries in our setting. The most intensive users, such as Earthenware & Bricks, Metal & Machinery, and Chemicals & Drugs, generally used coal heat material to high temperatures, for example, to melt

[21] Occupation data was gathered as part of the 1841 census, but because this was the Census' first experience in gathering the occupation data, concerns have been raised about the accuracy of these data. Detailed district-level occupation data were reported only for 1851 and 1861. In 1871, district-level data were reported with less detailed occupation categories, while after 1871 data were reported only at the county level and for a few large towns.

[22] See Hanlon & Miscio (2014) and the online data appendix to that paper, available at `http://www.econ.ucla.edu/whanlon/`, for further details about the Census of Population Occupation data.

iron or fire bricks. These industries used more than 40 tons of coal per worker per year.[23] Moderate coal-using industries such as Textiles, Mining, and Leather, used coal primarily to run engines for motive power. Coal use per worker in these industries was around 10 tons per year. Industries such as Apparel, Tobacco, and Instruments & Jewelry, used less than two tons of coal per worker per year, as they largely relied on coal for heating only. Services are assumed to have a negligible amount of coal use per worker.[24] For a full breakdown of coal use intensity by industry, see Appendix Table 9.

Following Hanlon (2016), we model coal use at the district level in a particular year t as made up of three components: local employment in industry i in district d and year t, denoted L_{idt}, the coal use intensity in that industry θ_i, and a time-varying term representing efficiency gains in coal use, which we denote ρ_t. Putting these together, the overall level of coal burned in district d in year t is,

$$COAL_{dt} = \rho_t \sum_i \theta_i L_{idt} , \tag{1}$$

District employment in industry i is available from the Census of Population occupation data, while industry coal use per worker is obtained from the 1907 Census of Production. The third term, ρ_t, allows for changes in the efficiency of coal use per worker over time that are common across all industries. This feature is suggested by the national data and included for accuracy. However, because we will be using a log specification and looking across districts within the same time period, this component will not affect our results.

Our approach relies on two important assumptions. First, we are assuming that *relative* coal intensity per worker across industries did not change substantially over time, so that the relative levels of coal use per worker across industries obtained from the 1907 Census of Manufactures can be applied in the 19th century. Second, we are assuming that the variation in the level of coal use across locations is driven primarily

[23] These values are based on data for 1907 from the first Census of Manufactures.

[24] We exclude public utilities when constructing the pollution measures. Some public utilities, particularly gas, were important coal users and did create local pollution. However, by converting coal into gas, which was then pumped into cities, this industry may have actually decreased pollution in city centers. Thus, these industries are excluded because of their ambiguous effects on local pollution and local health. In our robustness results we show that including coal use by utilities does not substantially affect our findings.

by industry coal use intensity, which is determined by local industrial structure and the technological features of industries. Put another way, we assume that across locations, variation in coal use intensity within an industry as an endogenous response to local factor prices is small relative to the variation in coal use intensity across industries due to technological factors. Hanlon (2016) performs two checks in order to assess that validity of these assumptions. First, by comparing industry coal use intensity in 1907 and 1924, Hanlon (2016) shows that the relative coal use intensity of industries tends to be quite stable over time.[25] Further support for this feature comes from a list of heavily polluting industries today, produced by the government of China, which closely matches our estimates of industry coal use intensity.[26] Second, Hanlon (2016) compares county-level coal use for 1871 from the method described above to data on county-level coal use from the 1871 Coal Commission report. That analysis shows that coal use levels based on local industry employment interacted with the coal use intensity measures from the Census of Manufactures does a good job of reproducing actual county-level industrial coal use in 1871.

We add a third test which is described in A.2.4. In this check, we estimate the relationship between county mortality rates in 1871 and an estimate of county-level coal use in 1871 based on the 1871 Census of Population occupation data interacted with the Census of Manufactures coal use intensity data from 1907. We show that the results of this exercise are very similar to what we obtain when we compare county mortality rates to the county industrial coal use levels obtained from the 1871 Coal Commission report. This test shows that our approach for estimating local industrial coal use can accurately reproduce the coal use-mortality relationship obtained when using direct observations of local coal use levels, even in the middle of the 19th century.

Districts in the data often specialized in particular industries. This variation, together with the large differences in coal use intensity across industries, generates substantial variation in local industrial coal use across districts. Thus, districts specializing in sectors such as iron and steel production had much higher overall coal use than those specializing in services, trade, or light manufacturing. This variation is illustrated in Table 1, which describes various pollution measures for a set of dis-

[25]This is a particularly strong test given that the period from 1907 to 1924 saw the widespread adoption of electricity as a power source, which disrupted the level of industry coal use. In contrast, there was much less change in the sources of industrial power in the period from 1851-1907.

[26]See Hanlon & Tian (2015) for a discussion of those data.

tricts with similar populations but widely varying levels of heavy industry. Coal use was substantially higher in districts specializing in heavy industry, such as Stoke-on-Trent, where pottery was a major part of the economy, and Durham, a coal mining and metals center. Districts such as Macclesfield and Norwich, which specialized in textiles and other light manufacturing, show moderate levels of pollution intensity. Bath, a resort district with an economy largely specialized in services, shows much lower levels of pollution intensity than the others.

Table 1: Pollution and mortality indicators for a set of districts of similar size

District	**Mean District Pop.**	**District Pop. Density**	**Mortality Rate (age std.)**	**Log Coal Use**	**Coal use per worker**
STOKE-UPON-TRENT	64,625	5.52	27.07	13.16	17.37
DURHAM	63,113	0.57	21.66	12.41	8.40
MACCLESFIELD	62,434	0.78	25.53	12.14	5.35
NORWICH	71,317	15.77	23.72	11.90	3.65
BATH	69,091	2.30	20.92	11.34	2.03

The data in Table 1 suggest that there may be a link between local industrial coal use and the mortality rate. However, it is clear that other factors, particularly population density, are also likely to play an important role. Another lesson from Table 1 is that, while population density and coal use are related, there are substantial differences between these to variables. Further evidence on this point is provided in Figure 5 in the Appendix, which plots district population density against district coal use. Figure 5 shows that that districts sharing similar levels of population density can differ substantially in their coal use levels, in many cases by as much as two to four log points.

3.3 Additional control variables

We have also collected a rich set of additional variables reflecting factors that may have influenced mortality patterns across locations. Here we briefly describe these variables; further details are available in Appendix A.2.3. One useful set of variables reflect district topographical features: the mean altitude and the standard deviation of altitude (which we refer to as *hilliness*). The latter of these two variables is particularly important because it can also be used as an additional identification check for our main results. Specifically, contemporary reports indicate that the air pollution generated by coal burning was particularly severe in hilly locations, where the smoke was likely to be trapped in the valleys where most production took place and where most residents lived. Motivated by this, we will assess whether the impacts of local industrial coal use were intensified in hillier locations.

We also collected information on female labor force participation, which was high during this period and likely affected mortality through channels such as reduced breastfeeding or supervision of children.[27] These data are constructed using the occupation reports contained int he 1851 Census of Population. Another useful control is agricultural suitability, which may have influenced income or access to nutrition. These data, which come from the Food and Agricultural Organization of the United Nations (FAO) are discussed in more detail in Appendix A.2.3. Finally, we have constructed an indicator for whether each district contained a seaport, and if so, a measure of the tonnage passing through the seaport. These controls are meant to capture the role played by international trade in spreading disease.

4 Analysis

Our analysis proceeds in four steps. First, we review the key patterns observed in the raw data. Second, we use some simple cross-sectional results to examine the relationship between local industrial coal use and infant mortality. These results provide a useful baseline for thinking about the extent to which local industrial coal use may help explain the urban mortality penalty. Because we may worry that these results are subject to bias from omitted variables or other factors, in the third part of the analysis, we draw on wind patterns in order to provide results that should be free of these concerns. We then show how our wind pattern results can be used to check

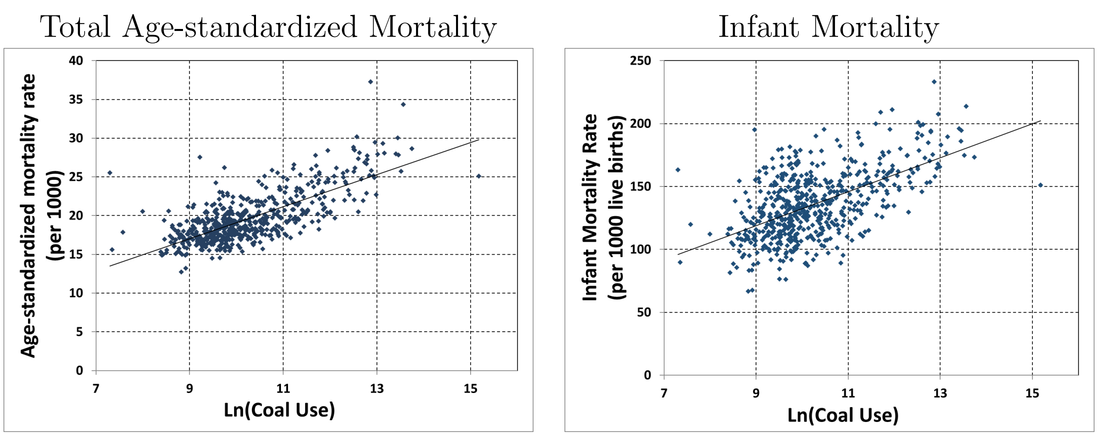
[27] One example of the role that female labor force participation played in influencing child health is provided by the large-scale female unemployment in the textile industries during the U.S. Civil War. During this period, Dr. Buchanan in his *Report on the Sanitary Conditions of the Cotton Towns* to Parliament described how infant and child health improved during this period despite the lost income, which he attributes to the "greater care bestowed on infants by their unemployed mothers than by the hired nursery keepers" (Report on the Sanitary Conditions of the Cotton Towns, Reports from Commissioners, British Parliamentary Papers, Feb-July 1863, p. 304).

for bias in the results obtained using simple cross-sectional regressions. Finally, we study the relationship between coal use and mortality across all age groups.

4.1 Patterns in the raw data

Figure 2 describes the raw relationship between local industrial coal use and mortality across all ages (left panel) or infant mortality (right panel), at the district level.[28] In addition to showing a strong positive relationship between coal use and mortality, this figure also sheds light on the appropriate way to model the relationship between these variables. In particular, the relationship described in Figure 2 appears to be close to linear when coal use is in logs, suggesting that this is a reasonable way to model pollution effects. This implies a concave relationship between coal use and mortality which is consistent with the concave relationship between pollution and mortality found in existing papers such as Pope *et al.* (2011) and Clay *et al.* (2016).

Figure 2: Coal use and mortality in England and Wales in 1851-1860

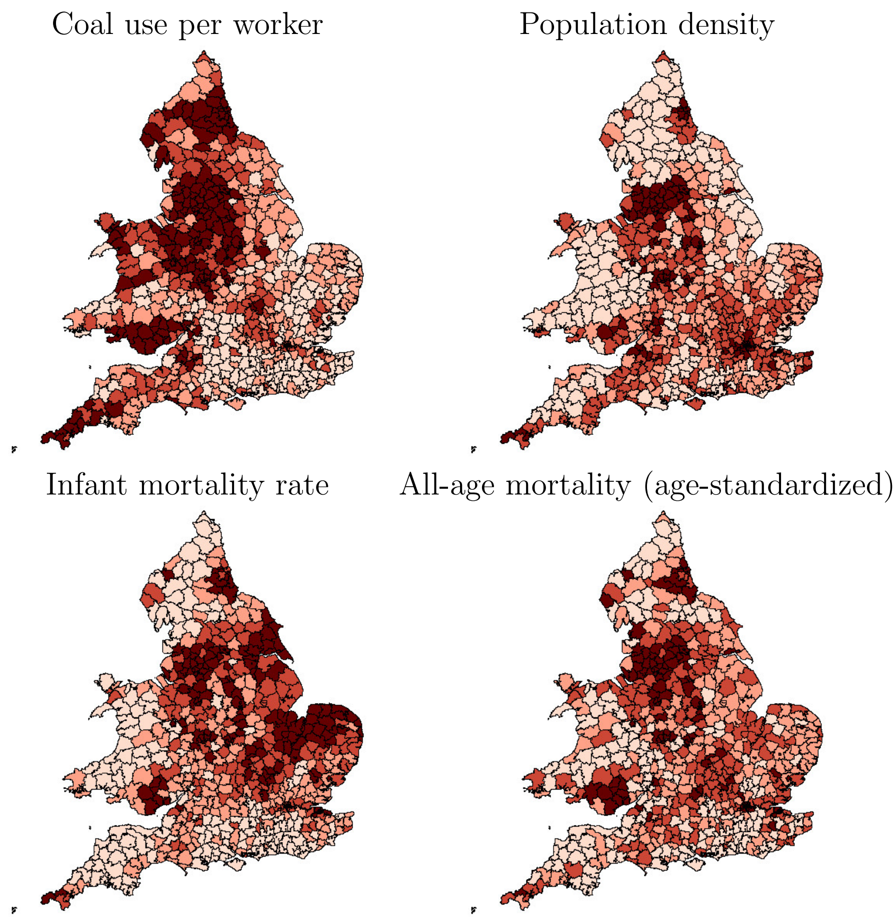


Local industrial coal use is based on the industrial composition of districts in 1851. The mortality rates are calculated using data from 1851-1860. The infant mortality rates is calculated relative to the number of births, while the all-age mortality rate is calculated relative to population.

[28]The all-age mortality rates are age-standardized to account for differential mortality patterns at different ages. The formulate is $MORT_d = \sum_g^G MR_{gd} PS_g$ where $MORT_d$ is the age-standardized mortality rate for district d, MR_{gd} is the raw mortality rate in age-group g in district d and PS_g is the share of population in age-group g in the country as a whole. Thus, this formula adjusts a location's mortality rate to account for deviations in the age distribution of residents from the national age distribution.

A second look at the raw data is provided by Figure 3, which describes the spatial variation of the key variables used in the analysis: coal use, population density, infant mortality and the mortality rate across all ages. All of these variables display some similar geographic patterns, with high levels in the industrial districts of Northwest England, as well as the areas around London, Birmingham, Cardiff, Bristol, Newcastle-upon-Tyne, and in Cornwall.

Figure 3: Maps of industrial coal use, population density and mortality



Colors correspond to quartiles of each variable, where darker colors indicate higher values. We are grateful to the Cambridge Project on The Occupational Structure of Nineteenth Century Britain (funded by the Economic and Social Research Council) for their generosity in providing us with shapefiles for the 1851 Registration Districts. The infant mortality rates is calculated relative to the number of births, while the all-age mortality rate is calculated relative to population.

4.2 Baseline results and the urban mortality penalty

We begin our econometric analysis by studying mortality among those under age one. One advantage of focusing on infant deaths is that infants are unlikely to be exposed to pollution in one location and then die in another, which can be an important issue when studying adult mortality. Another advantage is that infant death rates are calculated using births as the denominator rather than population, and unlike overall population, births are observed on an annual basis.

Our baseline regression specification for this analysis is,

$$IMR_d = \alpha_0 + \alpha_1 \ln(DENSITY_d) + \alpha_2 \ln(COAL_d) + X_d\Lambda + \epsilon_d \,, \tag{2}$$

where IMR_d is the number of deaths of children under one in district d divided by the number of births over the 1851-1860 decade, $DENSITY_d$ is the population density (measured in 1851), $COAL_d$ is local industrial coal use, and X_d is a vector of control variables. To ease interpretation of the results, we standardize the $\ln(DENSITY_d)$ and $\ln(COAL_d)$ variables to have a mean of zero and standard deviation of one. Because spatial correlation may be an issue here, we allow correlated standard errors between any pair of districts within 50km of each other, following Conley (1999).[29]

Table 2 presents our first set of results. Columns 1 and 2 present univariate regressions with coal use and population density, respectively, as explanatory variables. Both of these are strongly related to infant mortality. In particular, the results in Column 2 document the substantial urban mortality penalty that existed in 19th century Britain. However, from historical evidence we know that coal use and the resulting air pollution was more severe in urban areas, so we expect these two variables to be correlated. In Column 3, we add in the available set of control variables as well as log district population. Here we observe that both district population and population density have a strong positive association with the infant mortality rate.

Column 4 adds the coal use variable to the specification shown in Column 3. Note that because log district population is included as an explanatory variable, the coal use variable can be interpreted as changes in the intensity of district industrial

[29]We use 50km as our cutoff for spatial correlation throughout the analysis. This is motivated in part by, Clay *et al.* (2016), who argue that most of the air pollution exposure from coal burning power plants occurred within 30 miles (48km).

coal use per person.[30] There are a couple of important points to notice in Column 4. First, there is a strong positive and statistically significant correlation between local industrial coal use and the infant mortality rate which is only slightly weaker than the association suggested by Column 1. Second, the estimated coefficient on population density drops from 7.8 in Column 3 to 5.25 in Column 4, a reduction of one-third. This suggests that coal use may help explain about one third of the urban mortality penalty. The impact of overall district population on mortality also completely disappears.

There are two natural concerns with the results presented in Column 4. First, is the possibility of omitted variables that are correlated with local industrial coal use and also affect infant mortality. The set of control variables that we have constructed can partially address this issue, but in the tables below we offer several additional approaches to addressing concerns about omitted variables. Second, we may be concerned that less healthy populations sort into more polluted areas, so that the estimated relationship between coal use and infant mortality is not driven by a causal effect of coal use on health.

To help address issues of population sorting, in Columns 5 and 6 we include two additional controls based on mortality rates in disease categories and populations that were less likely to have been affected by air pollution due to coal use. Here the logic is that if the sorting of less healthy populations into more polluted areas is driving the relationship between pollution and infant mortality, then these sorting effects should also show up in diseases that are less directly affected by air pollution. This is similar to the approach used to deal with sorting concerns in recent papers such as Galiani *et al.* (2005) and Alsan & Goldin (2014), in settings where alternative approaches for dealing with this issue were unavailable.

In Column 5 we include our Child NPR mortality control, which is based on infant deaths due to cholera, diarrhea & dysentery, diphtheria, smallpox, scarlet fever, and typhus.[31] In Column 6 we add a second control, Adult NPR mortality, which is based on mortality in the same set of diseases among those over age 5. In both Column 5 and 6 we continue to find strong evidence of a relationship between coal use and

[30]If we do not include log district population in the regression in Column 3, the estimated coefficient on coal use is 11.461 with a standard error of 1.15, which is not statistically different from the coefficient obtained when log district population is included.

[31]See Section 3 for further details about why we use this set of diseases.

infant mortality and the coefficient on coal use falls only slightly relative to Column 4 despite the fact that the R-squared value increases substantially. It is worth noting that coal use is likely to have some positive influence on each of the mortality-based control variables, for example through the impact of in utero or early-life exposure on health later in life, or through the interaction of pollution with infectious disease (Clay *et al.* (2015)). Any such effects will generate a downward bias in the estimated coefficient on coal use.

At the bottom of Table 2, we conduct a bounding exercise on the coal use coefficient following Oster (Forthcoming). The intuition behind this exercise is to use the movement of the coal use coefficient in response to the inclusion of the control variables, relative to the amount of variation in the dependent variable that these controls explain (the change in R-squared), to make inferences about the expected impact of including other unobserved controls. The key assumption that we make in this exercise is that the unobserved controls are as related to log coal use as the observed controls.[32] We also need to pick a maximum R-squared value, $Rmax$, that the unobserved control variables could achieve. We consider two alternatives here. First, we follow Oster's recommendation of setting $Rmax = 1.3 * \hat{R}$ where $\hat{R}$ is the R-squared value from the fully controlled regression. Second, we consider the most conservative option, $Rmax = 1$. In either case, the lower bound estimate of the impact of coal use on infant mortality continues to imply substantial mortality impacts.

In terms of magnitude, our preferred results, in Column 6, imply that a one s.d. increase in local industrial coal use raises infant mortality by just over 10.7 deaths per thousand births, or 7.9%. This is a substantial increase in an important mortality category. Even the most conservative lower-bound estimate on the coal use effect, at the bottom of Column 5, implies that a one s.d. increase in industrial coal use raises infant mortality by 4.1%.

[32] In Oster's notation, we are assuming $\delta = 1$.

Table 2: Baseline infant mortality regression results

	DV: Infant mortality rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Coal use)	15.09***			13.68***	10.92***	10.71***
	(1.358)			(2.462)	(2.328)	(2.278)
Ln(Pop. Density)		16.55***	7.797***	5.255***	-1.351	-1.961
		(1.440)	(1.531)	(1.432)	(1.521)	(1.413)
Ln(District pop.)			8.503***	-2.465	-1.924	-1.911
			(1.421)	(2.612)	(2.393)	(2.291)
Child NPR mort.					1.500***	1.178***
					(0.170)	(0.181)
Adult NPR mort.						12.52***
						(2.742)
Mean Altitude			1.222	-1.407	-0.0218	-0.502
			(1.861)	(1.826)	(1.769)	(1.730)
Hilliness			-8.985***	-8.715***	-7.007***	-6.251***
			(2.202)	(2.055)	(2.095)	(2.049)
Seaport indicator			-3.917	-3.456	-3.492	-3.050
			(2.840)	(2.785)	(2.435)	(2.393)
Seaport tonnage			-5.857	0.0202	2.623	-0.398
			(10.36)	(9.952)	(7.562)	(7.336)
FLFP			31.09*	31.81**	15.59	21.89**
			(16.32)	(13.93)	(11.39)	(10.52)
Ag. Suitability			-27.44***	-17.41*	-10.20	-5.680
			(8.600)	(8.960)	(8.419)	(8.023)
Constant	135.6***	135.6***	151.9***	142.5***	116.8***	88.65***
	(1.859)	(1.961)	(8.398)	(9.009)	(8.143)	(9.973)
Observations	581	581	581	581	581	581
R-squared	0.324	0.390	0.498	0.530	0.621	0.644
Implied lower bound coal use coefficient using Oster (Forthcoming) approach						
Recommended approach ($\tilde{R} = 1.3 * \hat{R}$):				12.6	8.3	8.1
Most conservative approach ($\tilde{R} = 1$):				10.5	5.6	5.8

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. The dependent variable is the infant mortality rate: deaths under age one divided by births using data from 1851-1860 and excluding deaths due to accidents or violence. Pollution measures are based on each district's industrial composition in 1851. The population, population density and pollution variables are standardized. The Child NPR mortality is based on the mortality rate per 1000 births from a basket of childhood infectious diseases that are less likely to be affected by pollution: cholera, diarrhea/dysentery, diphtheria, smallpox, scarlet fever, and typhus. Adult mortality values are for those aged 20 and over. Adult NPR mortality is based on the mortality rate from a basket of diseases that are less likely to be affected by pollution: cholera, diarrhea/dysentery/digestive diseases, diphtheria, scarlet fever, and typhus.

In Appendix A.4 we present a variety of robustness results using the approach shown in Table 2. In one set of robustness exercises, we show that results similar to those shown Table 2 are obtained if we use alternative approaches to measuring local industrial coal use, such as coal use per acre, coal use per worker, or an indicator variable for whether industries tended to be heavily polluting. We also show that the results in Table 2 are largely unchanged if we include a control for medical employment in each district or if we run regressions weighted by district population.[33]

While the results in Table 2 suggest that local industrial coal use was associated with increased infant mortality, we may be worried that this relationship is driven in part by omitted variables. Below, we offer several strategies for dealing with these concerns. Before doing so, however, it is interesting to explore in more detail the extent to which local industrial coal use can help us explain the urban mortality penalty.

Looking back at Table 2, we can see in Columns 5-6 that in regressions which include both local industrial coal use as well as controls for the local infectious disease mortality rate (Child NPR mortality and Adult NPR mortality), we observe that the positive relationship between infant mortality and either district population or population density completely disappears. This suggests that these two factors – infectious diseases and coal-based pollution – together explain the urban mortality penalty. To make this point more concrete, in Table 3 we look at what happens when we do not account for local industrial coal use. In Columns 1-3 we consider regressions that include controls for local infectious disease mortality as well as district population density, but not local industrial coal use. We can see that population density always has a positive and statistically significant impact on mortality, even when all controls are included. This suggests that there is a portion of relationship between population density and mortality that remains after accounting for the local infectious disease environment. In contrast, in the results in Columns 4-5, which include local industrial coal use, the relationship between population density and infant mortality disappears.[34] This suggests that the portion of the urban mortality

[33]When running weighted regressions we drop London, which would otherwise dominate the results.

[34]The coefficient on coal use in Table 3 differ somewhat from those shown in Table 2. This is because we do not include log population among the control variables in Table 3 so that the urban mortality penalty is not mixed between the log population and log population density variables. If log population is included in the regressions shown in Table 3 the qualitative results are similar, i.e., log population has a statistically significant relationship to infant mortality when the coal use variable is not included but this relationship becomes small and statistically insignificant when we

penalty not explained by the local infectious disease environment can be explained by coal use.

Table 3: Local industrial coal use and the urban mortality penalty

	DV: Infant mortality rate				
	(1)	(2)	(3)	(4)	(5)
Ln(Pop. Density)	4.832***	4.037***	3.107*	1.131	-1.993
	(1.720)	(1.529)	(1.596)	(1.530)	(1.407)
Ln(Coal use)				5.658***	8.983***
				(1.156)	(1.072)
Child NPR mort.	1.860***	1.505***	1.367***	1.437***	1.182***
	(0.179)	(0.188)	(0.194)	(0.179)	(0.180)
Adult NPR mort.		13.74***	13.12***	12.62***	12.52***
		(2.866)	(3.150)	(2.564)	(2.737)
Other controls			Yes		Yes
Observations	581	581	581	581	581
R-squared	0.538	0.561	0.581	0.592	0.634

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. The additional controls include mean altitude, hilliness, female labor force participation, agricultural suitability, a seaport indicator, and seaport tonnage. Child NPR mortality is based on the mortality rate per 1000 births from a basket of childhood infectious diseases that are less likely to be affected by pollution: cholera, diarrhea/dysentery, diphtheria, smallpox, scarlet fever, and typhus. Adult mortality values are based on deaths from the same set of diseases for those aged 20 and over.

4.3 Results using wind patterns and hilliness

In this subsection, we exploit wind patterns in order to strengthen our ability to identify causal pollution effects. Across Britain the predominant wind direction is from the south and west towards the north and east.[35] Exploiting this fact, for each district we identified every district lying within 25 km to the south and west (upwind districts) and those within 25 km to the north and east (downwind districts).[36] We then

account for coal use.

[35]See Appendix A.1.4 for information on wind patterns in Britain.

[36]Distances were measured between the district center points, which were assigned to either the main district town or, for very rural districts, the geographic center. Using a 25 km window around the center of a district allows us to capture most neighboring districts but is small enough that the impacts of nearby pollution should be substantial. If we use values under 25 km, we will lose some direct neighbor districts from the sample.

summed up the coal used in each of these two sets of nearby districts. Because wind patterns are unlikely to affect health other than through transmitting air pollution, a comparison of the effects of log coal use in upwind districts relative to downwind districts should be free of concerns about omitted variable bias. Because we want to work in logs, this analysis focuses only on the 422 districts where there are other districts in both the upwind and downwind quadrants, so that neither upwind nor downwind coal use is missing once we take logs.[37]

These results are presented in Table 4. Column 1 presents results including only coal use and population density within a district as well as coal use in upwind and downwind districts. In Column 2 we include population in all districts within 25km. This term is included to ensure that the upwind and downwind coal use variables are not simply reflecting overall population in nearby districts. We progressively add controls in Columns 3-6 with Columns 5 and 6 containing the most demanding specification, which includes controls for child and adult NPR mortality in each district.

The key statistic to look at in these tables is the difference between the upwind and downwind coal use coefficients. These differences, shown at the bottom of the table, range from 2.3-2.9 and remain fairly consistent as we add control variables to the specifications. F-tests suggest that the upwind and downwind coefficients are statistically different at the 90% or 95% confidence level. Because these differences are driven only by wind patterns, they should be free of other influences that nearby coal use might have had on district outcomes. In contrast, if we look at the upwind or downwind coefficients alone then we may worry that they include the impact of having more coal-using industries in nearby districts, which could affect health in a district in a myriad of ways. Looking at the difference is a cleaner approach because we would not expect that the impact of proximity to districts with more coal using industries would differ depending on whether those districts were in an upwind or downwind direction except through air pollution spillovers.

[37]An alternative is to add one to the coal use in all districts, take logs, and then conduct the analysis using all of the districts in the data. Results in Appendix Table 18 show that this generates qualitatively similar results, but that adjusting the upwind and downwind coal use values in this way affects the estimated magnitude of the effect of coal use.

Table 4: Effect of coal use in upwind and downwind districts

	DV: Infant mortality rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Coal use)	8.727***	8.441***	10.06***	13.63***	10.74***	11.11***
	(1.752)	(1.867)	(2.855)	(2.722)	(2.674)	(2.604)
Ln(Upwind coal)	1.694	2.849*	2.638*	1.424	1.907*	1.573
	(1.228)	(1.549)	(1.426)	(1.149)	(1.137)	(1.082)
Ln(Downwind coal)	-1.285	0.00599	-0.227	-1.420	-1.012	-0.764
	(1.070)	(1.489)	(1.362)	(1.211)	(1.173)	(1.046)
Ln(Nearby pop.)		-2.659	-2.367	-3.057*	-4.508***	-4.490***
		(2.324)	(2.157)	(1.582)	(1.590)	(1.350)
Ln(Pop. Density)	9.983***	10.68***	10.85***	4.950***	-1.509	-2.172
	(1.486)	(1.492)	(1.608)	(1.615)	(1.546)	(1.463)
Ln(District pop.)			-1.836	-1.881	-1.112	-1.297
			(3.016)	(2.673)	(2.457)	(2.376)
Adult NPR mort.						11.13***
						(2.842)
Child NPR mort.					1.506***	1.263***
					(0.177)	(0.179)
Other controls				Yes	Yes	Yes
Observations	422	422	422	422	422	422
R-squared	0.463	0.467	0.467	0.566	0.664	0.682
Difference between downwind and upwind coefficients						
Coef. difference	2.979	2.843	2.865	2.844	2.919	2.337
Test for significance of difference between downwind and upwind effects						
F-stat	3.55	3.45	3.52	3.74	4.14	3.21
p-value	0.0602	0.0640	0.0614	0.0538	0.0426	0.0739

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. The additional controls include mean altitude, hilliness, female labor force participation, agricultural suitability, a seaport indicator, and seaport tonnage. $Ln(Nearbypop.)$ is the population of districts within 25km. The dependent variable in all regressions is the infant mortality rate. Pollution measures are based on each district's industrial composition in 1851. The coal use variables are all standardized. Child NPR mortality is based on the mortality rate per 1000 births from a basket of childhood infectious diseases that are less likely to be affected by pollution: cholera, diarrhea/dysentery, diphtheria, smallpox, scarlet fever, and typhus. Adult mortality values are based on deaths from the same set of diseases for those aged 20 and over.

Because wind patterns are plausibly exogenous to other factors affecting mortality we view the results in Table 4 as providing our cleanest identification approach. Yet in order to consider the role of industrial pollution in explaining the urban mortality penalty we need reliable estimates of the within-district effect of pollution, such as those shown in Table 2. We can bridge this gap by bringing in additional information about the diffusion rate of pollution across space in England & Wales. Using this, together with the effects of coal use on mortality in upwind and downwind districts, we can generate back-of-the-envelope estimates of the within-district pollution effect, which can then be compared to the within-district estimates shown in Table 2. In the following paragraphs, we briefly describe how this is done. A more detailed description is available in Appendix A.3.

The key input needed in order to relate the estimated upwind/downwind coal use effects to the impact of coal use within a district is an estimate of how the concentration of coal-based pollution diminishes with distance. We generate these using the ADMS 5 pollution dispersion modeling software package.[38] We feed into the ADMS 5 software parameters describing a typical 19th century industrial smokestack.[39] The software then uses these parameters together with 10-year average meteorological data for four regions of Britain in order to model the pattern of pollution diffusion from our hypothetical smokestack.[40] The output provides ground-level pollution concentrations for 50 m x 50 m cells across a 20km by 20km grid with the smokestack at the center.[41]

These pollution diffusion patterns allow us to estimate the average concentration of pollutants that coal burning generates within its own district, in a representative upwind district, and in a representative downwind district. These estimates suggest that, for a fixed amount of coal use, the average concentration experienced in the source district is four times higher than the average concentration experienced in a representative downwind district, while the concentration in the downwind district is 53% higher than in the representative upwind district.

Next, we relate the difference between the estimated effect of a given amount of coal use in upwind and downwind districts (without standardizing the variables) to the difference in pollution concentration that we expect in these districts. This implies

[38]This software package was developed by Cambridge Economic Research Consultants and has previously been used by Heblich *et al.* (2016) to model the dispersion of coal smoke in 19th century Britain.

[39]Specifically, we consider a 25 m tall smokestack with a 1.5 m diameter, an exit velocity of 4m/s and a temperature of 120 degrees Celsius. These parameters are the same as those used by Heblich *et al.* (2016).

[40]The meteorological data come from the Met and are from the 1980s or early 1990s.

[41]The original output is provided for four regions of England using the meteorological data specific to each region. Our analysis averages across the four different regional grids. The concentrations generated by the model should be thought of as representing a generic type of air pollution that is similar to total suspended particulates.

a relationship between the change in pollution concentration and the difference in infant mortality rates. Finally, we use this relationship together with the difference in expected pollution concentrations in the downwind and source districts in order to back out the expected impact of the same amount of coal use on mortality in the source district.

The results of this exercise suggest that increasing a source district's industrial coal use by one log-point would raise infant mortality in the source district by 7.26-9.67 deaths per 1000 live births. For the sake of comparability with earlier results, this implies that a one s.d. increase in district log coal use would raise infant mortality by 8.12-10.82 deaths per 1000 live births, or 6-8%. These values are just a bit below the within-district estimated coal use effects shown in Tables 2 and in the top row of Table 4. This suggests that, while the within-district effects estimated in Tables 2 and 4 may be biased upwards, this bias is not likely to be large. Also note that the values obtained using the upwind/downwind results are well within the bounds obtained using the approach from Oster (Forthcoming).

Finally, in Table 5 we consider results in which we interact coal use with the hilliness of the topography in each district (or more precisely, the s.d. of altitude). This identification approach is based on the idea that in hilly areas coal smoke was more likely to be trapped in the valleys, increasing exposure.[42] Other than by trapping in pollution, local hilliness tended to decrease infant mortality, most likely because it was associated with cleaner water due to faster running streams (Antman (2016)).

The results in Table 5 suggest that district hilliness was associated with greater impact of industrial coal use on infant mortality. These effects are quite large; a one standard deviation increase in district hilliness raised the impact of local industrial coal use by about one third. These results provide an alternative check on our finding that air pollution associated with coal use substantially raised infant mortality during the period that we study.

[42] In hilly areas of Britain population centers tended to locate in valleys.

Table 5: Effect of coal use interacted with hilly topography

	DV: Infant mortality rate			
	(1)	(2)	(3)	(4)
Ln(Coal use)	11.80***	12.45***	9.462***	9.608***
	(1.364)	(2.480)	(2.275)	(2.308)
Ln(Coal use) x Hilliness	3.535***	3.783***	4.239***	3.343***
	(1.091)	(0.961)	(0.845)	(0.851)
Ln(Pop. Density)	6.739***	5.618***	-1.129	-1.643
	(1.576)	(1.434)	(1.454)	(1.382)
Ln(District pop.)		-1.842	-1.210	-1.351
		(2.543)	(2.262)	(2.243)
Mean Altitude	1.149	-0.737	0.768	0.233
	(1.730)	(1.744)	(1.672)	(1.693)
Hilliness	-9.334***	-9.496***	-7.834***	-7.080***
	(1.761)	(1.888)	(1.961)	(1.986)
Other controls		Yes	Yes	Yes
Child NPR mortality control			Yes	Yes
Adult NPR mortality control				Yes
Observations	581	581	581	581
R-squared	0.527	0.549	0.645	0.658

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. Hilliness is the standard deviation of altitude within a district. The additional controls include female labor force participation, agricultural suitability, a seaport indicator, and seaport tonnage. Pollution measures are based on each district's industrial composition in 1851. The coal use variables are all standardized.

4.4 Effects across all age categories

Thus far we have focused on infant mortality, where concerns about selective migration occurring between pollution exposure and death are minimized. Next, we broaden our analysis to look at how local industrial coal use is related to mortality across all age categories.[43] To generate these results, we run regressions mirroring those reported in Table 4, which include upwind and downwind coal use, but with the mortality rate in different age groups as the dependent variable. These mortality

[43]Our estimates of the effect of local industrial coal use on mortality among adults should be thought of as a lower bound on the true effect. This is because pollution can increase mortality through both acute effects, such as heart attacks due to exposure to high levels of pollution at a particular point in time, and chronic effects, such as lung diseases related to long-term pollution exposure. Migration will cause us to miss some of the chronic effects of pollution exposure, because people who are exposed to pollution in one location may die somewhere else.

rates are calculated using denominators based on the average population in the district during the sample decade, which were produced by the Census using data from the 1851 and 1861 population Censuses.[44]

Table 6 describes the coefficients on both upwind and downwind coal use variables for age-group regressions, as well as F-statistics testing for the difference between upwind and downwind effects. For comparison, at the bottom of the table we list the overall mortality rate for each age group in our data. All of the regressions in Table 6 include our full set of controls for district characteristics, including district coal use, population density, population, etc. The results indicate that coal use in upwind districts increased mortality among those under 5 years old. There is also evidence of smaller increases among the working age and older populations. The increases in mortality observed among the working age population may be due either to migration or because there are channels specific to this age group through which pollution affects mortality. One potential channel is tuberculosis, a respiratory disease, which was an particularly important killer among this age group. A second potential channel is that pollution may have increased death in childbirth.[45]

[44]We may worry that, because we are using deaths across the full 1851-1861 decade but we only have population observations in the Census years at the beginning and end of the decade, measurement error in the population denominators may be affecting our results. To check this, in Appendix A.6 we calculate some additional results using only deaths in 1851-1853 compared to population denominators based on the 1851 census. Because the mortality observations are closer to the census year, concerns about the population denominator should be less important in these regressions. These regressions deliver results that are very similar to those shown in Table 6.

[45]Additional results, available upon request, suggest that local industrial coal use was associated with increased mortality in both of these cause of death categories. However, because we cannot separate these channels from the role of migration in this paper, we leave further explanation of these channels for future work.

Table 6: Upwind vs. downwind coal use effects by age group

DV: Mortality rate in each age category (per 1000 persons)									
Under 5	**5-9**	**10-14**	**15-19**	**20-24**	**25-34**	**35-44**	**45-54**	**55-64**	**65 up**
Coefficient on coal use in upwind districts									
0.681	0.102*	-0.0002	0.0804	0.168	0.0806	-0.224**	-0.173	-0.136	-0.161
(0.416)	(0.0547)	(0.0433)	(0.0643)	(0.103)	(0.0828)	(0.112)	(0.128)	(0.170)	(0.360)
Coefficient on coal use in downwind districts									
-0.756	-0.0188	-0.0504	-0.0782	-0.0943	-0.139*	-0.248*	-0.200	-0.348**	-0.403
(0.477)	(0.0595)	(0.0411)	(0.0741)	(0.0864)	(0.0761)	(0.128)	(0.141)	(0.173)	(0.314)
Difference between upwind and downwind coefficients									
1.437	0.1208	0.0502	0.1586	0.2623	0.2196	0.024	0.027	0.212	0.242
F-test for significance of difference between upwind and downwind effects (F-stat & p-value)									
6.14	2.71	0.88	4.8	5.62	8.41	0.05	0.05	1.28	0.53
0.0136	0.1004	0.3495	0.029	0.0183	0.0039	0.8176	0.8284	0.2588	0.4652
Overall national mortality rate by age group									
68.23	8.52	4.93	6.96	8.58	9.74	12.46	16.85	29.36	91.62

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. All regressions include controls for district coal use, population density, population, female labor force participation, agricultural suitability, a seaport indicator, and seaport tonnage. All regressions use observations for 422 districts with non-zero upwind and downwind coal use values.

Given the substantial impact of coal use on mortality for children under 5 shown in Table 6, it is useful to use the upwind/downwind effects estimated in this table to validate estimates of the within-district effects, as we did for infant mortality. Given the rate of pollution diffusion in Britain obtained from the ADMS 5 model, the estimated upwind and downwind effects for children under 5 shown in Table 6 imply that a one log point increase in source district coal use raises under-5 mortality in that district by 5.45 deaths per 1000. This suggests that a one s.d. increase in log coal use in a district generates an increase in under 5 mortality of 6.1 deaths per 1000. Direct estimates of the relationship between coal use and under 5 mortality (see Appendix Table 21) suggest that a one s.d. increase in log coal use raises district mortality by 4.5-8.27 (8-15% of the under 5 mortality rate). Thus, results obtained by extrapolating from the effects observed in upwind and downwind districts fit near the middle of this range, suggesting that, as with the infant mortality analysis, any bias in the within-district estimates is likely to be small.

5 Discussion

Because we do not have direct measures of pollution levels, it is difficult to compare the effects we have estimated to the existing pollution literature. However, one way to put our findings into perspective is to calculate the impact on life expectancy implied by our results. Our basis for calculating life expectancy is a set of mortality rates obtained from the Registrar General's reports for 5 year age bins up to age 75. Given these coarse values, our estimates are necessarily rough, so they are intended only to provide a sense of magnitude of the effects that we document.

The results above suggest that the impact of a one s.d. increase in district log coal use on infant mortality falls in a range from 8.12-13.68 with the lower of these values based on results extrapolated from the effects observed in upwind and downwind districts and the higher value from Column 4 of Table 2. Applying these effects to mortality for those under one year of age suggests a reduction in life expectancy ranging from 0.33-0.56 years, which is 0.86-1.44% of total life expectancy (up to age 75) based on the mortality rates observed in 1851. If we conduct a similar exercise using the estimated impact on those under age 5 (from Appendix Table 21) the results suggest that a one s.d. increase in local industrial coal use raised mortality by 4.37-8.27 deaths per 1000 persons. These estimates suggest a decrease in life expectancy ranging from 0.84-1.58 years, which is equal to 2.19-4.11% of total life expectancy during this period.[46]

Another way to put our results into perspective is to use recent findings relating pollution levels to mortality, together with our estimated pollution impacts, to back

[46] As a point of comparison, one of the few modern studies that considers the mortality effects of a high-pollution environment, Chen *et al.* (2013), estimates that increased coal use north of the Huai River in China due to a government policy that provided free winter heating lowered life expectancy by 8 percent. We focus on the percentage change in life expectancy when comparing our effects to those of Chen *et al.* (2013) rather than comparing the actual impact on life expectancy because the life expectancy impact of pollution depends in part on overall life expectancy, which was much shorter in Britain during the period that we study than it was in China during the period studied by Chen *et al.* (2013). To calculate the percentage change in life expectancy found by their paper we use the impact on life expectancy that they find, 5.5 years, divided by the life expectancy in China in 1990, the middle of their study period. Compared to these findings, the magnitude of our results seems reasonable.

out the implied difference in pollution levels between high and low coal-using regions in 19th century Britain. Specifically, we draw on the work of Arceo *et al.* (2016), which estimated the effect of PM10 exposure in Mexico and then compared the impact to estimates of the exposure in the U.S., where pollution levels were much lower. Their results suggest that the relationship between PM10 and infant mortality is close to linear. Assuming linearity, we can then use the estimated relationship between infant mortality and PM10 concentrations from their paper to generate implied differences in PM10 concentrations across the districts in our data.

Their study finds that a one microgram per cubic meter increase in PM10 raised infant mortality by 0.123 deaths per 1000 births during a year.[47] We find that a one log point increase in coal use increases infant mortality by between 7.26 to 9.67 deaths per 1000 births.[48] Using these facts, we consider the implied difference in PM10 levels in a district lying at the 25th percentile of the coal use distribution in our data compared to a district lying at either the 75th or 90th percentile. Specifically, moving from the 25th to the 75th percentile of coal use in our data involves a 1.3 log point increase in coal use, which is associated with an increase in infant mortality of 9.4-12.6 additional deaths per 1000 births. Dividing these effects by 0.12 (the marginal effect of PM10 on infant mortality) implies that moving from the 25th to 75th percentiles in coal use would increase pollution concentrations by 78-103 micrograms per cubic meter. Moving from the 25th to the 90th percentile implies an increase in PM10 concentrations ranging from 137-183.[49] As a point of comparison, rough estimates from Greenstone & Hanna (2014) suggest mean PM10 concentrations in the U.S., India and China from 1990-95 of 25, 133, and 178 respectively.[50] This comparison suggests that pollution levels in British cities in the 19th century were likely to have been comparable to the levels experienced in some of the most polluted modern cities.

[47] This statistic comes from Table 6 in their paper, from the top row of Column 6.

[48] These results are from the exercise (Appendix A.3) where we aggregate our estimates relying on wind variation to estimate the effect of exogenous coal use (within a district) on infant mortality.

[49] If we instead use the results from Chay & Greenstone (2003) provided by Arceo *et al.* (2016) (their Table 6, Column 6, Row 5), we calculate somewhat larger implied PM10 differences; a movement from the 25th to the 75th percentile of coal use in our data is associated with an increase in PM10 concentration of 101-135 micrograms per cubic meter, while a movement from the 25th to the 90th percentile is associated with an increase ranging from 179-238.

[50] To obtain estimated PM10 concentrations we convert the TSP values reported by Greenstone & Hanna (2014) using the formula PM10 = 0.55 TSP, following Arceo *et al.* (2016) and Knittel *et al.* (2016). The WHO air quality standard limits annual PM10 averages to below 20 micrograms per cubic meter. Arceo *et al.* (2016) report mean PM10 levels of 67 in Mexico using data from 1997-2006.

6 Conclusions

Due in part to lack of evidence, recent surveys of health and mortality during the 19th century have largely ignored the role of pollution. Cutler *et al.* (2006), for example, discusses the health effects of urbanization in Britain, but never directly addresses pollution. In Deaton (2013), pollution merits only a passing remark (p. 94). Szreter (2005) spends just one out of four hundred pages (p. 126) discussing the role of pollution, and draws primarily on anecdotal evidence. Focusing on the U.S., Costa (2013) describes Pittsburgh skies darkened by pollution, but argues that the lack of reliable particulate data limit our ability to measure the impact of pollution, or to assess the benefits generated as air quality improved. This study fills this gap in the literature by providing broad-based and well-identified evidence of the impact of industrial pollution on mortality in the middle of the 19th century.

Our results show that local industrial pollution had a powerful impact on mortality during this period. Raising local industrial coal use by one s.d. from the mean is associated with an increase in infant mortality ranging from roughly 6-8% an for under-5 mortality ranging from 8-15%. In terms of life expectancy, given mortality patterns in the 1851-1860 decade, the impact of a one s.d. increase in local industrial coal use on under-5 mortality is associated with a reduction in life expectancy at birth of 0.84-1.58 years or 2.19-4.11%. In the most heavily polluted cities, such as Sheffield, Manchester or Birmingham, where coal use was more than two standard deviations above the national mean, the effects could have been very large.

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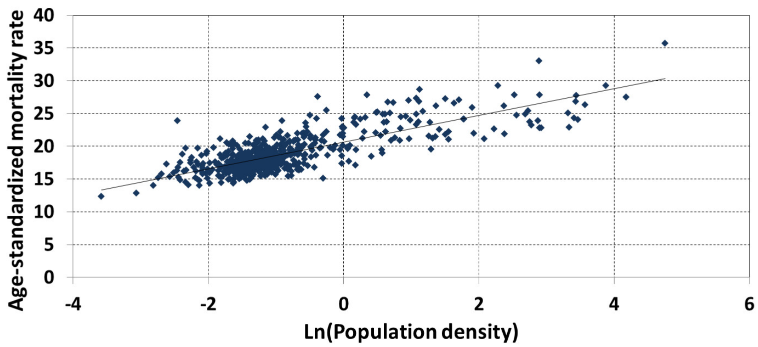
A Appendix

A.1 Empirical setting appendix

A.1.1 The Urban Mortality Penalty across all ages

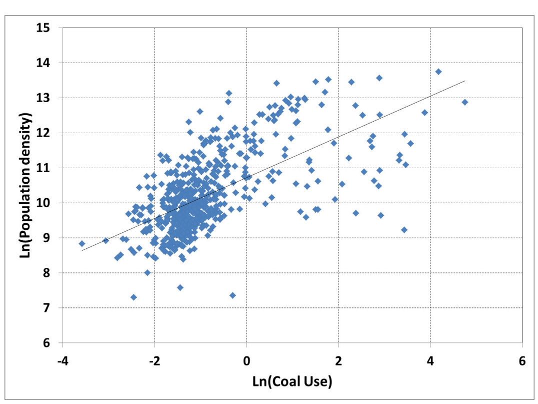
Figure 4: The urban mortality penalty for all ages, 1851-1860



Notes: Mortality data were digitized by Woods (1997) and were obtained through the UK Data Archive. Population density data come from the 1851 Census. The mortality data have been age-standardized to adjust for variation in the age distribution of the population across districts.

A.1.2 Comparing coal use to density

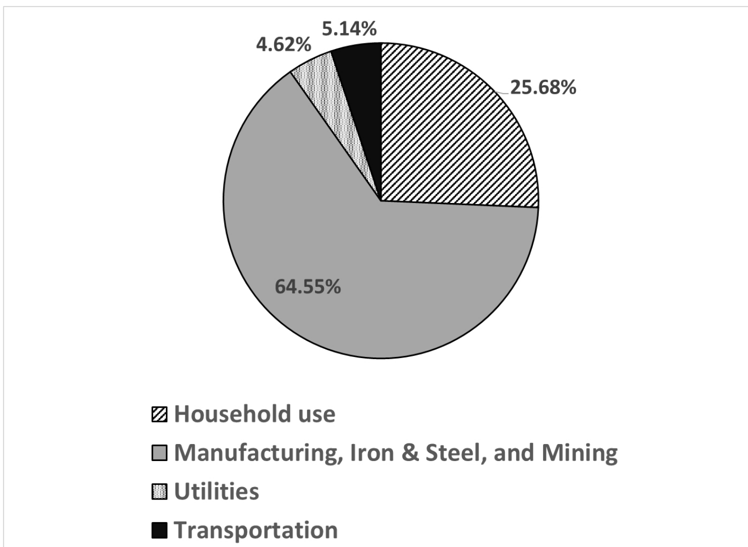
Figure 5: Coal use and population density, 1851-1860



A.1.3 National coal consumption by use

Figure 6 breaks down domestic coal consumption by use based on data from 1855. The industrial coal use data used in this study span manufacturing, iron & steel production and mining.

Figure 6: Coal usage shares for the U.K. in 1855



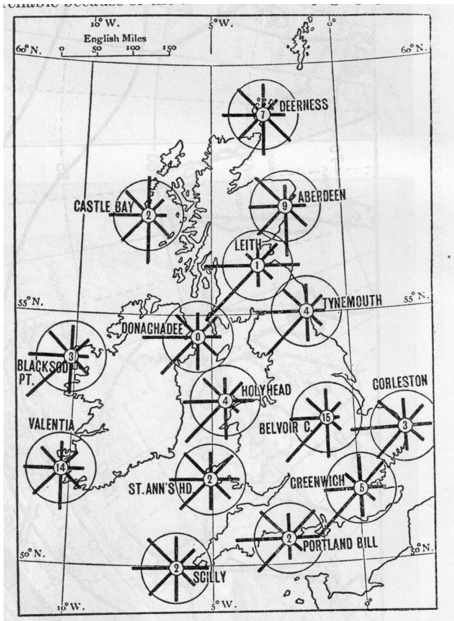
Data from Mitchell (1988).

A.1.4 Wind patterns in Britain

This appendix describes wind patterns in Britain, drawing on information from a detailed report by the Directorate of Weather, U.S. Army Air Force in 1942, "Climate and Weather of the British Isles" (Vol. VI, No. 2). The left-hand panel of Figure 7 shows the wind direction at different points in the British Isles. Each point is based on a weather station. The length of the bars emanating from each point reflect the percentage of time that the wind blows from a particular direction. The right-hand panel shows the directions by month and season for the country as a whole. Across the entire country the predominant wind direction ranges from west to south, with a southwest wind most common.[51]

[51]As an interesting aside, pollution remained so substantial at the time of this report, and the wind so consistent, that the report describes how, "The trails of smoke from industrial areas have

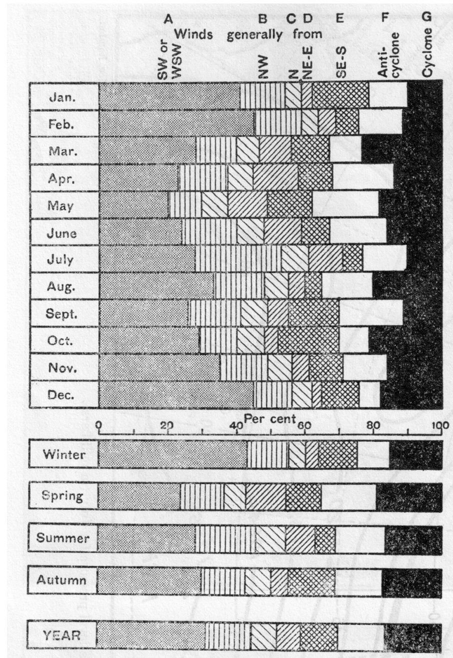
Figure 7: Wind direction in England



(The difference between the radii of the large and small circles represents 12½ per cent. The figures in the small circles show the percentage frequencies of calms.)

Source: Bilham, *The Climate of the British Isles.*

FIGURE 5.—Average annual percentage frequencies of winds from each direction.



(Each type is represented by a shaded band, the breadth of which is proportional to the percentage frequency.)

Source: Bilham, *The Climate of the British Isles.*

FIGURE 4.—Monthly and seasonal percentage frequencies of predominating weather types.

been utilized by British pilots as a guide to location, especially over the North Sea...For example, the pilot coming down the North Sea from the north with a westerly wind near the surface, meets successively the Tyne smoke belt, the Tees belt, and the Yorkshire and Midlands belt" (p. 50).

A.1.5 Mortality patterns in Britain, 1851-1860

Table 7: Contribution of different causes of death to mortality, 1851-1860

Cause of death	Avg. annual deaths (1851-1860)	Mortality rate (per 1000)	Share of total mortality
Respiratory system	57,384	3.02	0.136
Nervous system	52,082	2.74	0.124
Tuberculosis	50,891	2.68	0.121
Circulatory system	23,698	1.25	0.056
Cholera, diarrhea and dysentery	20,517	1.08	0.049
Digestive system	18,946	1.00	0.045
Typhus	17,237	0.91	0.041
Scarlet fever	16,646	0.88	0.040
Violence and accidents	13,937	0.73	0.033
Whooping cough	9,563	0.50	0.023
Measles	7,822	0.41	0.019
Cancer	6,019	0.32	0.014
Smallpox	4,206	0.22	0.010
Kidneys and urinary system	4,072	0.21	0.010
Childbirth	3,104	0.16	0.007
Diphtheria	2,070	0.11	0.005
Generative organs	1,044	0.05	0.002
Other/unknown causes	111,833	5.89	0.266

A.2 Data appendix

A.2.1 Cause-of-death data

In this subsection we discuss the quality of the cause-of-death data available in the Registrar General's report, with a particular focus on the categories included in our control variables. Accurately classifying every death is difficult even in modern data. In the middle of the 19th century there was certain to be substantial misclassification, and in fact many deaths ended up in an unknown category. However, some causes of death present with very clear distinguishing features which would have been well know to doctors, even in the 19th century, and even to many regular people. In our analysis, we focus on deaths in these categories, where we believe that the cause-of-death data should be reasonably accurate.

Table 8 describes how the main infectious diseases that used in constructing our non-pollution related controls were transmitted and identified based on descriptions from the mid-19th century. As these descriptions show, each of the infectious diseases used in our control variable came with some clearly identifiable symptoms.[52]

Because many infectious diseases can bring about fatal complications, it is worth noting how those deaths would be classified. The cause of death certificate, an example of which is provided in Figure 8, instructed doctors to list both the primary and secondary causes of death. The intention was to identify the infectious disease as the primary cause of death and the fatal complication as the secondary cause of death. This certificate shown in Figure 8 was taken from the 7th annual registrar generals report and is an example of how to fill out the death certificate. In this example measles is listed as the primary cause of death, while pneumonia, a common complication of measles, is ultimately listed as the secondary cause of death. That fatal complications associated should be listed as the secondary cause of death is also clearly specified in the statistical nosologies that the Registrar circulated to medical officials. Similarly, under diarrhea the instructions state "When the diarrhea occurs in the course of typhus, or of consumption, or of other diseases, it should be so registered". Further evidence consistent with this intention is that, when describing each cause of death, the nosology also lists common secondary afflictions.

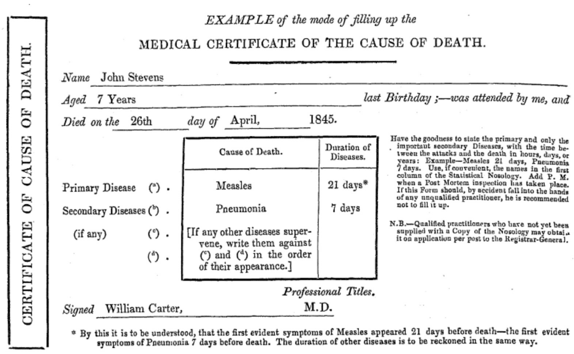
[52]While one may be concerned about misclassification amongst these categories (e.g. Cholera from general diarrhea and dysentery) it is important to note that this type of misclassification does not affect our analysis so long as these diseases are ultimately classified as one of our included categories. This is because we aggregate all of these causes of death to generate our control variables. Thus, misclassification will only matter if any of these diseases could have been categorized as some excluded cause of death or if some other causes of death could have been misclassified as one of these categories. Since the excluded categories include things like respiratory diseases, cancer, kidney failure, etc. this seems unlikely.

Table 8: Infectious disease transmission and diagnosis

Disease	**Transmission**	**Diagnosis**
Cholera	Bacterial; tainted food and water	Watery diarrhea. Severe dehydration that leads to sunken eyes and decreased skin elasticity. Weak pulse.
Diarrhea and dysentery	Bacterial, viral, or parasitic	Diarrhea, fever and abdominal pain.
Diphtheria	Airborne virus	Fever and sore throat. Large patches of whitish lymph in throat. Sometimes mistaken as scarlet fever but without rash.
Smallpox	Airborne virus	Initial fever accompanied by severe back pain and vomiting. Eruptions of a papular form appear on on face, neck, and wrists, on second or third day. Eruptions become pustular five to six days later and ooze on day eight.
Scarlet fever	Airborne virus	Continued fever. Uniform crimson rash appears on neck and face on the second day. Copious skin peeling. Sore throat, distinct "strawberry tongue", warm skin, and rapid pulse.
Typhus	Virus spread by lice, fleas, and ticks	Continued fever. Dark, slightly elevated rash appears on body and limbs on fifth to seventh day. Rash flattens after a few days. Pressure makes rash paler. Tongue is swollen and pale at first but becomes covered with a yellow-brown fur. Loss of muscular power, muscle twitches, and hand trembles. Rapid pulse.

Descriptions drawn primarily from two 19th century medical guides: Barclay, Andrew Whyte. (1862) *A Manual of Medical Diagnosis: Being an Analysis of the Signs and Symptoms of Disease,* Blanchard and Lea; and Fenwick, Samuel (1873) *The Students guide to Medical Diagnosis,* Henry C. Lea.

Figure 8: Example cause of death certificate


CERTIFICATE OF CAUSE OF DEATH.

EXAMPLE of the mode of filling up the

MEDICAL CERTIFICATE OF THE CAUSE OF DEATH.

Name John Stevens

Aged 7 Years *last Birthday ;—was attended by me, and*

Died on the 26th *day of* April, 1845.

	Cause of Death.	Duration of Diseases.
Primary Disease (a) .	Measles	21 days*
Secondary Diseases (b) .	Pneumonia	7 days
(if any) (c) .	[If any other diseases supervene, write them against (c) and (d) in the order of their appearance.]	
(d) .		

Have the goodness to state the primary and only the important secondary Diseases, with the time between the attacks and the death in hours, days, or years: Example—Measles 21 days, Pneumonia 7 days. Use, if convenient, the names in the first column of the Statistical Nosology. Add P. M. when a Post Mortem inspection has taken place. If this Form should, by accident fall into the hands of any unqualified practitioner, he is recommended not to fill it up.

N.B.—Qualified practitioners who have not yet been supplied with a Copy of the Nosology may obtain it on application per post to the Registrar-General.

Professional Titles.

Signed William Carter, M.D.

* By this it is to be understood, that the first evident symptoms of Measles appeared 21 days before death—the first evident symptoms of Pneumonia 7 days before death. The duration of other diseases is to be reckoned in the same way.

This figure is reproduced from the 7th annual report of the Registrar General.

A.2.2 Coal using industries in the data

Table 9 lists the polluting industries used to construct the local industrial coal use measure, together with their 1851 employment and coal use per worker level.

Table 9: Industry coal use per worker and employment in 1851 (workers over 20)

Industry	**National employment**	**Coal use per worker**
Earthenware, bricks, etc.	58,384	48.9
Metal and engine manufacturing	331,919	43.7
Chemical and drug manufacturing	16,398	40.1
Mining related	223,428	28.9
Oil, soap, etc. production	14,168	20.7
Brewing and beverages	25,940	19.4
Leather, hair goods production	47,021	12.1
Food processing	254,968	12.0
Textile production	621,303	10.1
Paper and publishing	49,594	9.7
Shipbuilding	21,743	6.1
Wood furniture, etc., production	115,254	5.4
Vehicle production	13,245	2.6
Instruments, jewelry, etc.	34,844	2.0
Apparel	681,557	1.6
Construction	335,350	1.6
Tobacco products	3,379	1.1

Coal per worker values come from the 1907 Census of Production. The number of workers in the industry in 1851 come from the Census of Population Occupation reports at the district level, which report employment for workers over 20 years old only.

A.2.3 Additional data

In addition to our main data sets, we also collected data describing population density, district location, and several other factors that may have influenced health during this period. The district location data, which are needed in order to allow spatial correlation in the standard errors and for looking at spillovers into downwind districts, are based on geographic coordinates that were collected by hand. These reflect the latitude and longitude for the main population or administrative center of each district. For a few very rural districts, where there was no clear population or administrative center, the geographic center was used.

The agricultural suitability control is based on data from the Food and Agricultural Organization of the United Nations (FAO). Our main suitability measure is based on agricultural suitability across all crops with a medium level of input (e.g., capital). It is not possible to calculate agricultural suitability for many of our districts because they are currently covered by urban areas and so agricultural suitability measures are unavailable. To deal with this, we focus on agricultural suitability at the county level. The FAO suitability index is based on the following scale:

- 0: Land not suited for pasture of rained crops
- 1: Land very poorly suited for pasture and at best poorly suited for rained crops
- 2: Land poorly suited for pasture and at best poorly suited for rained crops
- 3: Land suited for pasture and at best poorly suited for rained crops
- 4: Land suited for rained crops and pasture possible
- 5: Land well suited for rained crops and pasture possible
- 6: Prime land for rained crops and pasture possible

As our measure of agricultural suitability, we use the share of total agricultural land within each county composed of land rated 4 or above on the FAO scale. For two urban counties, London and neighboring Middlesex, there is not enough non-urban land to obtain an agricultural suitability measure. For these counties we use the agricultural suitability in the neighboring county Surrey (these are the same as in other neighboring counties such as Essex and Kent).

We also constructed a control for female labor force participation. This is a potentially important factor in determining mortality patterns because during this period female employment was often associated with higher infant and child mortality rates because working mothers had less time to breastfeed or take care of children. Female labor force participation was also highly correlated with child labor force participation. To construct our female labor force participation variable (FLFP), we use the district-level occupation data from the Census of Population, which reports occupations for both males and females. Our FLFP variable is the number of working women 20 and over as a share of the total female population 20 and over. We exclude from the set of working women those employed in medical professions (e.g., midwives), which may impact mortality in a different way than overall female labor force participation and is likely to be endogenous.

We also collected information on whether each district contained a major port, and if so, the volume of seaborne trade. These data are based on the Annual Statement of Trade and Navigation for 1865. These are potentially important controls because of the role that international trade played in transmitting disease.

Finally, we constructed a control for the number of persons in medical occupations in each district (per. 10,000 residents). We omit this control from our main analysis due to endogeneity concerns, but it is useful as a robustness check. The medical services variable is based on Census of Population occupation data. The medical occupation category includes physicians, surgeons, other medical men, dentists, nurses (not domestic) and midwives.

A.2.4 Comparing to 1871 county-level coal use

As an additional check of the coal use measure, we compare results obtained using county-level industrial coal use levels for 1871 calculated using our methodology to result obtained using county-level industrial coal use data from the 1871 Coal Commission Report. This report, commissioned by Parliament in response to fears of a shortage of coal in the 1870s, was conducted by some of the leading experts on coal mining and coal use in Britain. The final report, titled *Report of the Commissioners Appointed to Inquire into the Several Matters Relating to Coal in the United Kingdom*, stretches to over 1,300 pages and includes a variety of useful information.

As part of this report, circulars were sent to firms in each major coal-using county asking them about their coal consumption. Using these reports, and adjusting for the number of circulars returned in each county, we are able to calculate industrial coal use levels in the counties surveyed, though these figures are imperfect because only major industrial establishments were surveyed. Hanlon (2016) compares the resulting values to estimates of county-level coal use based on Census of Population occupation data for 1871 and industry coal use per worker values from the 1907 Census of Manufactures and shows that these estimated values do a reasonable job of reproducing the levels given by the Coal Commission report (the correlation is 0.912).

Another way to compare these two measures of coal use is to look at their relationship to mortality, using mortality data based on the Registrar General's report from Woods (1997). This is done in Table 10, where we run cross-sectional regressions of county-level mortality in 1871-1880 on each of the two coal use measures. Columns 1-2 present results for infant mortality while Columns 3-4 present results for total mortality (age standardized). Results are nearly identical whether we use our measure of coal use or coal use based on the 1871 Coal Commission Report. This suggests that regressions that use our inferred coal use measure will deliver results that are very similar to those obtained using coal use estimates based on the 1871 data.

Table 10: Comparing the mortality impact of different coal use measures

	DV: Infant mortality		**DV: Total mortality**	
	(1)	(2)	(3)	(4)
Ln(Pop. Density)	0.251	-1.755	0.314	0.125
	(1.330)	(1.446)	(0.237)	(0.269)
Ln(Coal Use) – Coal Commission Report	12.23***		2.227***	
	(2.200)		(0.297)	
Ln(Coal Use) – our measure		14.40***		2.315***
		(2.220)		(0.332)
Constant	143.6***	143.6***	20.05***	20.05***
	(2.857)	(2.605)	(0.312)	(0.316)
Observations	23	23	23	23
R-squared	0.472	0.561	0.740	0.732

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis. The density and coal use variables are standardized. The total mortality rate used in Columns 3-4 is age-standardized.

A.2.5 Summary statistics for analysis data

Table 11 provides summary statistics for data used in the analysis.

Table 11: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Baseline regressions variables (581 districts)				
Total age-std. mortality (all ages)	18.952	3.075	12.365	35.731
Ln(Population Density)	-0.843	1.191	-3.583	4.756
Ln(Coal Use)	10.237	1.119	7.3	15.18
Mean Alt.	104.466	80.838	0	487.748
Hilliness	46.884	38.6	0	240.254
Seaport ind.	0.126	0.332	0	1
Seaport tons (mil.)	0.021	0.178	0	2.653
FLFP rate	0.287	0.096	0.101	0.746
Ag. suitability	0.899	0.167	0.354	1
Mortality variables (581 districts)				
Infant mortality rate	135.575	26.507	66.782	233.183
Child NPR mortality rate	15.907	8.454	2.79	60.739
Under 5 mortality rate	53.759	15.128	22.782	128.559
Adult total m.r. (age std)	11.809	1.353	8.957	18.647
Adult NPR m.r. (age std)	2.188	0.424	1.104	4.043

Notes: Total mortality rates exclude mortality from accidents or violence.

A.3 Using wind-pattern results to validate within-district estimates

In this appendix we describe how we use the results based on coal use in upwind and downwind districts to validate the estimated effect of coal use within a district on infant mortality. The key input into this exercise is a measure of how rapidly coal-based pollution diffuses across space in Britain. To obtain this, we begin by utilizing the ADMS 5 pollution modeling software provided by Cambridge Economic Research Associates.[53] This software package was designed to model the environmental impacts of industrial installations. It has previously been applied to study pollution in the 19th century by Heblich *et al.* (2016).

[53]Further details about this software package are available at `http://www.cerc.co.uk/environmental-software/ADMS-model.html`.

The ADMS 5 pollution diffusion models that we obtain are based on modern meteorological data for four regions of England provided by the Met Office. Figure 9 describes the wind direction for each of the four regions. As these show, the predominant wind direction in all regions was from the south and west.

Figure 9: Wind roses for four regions of England

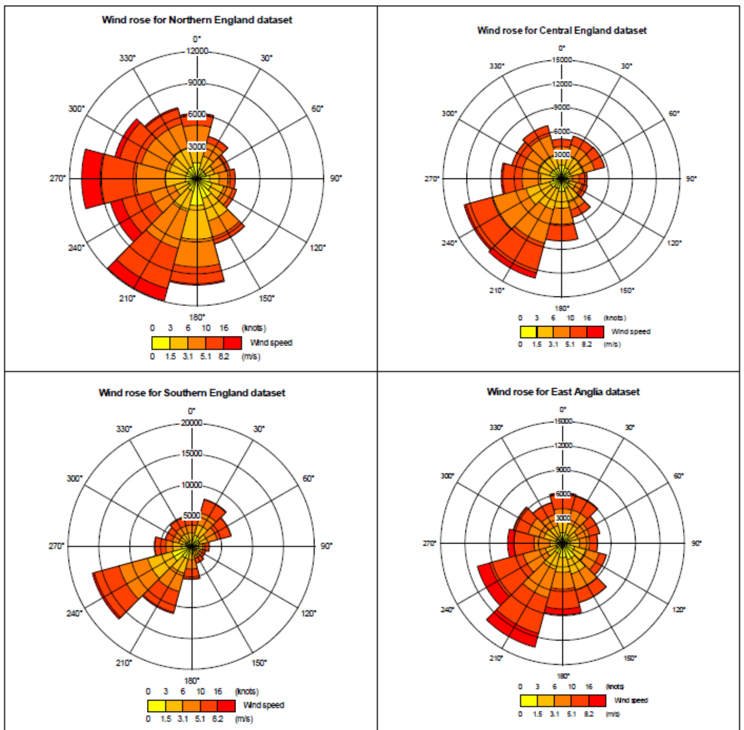
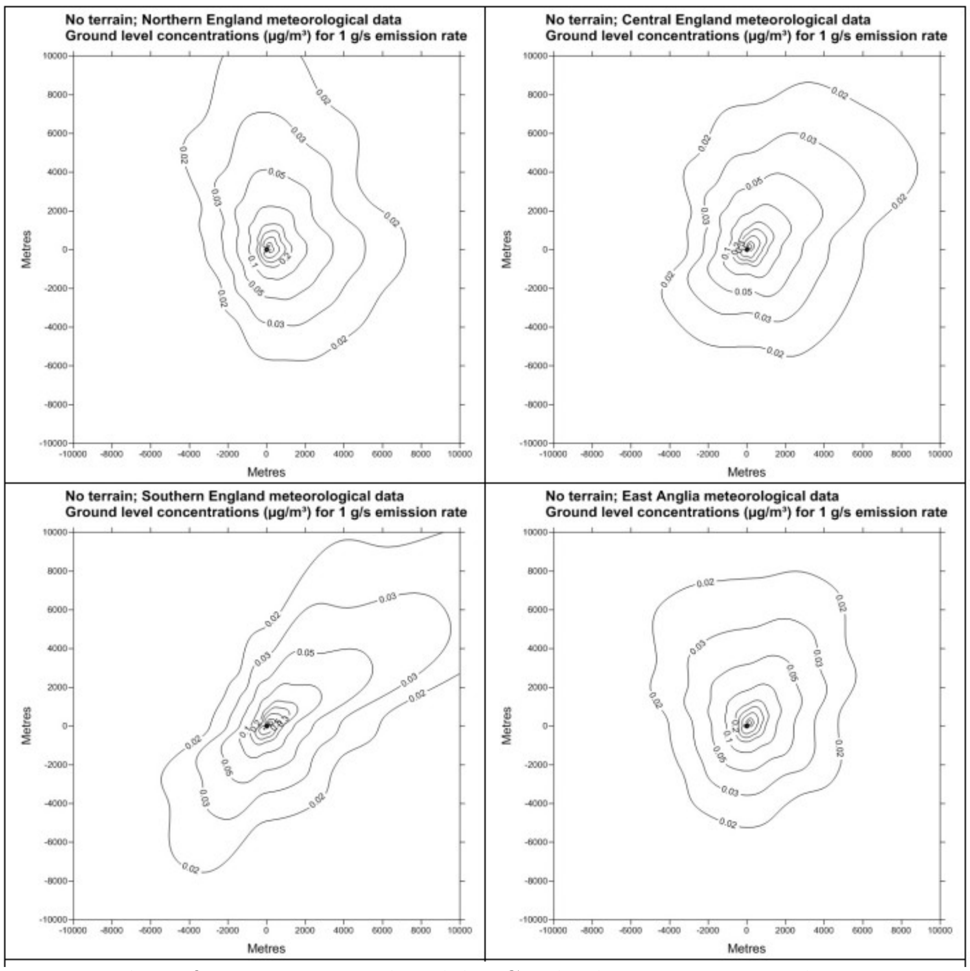


Figure 3.2: Wind roses for the four regional meteorological datasets

These figures were provided by Cambridge Environmental Research Consultants using data from the Met Office.

We need to feed into the model parameters describing the industrial installation that we want to model. Here we follow Heblich *et al.* (2016) in assuming parameters that are typical to 19th century factories: a smokestack that is 25m high with a diameter of 1.5 m, an exit velocity of 4 m/s and a temperature of 120 degrees Celsius. We use a surface roughness parameter of 0.5 m, representing parkland or open suburbia. Based on these parameters, we obtain four estimated pollution diffusion plumes, one for each region of England. Each of these provides an estimate of ground-level pollution concentrations for 50 m cells covering a 20 km x 20 km grid with the pollution source at the center. These pollution values should be thought of as representing a generic type of pollution, such as mixed-size particulate matter. Figure 10 describes the pollution diffusion patterns in the four regions of England. Because we estimate the effect of upwind pollution on mortality using data from the entire country, in these calculations we average across all four regional diffusion patterns.

Figure 10: Pollution diffusion patterns for the four regions of England



These figures were produced by Cambridge Environmental Research Consultants using the ADMS 5 software package.

Next, we use our average pollution diffusion plume to estimate the average concentration experienced in the pollution source districts as well as upwind and downwind districts. In our district data, the average nearby district (within 25 km) has a center that is 17.36 km from the source city, so we center our upwind and downwind districts at this distance from the source. Given the average area of the districts in our data, and assuming circular districts, we obtain an expected district radius of 9.09 km. Thus, we assume that the source district includes all areas within 9.09 km of the pollution source, while the upwind and downwind districts include areas within 9.09 km of their respective district centers.[54]

To obtain the average pollution concentration in the source district we simply take the mean across all cells within 9.09 km of the district center. Obtaining the average for the upwind and downwind districts requires slightly more work, since their boundaries extend past the edge of the 20 km x 20 km grid provided by the ADMS 5 software. To deal with this, we note that if we only look at cells 5 km or more from the source, log pollution concentration levels are very close to linearly related to distance. After observing this, we model the pattern of pollution concentration outside of 10 km using parameters obtained by regressing log concentration on distance using data for grid points from 5-10 km from the pollution source. This is done separately for downwind districts, those lying to the north and east of the source district, and upwind districts, those lying to the south and west of the source district. The R-squared values for these regressions are 0.9817 and 0.9842 for the downwind and upwind districts respectively, so the model is providing a very good fit for the data. We then take the average concentration for our downwind and upwind districts.

The average concentration values obtained from this exercise are described in Table 12. We can see that pollution concentrations in the source district are about four times higher than the average concentration in the downwind district. Concentrations in the downwind district are 53% higher than in the upwind district. At the bottom of the table we describe the log differences between the upwind and downwind concentrations, and between the downwind and source district concentrations.

The second input needed for this exercise is a set of results for the impact of coal use on upwind and downwind districts with non-standardized explanatory variables. These results are presented in Table 13. The key values in this table are the differences between the upwind and downwind coal use coefficients, which are shown at the bottom.

[54] In practice this will lead to a slight overlapping of the source and upwind/downwind districts, but this overlap is small and not likely to substantially influence the results.

Table 12: Average concentration values

Source district	Downwind district	Upwind district
0.0296386	0.0072977	0.0047825
Log difference between downwind and upwind district concentrations:		0.4226
Log difference between downwind and source district concentrations:		1.4015

Table 13: Estimated effects of upwind and downwind coal use (not standardized)

	DV: Infant mortality rate			
	(1)	(2)	(3)	(4)
Ln(Coal)	7.276***	11.75***	9.261***	9.578***
	(1.609)	(2.346)	(2.305)	(2.245)
Ln(Upwind coal)	2.243*	1.121	1.501*	1.238
	(1.219)	(0.905)	(0.895)	(0.852)
Ln(Downwind coal)	0.00455	-1.077	-0.768	-0.579
	(1.129)	(0.918)	(0.890)	(0.793)
Additional controls		Yes	Yes	Yes
Child NPR mort. control			Yes	Yes
Adult NPR mort. control				Yes
Difference between downwind and upwind coefficients				
Difference	2.238	2.198	2.269	1.817
F-test for significance of difference between downwind and upwind effects				
F-stat	3.56	3.75	4.19	3.25
p-value	0.0597	0.0536	0.0414	0.0723

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. The additional controls include mean altitude, hilliness, female labor force participation, agricultural suitability, a seaport indicator, seaport tonnage, and the population of districts within 25km. Child NPR mortality is based on the mortality rate per 1000 births from a basket of childhood infectious diseases that are less likely to be affected by pollution: cholera, diarrhea/dysentery, diphtheria, smallpox, scarlet fever, and typhus. Adult mortality values are based on deaths from the same set of diseases for those aged 20 and over.

The results in Table 13 suggest that a one log-point increase in coal use in a source district will cause infant mortality in the downwind district to increase by 1.82-2.27 deaths per live birth relative to the upwind district.

Next, we suppose that the relationship between infant mortality and the air pollution concentration has a common functional form across all districts which is given by,

$$IMR_d = \tilde{\beta} \ln(CONC_d) \tag{3}$$

where $\tilde{\beta}$ is a coefficient that is common to all districts and $CONC_d$ is the concentration of pollution in the district. Here we are making an important assumption that the concave relationship between coal use and the infant mortality rate observed in the data is due entirely to a concave relationship between pollution concentration and infant mortality. This implies that there is a linear relationship between coal use and the concentration of pollution. This is a conservative assumption; if we allow concavity in the relationship between coal use and concentration (or conversely, if we assume linearity in the relationship between pollution concentration and mortality) then we will obtain larger estimates of the within-industry relationship between coal use and mortality. It is also in line with some available studies providing evidence on the shape of the concentration-response function, such as Pope *et al.* (2011).

Now starting with Eq. 3 and taking differences we have,

$$\Delta IMR_d = \tilde{\beta} \Delta \ln(CONC_d) \, . \tag{4}$$

If we take the differences here as being between an upwind and downwind district, both of which are exposed to a one log-point increase in source-district pollution, then the change in infant mortality is equal to the difference between the upwind and downwind coefficients shown in Table 13, which range from 1.82-2.27. From Table 12 we have a difference log concentration levels between upwind and downwind districts of 0.4226. Together these imply values of $\tilde{\beta}$ ranging from 4.3-5.4.

Since the dose-response function parameter $\tilde{\beta}$ is common to all districts, we can also apply these values to the difference between concentration in the downwind and source district. Specifically, we can rewrite Eq. 4 to obtain,

$$IMR_{source} = \tilde{\beta}\left[\ln(CONC_{source}) - \ln(CONC_{downwind})\right] + IMR_{downwind}\,.$$

We can use this equation to recover the infant mortality effect of a one log point increase in source district coal use. The log difference in pollution concentration between the downwind and source districts, given in Table 12, is 1.4015, while our estimated infant mortality effect in the downwind districts ranges from 1.121-2.243. These, together with our calculated $\tilde{\beta}$ values imply that the impact of a one log point increase in coal use in the source district raises infant mortality in that district by 7.26-9.67 deaths per 1000 live births.

Finally, we can compare these source district coal use effects, which are calculated using only the estimated impact of coal use in upwind and downwind district, to our estimates of the impact of coal use within a district. One point of comparison is Table 14, which presents results from regressions matching Columns 4-6 of Table 2 but without standardizing the coal use or density variables. We can see that the estimated within-district impact of coal use ranges from 9.57-12.22. These are slightly higher than the estimates obtained using wind patterns, suggesting that there may be some upward omitted variable bias. However, this bias appears to be reasonably small.

We can also compare to the within-district results obtained while accounting for upwind and downwind coal use shown in Table 13. Here the estimated coefficients on within-district coal use range from 9.26-11.75 once controls are included. Again, comparing this to the estimates derived from only the upwind and downwind effects implies that any upward bias in the within-district coefficients is relatively small.

Table 14: Estimated effects of coal use without standardizing variables

	DV: Infant mortality rate		
	(1)	(2)	(3)
Ln(Coal use)	12.22***	9.756***	9.567***
	(2.199)	(2.080)	(2.035)
Ln(Density)	4.412***	-1.135	-1.646
	(1.202)	(1.277)	(1.186)
Ln(District pop.)	-3.552	-2.772	-2.753
	(3.763)	(3.447)	(3.301)
Child NPR mort.		1.500***	1.178***
		(0.170)	(0.181)
Adult NPR mort.			12.52***
			(2.742)
Additional controls	Yes	Yes	Yes
Observations	581	581	581

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. The additional controls include mean altitude, hilliness, female labor force participation, agricultural suitability, a seaport indicator, seaport tonnage, and the population of districts within 25km. Child NPR mortality is based on the mortality rate per 1000 births from a basket of childhood infectious diseases that are less likely to be affected by pollution: cholera, diarrhea/dysentery, diphtheria, smallpox, scarlet fever, and typhus. Adult mortality values are based on deaths from the same set of diseases for those aged 20 and over.

A.4 Additional within-district infant mortality results

Table 15 presents some additional results using the approach from Table 2 in the main text. In Columns 1-3 we consider some alternative pollution measures. Column 1 shows results using log coal per acre while in Column 2 we measure industrial pollution using coal per worker (and excluding log district population from the set of controls). We can see that both of these suggest a statistically significant positive relationship between local industrial coal use and infant mortality. In Column 3, we measure pollution using employment in a set of "dirty" industries, as measured by Hanlon & Tian (2015), which is based on a list of heavily polluting sectors generated by the government of China. We also include employment in clean industries. It is interesting to see that employment in dirty industries has a statistically significant positive impact on infant mortality while, if anything, employment in clean industries is associated with a mild reduction in infant mortality.

In Column 4, we include an additional control for medical employment in each district, which we do not include in our preferred specifications because of concerns that medical employment may change in response to mortality patterns. In Column 5, we present results from regressions that are weighted by district population in 1851. These are calculated while dropping the London "super-district" which would otherwise completely dominate the results. We can see that results obtained using weighted regressions are very similar to those obtained from unweighted regressions.

Table 15: Additional within-district infant mortality robustness results

	DV: Infant mortality rate				
	Ln(Coal per acre)	Coal per worker	Dirty industry emp.	With medical emp.	Weighted by population
	(1)	(2)	(3)	(4)	(5)
Coal per acre	14.72***				
	(3.130)				
Coal per worker		6.580***			
		(0.990)			
Dirty ind. emp.			10.03***		
			(1.683)		
Clean ind. emp.			-1.337		
			(1.538)		
Ln(Coal use)				9.029***	10.93***
				(2.336)	(2.323)
Ln(Pop. Density)	-13.36***	-0.0154	-1.513	-0.779	-1.612
	(2.886)	(1.504)	(1.406)	(1.687)	(1.335)
Ln(District pop.)	4.729***			-1.090	-2.304
	(1.240)			(2.270)	(2.188)
Child NPR mort.	1.178***	1.237***	1.270***	1.156***	1.069***
	(0.181)	(0.191)	(0.178)	(0.185)	(0.169)
Adult NPR mort.	12.52***	12.49***	11.78***	12.94***	14.02***
	(2.742)	(2.940)	(2.730)	(2.753)	(2.726)
Medical service emp.				-2.165	
				(1.423)	
Add. controls	Yes	Yes	Yes	Yes	Yes
Observations	581	581	581	581	580

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in Columns 1-4 allow spatial correlation over 50km. In Column 5, regressions are weighted by district population, dropping London, with standard errors clustered by county. The dirty and clean industry classifications used in Column 3 are from Hanlon & Tian (2015). The medical employment control used in Column 4 is based on medical workers per 1000 population using data from 1851. All of the coal use, dirty and clean industry employment variables are standardized. All regressions include additional controls for district altitude and hilliness, female labor force participation, agricultural suitability, a seaport indicator variable and seaport tonnage.

Next, we present within-district results using only those districts which are used in our main wind-pattern results, i.e., those districts which have non-zero coal use in both upwind and downwind districts. Table 16 presents these results using the same format as Table 2. We can see that the within-district estimates obtained using this more limited set of analysis districts is quite similar to the estimates obtained when using the full set of districts.

Table 16: Within-district results using only districts available in the wind-pattern analysis

	DV: Infant mortality rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Coal use)	15.95***			12.76***	10.13***	10.48***
	(1.456)			(2.621)	(2.532)	(2.515)
Ln(Pop. Density)		16.22***	6.764***	4.417***	-2.033	-2.721*
		(1.530)	(1.576)	(1.552)	(1.571)	(1.516)
Ln(District pop.)			7.535***	-2.362	-2.013	-2.205
			(1.805)	(2.822)	(2.586)	(2.473)
Child NPR mort.					1.445***	1.193***
					(0.170)	(0.176)
Adult NPR mort.						11.58***
						(2.940)
Add. controls				Yes	Yes	Yes
Observations	422	422	422	422	422	422
R-squared	0.382	0.395	0.526	0.553	0.644	0.663

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. The dependent variable is the infant mortality rate: deaths under age one divided by births using data from 1851-1860 and excluding deaths due to accidents or violence. Pollution measures are based on each district's industrial composition in 1851. The population, population density and pollution variables are standardized. Child NPR mortality is based on the mortality rate per 1000 births from a basket of childhood infectious diseases that are less likely to be affected by pollution: cholera, diarrhea/dysentery, diphtheria, smallpox, scarlet fever, and typhus. Adult mortality values are based on deaths from the same set of diseases for those aged 20 and over.

A.5 Additional infant mortality results using wind patterns

Table 17 presents additional infant mortality robustness results using wind patterns. In Column 1 we add in a control reflecting medical employment in each district. In Column 2 we calculate results weighted by population (dropping London). In Column 3 we use an alternative Child NPR mortality control. In all cases the estimated coefficient on both within industry coal use and upwind coal use looks similar the the results described in the main text.[55]

Table 17: Additional infant mortality results using wind patterns

DV: Infant mortality rate	With medical service employment (1)	Weighted by population (dropping London) (2)	Alternative mortality control (3)
Ln(Coal use)	8.503***	13.30***	10.75***
	(2.659)	(2.456)	(2.662)
Ln(Upwind coal)	1.337	1.130	1.685
	(1.107)	(1.138)	(1.086)
Ln(Downwind coal)	-1.694	-1.986*	-0.921
	(1.128)	(1.202)	(1.109)
Medical service emp.	-3.037**		
	(1.346)		
Child NPR mort.	1.454***	1.220***	
	(0.184)	(0.141)	
Alternative Child NPR mort.			1.589***
			(0.137)
Other controls	Yes	Yes	Yes
Observations	422	421	422
Difference between downwind and upwind coefficients			
Coef. difference	3.031	3.116	2.606
Test for significance of difference between downwind and upwind effects			
F-stat	4.82	4.40	3.57
p-value	0.0287	0.0366	0.0596

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in Columns 1 and 3 allow spatial correlation over 50km. Column 2 shows regressions weighted by district population, dropping London, with standard errors clustered by county. The medical employment control used in Column 1 is based on medical workers per 1000 population using data from 1851. In The alternative child NPR mortality control used in Column 3 adds deaths due to measles and whooping cough to our main child NPR mortality control. All regressions include controls for log population density, log district population, log population in nearby districts (25km), mean district altitude and hilliness, a seaport indicator and seaport tonnage, female labor force participation, and agricultural suitability.

Table 18 present results where, instead of dropping districts with missing log upwind or log downwind coal use values, we set these values to zero and run the

[55] We do not present robustness results using alternative measures of coal use here because it makes less sense to think that the impact of upwind coal use on downwind districts would depend on the size or the population of either the upwind or the downwind districts.

analysis across all districts. This allows us to use the full set of 581 district in the analysis, but this is likely to affect the magnitude of our results because it introduces a number of districts with zero upwind or downwind log coal use.

Table 18: Effect of coal use in upwind and downwind districts with all districts

	DV: Infant mortality rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Coal use)	7.703***	7.745***	7.777***	14.03***	11.35***	11.09***
	(1.349)	(1.380)	(2.916)	(2.523)	(2.419)	(2.336)
Ln(Upwind coal)	3.414***	3.472***	3.471***	2.485***	2.006**	2.035***
	(0.911)	(1.130)	(1.113)	(0.938)	(0.799)	(0.775)
Ln(Downwind coal)	-0.0669	-0.0140	-0.0161	-0.444	0.355	0.712
	(1.184)	(1.358)	(1.323)	(1.206)	(1.092)	(1.021)
Ln(Nearby pop.)		-0.165	-0.162	-1.995	-2.680	-2.901*
		(2.047)	(1.991)	(1.691)	(1.824)	(1.560)
Ln(Pop. Density)	10.93***	10.96***	10.96***	5.480***	-1.096	-1.765
	(1.293)	(1.266)	(1.319)	(1.372)	(1.438)	(1.311)
Ln(District pop.)			-0.0399	-2.305	-1.563	-1.457
			(2.911)	(2.519)	(2.285)	(2.212)
Child NPR mort.					1.498***	1.177***
					(0.170)	(0.179)
Adult NPR mort.						12.69***
						(2.742)
Other controls				Yes	Yes	Yes
Observations	581	581	581	581	581	581
R-squared	0.456	0.456	0.456	0.538	0.627	0.650
Difference between downwind and upwind coefficients						
Coef. difference	3.481	3.486	3.487	2.929	1.651	1.323
Test for significance of difference between downwind and upwind effects						
F-stat	6.49	6.52	6.56	5.66	2.21	1.68
p-value	0.0111	0.0109	0.0107	0.0177	0.1376	0.1957

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. The additional controls include mean altitude, hilliness, female labor force participation, agricultural suitability, a seaport indicator, and seaport tonnage. $Ln(Nearbypop.)$ is the population of districts within 25km. The dependent variable in all regressions is the infant mortality rate. Pollution measures are based on each district's industrial composition in 1851. The coal use variables are all standardized. Child NPR mortality is based on the mortality rate per 1000 births from a basket of childhood infectious diseases that are less likely to be affected by pollution: cholera, diarrhea/dysentery, diphtheria, smallpox, scarlet fever, and typhus. Adult mortality values are based on deaths from the same set of diseases for those aged 20 and over

Next, we consider results looking at coal use in different industries separately, focusing on seven of the largest coal using industries: metals & machinery, textiles, earthenware & bricks, mining, chemicals, leather, and oils & soaps. The results, shown in Table 19 show that similar differences between the upwind and downwind coefficients are obtained when looking at coal use in only one industry, though the results for individual industries are noisier and therefore less statistically significant than results obtained when using all industries together. This suggests that the impact of coal use on downwind districts is similar regardless of which industry we focus on.[56] This provides some indication that the estimates we have obtained are due to coal use, rather than to other factors that are specific to just one or two particular industries.

Table 19: Effect of coal use by major coal using industries

			DV: Infant mortality rate				
Industry:	Metals & Machinery	Textiles	Earthen-ware & Bricks	Mining	Chemicals	Leather	Oils & Soaps
Ln(Upwind coal)	0.494	0.851	0.743	0.501	0.367	0.755	0.139
Ln(Downwind coal)	0.175	0.365	0.257	0.140	-0.260	0.0868	-0.414
Difference	0.319	0.486	0.486	0.361	0.627	0.668	0.553
			Testing for equality of the upwind and downwind coefficients				
F-stat	1.43	2.31	2.16	1.67	3.21	3.05	1.77
p-value	0.2329	0.129	0.142	0.197	0.074	0.0811	0.184

All regressions include district log coal use, log population density, log district population, log nearby population (25km), mean altitude, hilliness, female labor force participation, agricultural suitability, a seaport indicator, seaport tonnage, and the Child NPR mortality and Adult NPR mortality controls. The dependent variable in all regressions is the infant mortality rate. Regressions are run on 581 district observations with missing log upwind or downwind coal use values set to zero (there are more missing values when looking at industry-specific upwind and downwind coal use, so it is not feasible to drop all districts with missing values).

A.6 Additional all-age regression results

One potential concern with the mortality results for different age groups shown in Table 6 is that across the entire 1851-1860 decade the population denominators based on the Census observations in 1851 and 1861 may not be providing an accurate accounting of the number of persons in each age group in each district. One way to check this is to generate results using just the mortality data for a few years at the

[56]It is worth noting that these measures are positively correlated so they are not necessarily reflecting independent measures of local coal use.

beginning of this decade and the population data from the 1851 Census. Comparing deaths near 1851 to population counts in 1851 alleviates concerns about measurement error in the population denominators.

In this section we estimate results using only deaths in 1851-1853 and compare to population in the 1851 census in each age group in each year. We use three years of data here because mortality rates could vary substantially across years during this period, so just one year of data can generate misleading results.

The results of this exercise are presented in Table 20. We can see that results using only data from 1851-1853 are quite similar to those obtained using data for the entire 1851-1860 period. In particular, we continue to see evidence that coal use was strongly associated with increased mortality among children under five. We also find evidence that coal use was associated with increased mortality among the working age population, which may be due to either migration or to the affect of air pollution through channels, such as tuberculosis or maternal mortality, which particularly affected the working age population. As before, there is weak evidence that coal use increased mortality among the elderly, but these results are not statistically significant.

Table 20: By-age results using only 1851-53 mortality data

DV: Mortality rate in each age category (per 1000 persons)								
Under 5	**5-9**	**10-14**	**15-24**	**25-34**	**35-44**	**45-54**	**55-64**	**65 up**
Coefficient on coal use in upwind districts								
0.936*	0.268**	0.0432	0.108	0.0108	-0.295**	-0.209	-0.108	-0.427
(0.535)	(0.109)	(0.0592)	(0.0842)	(0.105)	(0.120)	(0.153)	(0.230)	(0.449)
Coefficient on coal use in downwind districts								
-0.818	0.0700	-0.0136	-0.0740	-0.228**	-0.398**	-0.240	-0.292	-0.853**
(0.576)	(0.119)	(0.0817)	(0.0858)	(0.0899)	(0.167)	(0.175)	(0.228)	(0.379)
Difference between upwind and downwind coefficients								
1.754	0.198	0.0568	0.182	0.2388	0.103	0.031	0.184	0.426
F-test for significance of difference between upwind and downwind effects (F-stat & p-value)								
5.74	2.13	0.46	3.83	4.87	0.48	0.04	0.68	0.81
0.017	0.145	0.498	0.051	0.028	0.488	0.848	0.411	0.370

*** p<0.01, ** p<0.05, * p<0.1. Standard errors, in parenthesis, allow spatial correlation between any pair of districts within 50km of each other. All regressions include controls for district coal use, population density, population, female labor force participation, agricultural suitability, a seaport indicator, and seaport tonnage. All regressions use observations for 422 districts with non-zero upwind and downwind coal use values.

A.7 Additional results for children under age five

Table 21 presents regression results relating coal use within a district to under 5 mortality within that district. Columns 1-3 present results without standardizing the coal use and population variables, while the results in Column 4-6 use standardized coal use and population variables.

Table 21: Estimated effects of within-district coal use on children under five

	DV: Under 5 mortality rate per 1000 persons					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Coal use)	5.576***	7.393***	3.905***			
	(0.615)	(1.131)	(0.791)			
Ln(Pop. Density)	6.517***	5.268***	0.905*			
	(0.541)	(0.542)	(0.493)			
Ln(District pop.)		-2.583	-1.213			
		(1.832)	(1.294)			
Ln(Coal use) Std.				6.241***	8.275***	4.371***
				(0.689)	(1.267)	(0.886)
Ln(Pop. Density) Std.				7.762***	6.274***	1.078*
				(0.645)	(0.645)	(0.587)
Ln(District pop.) Std.					-1.793	-0.842
					(1.271)	(0.898)
Under 5 NPR mort.			2.048***			2.048***
			(0.131)			(0.131)
Other controls		Yes	Yes		Yes	Yes
Observations	581	581	581	581	581	581
R-squared	0.701	0.732	0.853	0.701	0.732	0.853

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors allow spatial correlation over 50km. All regressions include controls for mean district altitude and hilliness, a seaport indicator and seaport tonnage, female labor force participation, and agricultural suitability.