The Impact of Industrial Pollution on City Growth: Lessons from the "Dark Satanic Mills"*

PRELIMINARY

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Abstract

Industrialization and urbanization often go hand-in-hand with pollution. Growing industries create jobs and drive city growth, but may also generate pollution, an endogenous disamenity that drives workers and firms away. This study provides the first assessment of the impact of these positive and negative effects on long-run city growth by studying the impact of industrial coal use in British cities from 1851-1911. I begin by constructing a measure of industrial coal use in 25 British cities in each decade. I then show that industrial coal use was an important disamenity in these cities, with a substantial positive effect on mortality rates, particularly due to respiratory causes. Next, I introduce an approach that allows me to separate the negative impact of this endogenous disamenity on city size from the positive impact of industry employment growth. My approach suggests that for an industry using the average amount of coal per worker in a city, the disamenity reduces the positive effect of industry employment growth by at least 8%. This more than offsets any positive local multipier effect from industry employment growth. Finally, I provide evidence that this effect was generated in part by high-skilled workers and skill-intensive industries being driven away from more polluted cities.

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1 Introduction

From the mill towns of 19th century England to the mega-cities of modern China, urbanization has often gone hand-in-hand with pollution. Much of this pollution comes from industry, an unfortunate by-product of the job-creating engines that drive city growth. This pollution, in turn, represents an endogenous disamenity that acts as a drag on urban growth, driving residents away and forcing firms to pay higher wages to the workers they are able to attract. As a result, policymakers face a trade-off between encouraging the growth of industry and increasing local pollution. In choosing between the benefits of industrial jobs and the costs of pollution, it is important that policymakers have a sense of the magnitude of both the benefits and the costs involved, yet separating these effects can be difficult.

This study confronts these issues in the context of British cities in the late 19th and early 20th centuries, the "dark satanic mills" that drove much of their growth, and the local air pollution emitted by their coal-fired engines. Specifically, I consider the impact of pollution from coal-burning in industry on the long-run growth of British cities from 1851-1911[1]. This setting is of particular historical interest because it represents the first wide-spread case of modern urban industrial pollution. Air pollution driven by the burning of coal represented a clear and visible urban disamenity. This pollution became increasingly acute as cities and industry grew, culminating in the "killer fog" of 1952, which killed thousands of Londoners. This is exactly the type of disamenity that people are likely to respond to when choosing between cities. Moreover, the high internal migration rates in England during this period suggest that residents had the ability to respond to varying amenity levels across cities. The availability of detailed data allows me to analyze the impact of these decisions on

[1]While the impact of the airborne pollution on city growth continued, and may have intensified, after 1911, I end the study at that point to avoid the massive disruptions caused by World War I. The consistency of the key city-industry data series also becomes substantially worse after 1911, which provides further motivation to end the study in that year. The start year of the study is determined by the availability of high-quality city-industry data.

city size over a 60 year period. The combination of these features make this a fertile setting for studying the relationship between industrial pollution and city growth.

The first step in this study is to construct estimates of industrial coal use in each city in each decade from 1851-1911. I start by using detailed data from the Census of Population that give employment, by industry, for substantially all private sector workers in a city in each decade starting with 1851. These are combined with measures of coal use per worker for each industry from the 1907 Census of Production. The result is an estimated level of coal use in each city in each decade.

Next, I compare these estimated industrial coal use levels to city mortality rates in order to assess the importance of air pollution as a disamenity. I find a clear positive relationship between industrial coal use and overall mortality in cities. This relationship is particularly strong when I focus only on mortality due to respiratory system causes, which are the most likely to be linked to air pollution. In contrast, I find no strong relationship between industrial coal use and mortality due to heart or circulatory system failure, which is less directly related to air pollution levels. These results suggest that, in terms of mortality, air pollution represented an important disamenity in cities.

I then turn to the main focus of the paper, assessing the impact of industrial air pollution on city growth. They key challenge here is separating the positive direct impact of employment growth in polluting industries from the negative impact of additional pollution. To deal with this challenge, I begin by constructing predicted employment levels in each city in each decade after 1851 based on city-industry employment in 1851 and the growth rate of employment in each industry across all cities from 1851-1911, as in Bartik (1991). In addition, I calculate predicted city industrial coal use for decades after 1851 by interacting the predicted employment level in each city-industry with the data on coal use per worker in each industry. Finally, I run a regression comparing city working population to predicted city working population and predicted city industrial coal use. In this regression, the predicted city working population variable captures all of the direct effect of industry growth on city growth that otherwise would have been incorporated in the predicted city coal use variable, allowing the latter to isolate the additional effect of industrial air pollution on city growth.

My results show that airborne pollution exerted a strong negative influence on city size during the study period. Specifically, my preferred estimates suggest that employment growth in a non-polluting industry that is equal to 1% of city employment lead to an increase in overall city employment equal to 1.016%. This is consistent with a small local multiplier effect. However, employment growth in a polluting industry that is equal to 1% of city population and adds 1% to industrial coal use in the city leads to an increase in overall city employment of just 0.94%. Thus, for an industry that uses coal in proportion to its contribution to city employment, the disamenity associated with coal use reduces the benefits of employment growth by 8%. These negative effects would be much larger for industries, such as Chemicals or Metal & Machinery, that used coal 2-3 times more intensively than the average industry. To my knowledge, this is the first study to separately identify the direct positive and indirect negative effects of the growth in polluting industries on long-run city growth.

The last step in the analysis involves looking at the impact of industrial coal use in a city on employment outcomes for each industry. I find no evidence that overall coal use in a city reduces employment in industries that use coal more intensively. This suggests that regulations did not drive the negative employment effects I observe. However, I do find evidence that the negative impact of industrial coal use in a city is larger for industries that use a larger share of skilled workers. This result fits historical evidence suggesting that coal smoke drove wealthier and more skilled workers out of cities. If more skilled workers were more sensitive to coal-based pollution, a reasonable assumption, then this is consistent with the idea that coal use impacted city size through the level of city amenities.

This paper is closely related to a line of recent research studying endogenous city amenities. Much of the work in this area has focused on how the composition of city residents influences city amenities. For example, Moretti (2004) shows that high-skilled workers generate spillovers that act as a producer amenity. Similarly, Diamond (2012) provides evidence that high-skilled workers can increase local consumer amenities. The goal of these studies is to separate the endogenous amenities generated by worker sorting from the other direct economic impacts this sorting. This study also aims to separate the endogenous amenity values from direct economic effects. However, my focus is on how the composition of industries influences city affect amenities, rather than the composition of residents. In practice, since both of the resident and industry compositions are likely matter, I view these as complementary approaches to understanding endogenous amenities in cities.

By focusing on a specific amenity – coal-based pollution – it is possible to be explicit about the link between industrial composition and city growth. Because of this focus, this paper is related to a large existing literature on the impact of local pollution levels in the modern U.S. context.[2] Methodologically, this study draws on work by Kahn (1999) and Chay & Greenstone (2003), which use fluctuations in industrial activity to generate exogenous variation in local air quality. It is also closely related to studies that use hedonic models to assess the overall impact of air quality improvements (Kim *et al.* (2003), Chay & Greenstone (2005), Bayer *et al.* (2009)). As pointed out by Bayer *et al.* (2009), an important concern in this literature is that changes in air quality may be correlated with changes in local economic conditions. For example, regulations may affect both air quality and economic activity in polluting industries. Bayer *et al.* (2009) offer one approach for dealing with this issue, by looking at affects on downwind communities. This study offers an alternative approach to addressing this concern, but one that allows me to study impacts in the

[2]This literature studies the impact of air quality regulation on local outcomes such as industrial activity (Henderson (1996), Becker & Henderson (2000), Berman & Bui (2001), Greenstone (2002)), employment (Berman & Bui (2001), (Walker, 2011, 2013)), overall population size or density ((Kahn, 2000, 2009) and Banzhaf & Walsh (2008)), and a host of other outcomes.

main pollution-producing centers, where the effects may be much larger than in the downwind communities.

An important difference between this paper and previous work in the hedonic literature is that I focus on city population as the outcome variable of interest, rather than housing prices. The hedonic approach is based on the idea that improvements in air quality cause population inflows into a location which are then reflected in housing prices. Thus, housing prices and population are essentially two sides of the same coin. The main advantage of using housing prices is that it allows one to calculate the monetary value of the air quality improvement, which is not possible in this study. On the other hand, policymakers often focus on job creation, which will be directly addressed by my approach.

Within the historical literature, this study is related to work by Williamson (1981), which uses a cross-section of data from 1905 to estimate the urban disamenity premium in British cities as reflected in wages and the cost of living. There is also a direct link to two studies focused specifically on the role of coal in generating air pollution during the late 19th and early 20th centuries. Troesken & Clay (2010) studies the evolution of pollution levels in 19th century London using data on fog days that follows up on contemporary work (Brodie (1905)). There are several connections between this paper and their results which I will discuss as they arise. In the U.S. context, Barreca *et al.* (2014) show that the burning of bituminous coal for home heating increased mortality rates in the winter months. Both of these studies document a clear relationship between coal burning and mortality, consistent with my findings.

The next section describes the empirical setting. The analytical framework is introduced in Section 3 followed by the data, in Section 4. Section 5 presents the analysis and results, while Section 6 concludes.

2 Empirical setting

Coal-based air pollution was endemic to the industrial cities of England in the late 19th and early 20th centuries, and became worse as coal-using industries expanded. British coal consumption increased from an annual average 65 million tons in 1852-1862 to 181 million tons in the 1903-1912 period.[3] This came to about 4.3 tons per person in 1911.[4] The foul smell, reduced visibility, and negative health effects of coal-based pollution were widely recognized and discussed. Numerous anecdotes and discussions of polluted air and its health effects can be found in newspapers, medical journals, and other contemporary sources. A number of these are presented by Troesken & Clay (2010), including this quote from the *Times* (Feb. 7, 1882, p. 10) following a particularly bad London fog: "There was nothing more irritating than the unburnt carbon floating in the air; it fell on the air tubes of the human system, and formed a dark expectoration which was so injurious to the constitution; it gathered on the lungs and there accumulated." The winter of 1890-91 was particularly bad in London; Troesken & Clay (2010) estimate that polluted fog generated 7,405 excess deaths in London alone during that period.

In terms of mortality, the most direct and visible effects of air pollution was in deaths related to the respiratory system. For example, following a particularly bad London fog event in the winter of 1880, the *British Medical Journal* reported that (Feb. 14, 1880, p. 254),

[3]These figures provided by the U.K. Department of Energy and Climate Change.

[4]This and all other figures are in imperial tons per year. As a point of comparison, in 2012 the U.S. consumed about 2.5 tons of coal per person annually while China consumed about 2.7 tons per person and Australia, one of the heaviest users, consumed around 5.8 tons per person.

> *If one or two weeks during the cholera epidemic of 1849 and 1854 be excepted, the recorded mortality in London last week was higher than it has been at any time during the past forty years of civil registration. No fewer than 3,376 deaths were registered within the metropolis during the week ending Saturday, showing an excess of 1,657 upon the average number in the corresponding week of the last ten years…The excess of mortality was mainly referred to diseases of the respiratory organs, which caused 1,557 deaths last week, against 559 and 757 in the two preceding weeks, showing an excess of 1,118 upon the corrected weekly average.*

While the experience of London with polluted air gained the most attention, the phenomenon was not confined there. Other industrial cities faced similar issues. For example, Troesken & Clay (2010) describe the experience of Glasgow with similar levels of polluted fog. Later, I will present evidence that the negative effects of pollution stretched across all major English cities, and were particularly acute in cities reliant on heavy industry.

Coal-based air pollution came from both industrial and residential sources during this period. Much of the literature on this topic has focused primarily on pollution based on residential use. This is due in part to the fact that residential use was generally less efficient, generating more smoke, and that chimneys deposited the residential pollution at a lower height than factory smokestacks. Yet balanced against this is the fact that overall coal use by industry substantially exceeded residential use. For example, in his 1872 address to the Royal Association for the Advancement of Science's Mechanical Section, F.J. Bramwell, the section president, estimated that of the 98-99 million tons of coal retained for home use in Britain, about 18.5 million tons were residential consumption and the remainder, over 80%, were consumed by industry. This suggests that industrial pollution deserves as much attention, if not more, than residential pollution during this period.

The public awareness and response to airborne pollution grew over the 1851-1911 period. This is reflected in new legislation passed during the period. The Sanitary Act of 1866 empowered local sanitary authorities to take action against local polluters. The Public Health Act of 1875 expanded these powers outside of London, while The Public Health (London) Act of 1891 expanded them within London. The 1875 Act defines a public nuisance to include,

> *Any fireplace or furnace which does not as far as practicable consume the smoke arising from the combustion used therein...*
> *Any chimney (not being the chimney of a private dwelling-house) sending forth black smoke in such a quantity as to be a nuisance...*

However, this Act allowed for substantial interpretation:

> *That where a person is summoned before any court in respect to a nuisance arising from a fireplace or furnace that does not consume the smoke arising from the combustible...the court shall hold that no nuisance is created within the meaning of this Act, and dismiss the complaint, if it is satisfied that such fireplace or furnace is constructed in such manner as to consume as far as practicable, having regard to the nature of the manufacture or trade, all smoke arising therefrom...*

Thus, these regulations essentially aimed to reduce factory smoke production to the level practical for each manufacturing trade, but not to eliminate those trades, such as steel and chemicals, that necessarily produced high levels of air pollution. While it is impossible to quantify the impact of these regulations in a rigorous way, a review of the historical evidence by Thorsheim (2006) concludes that these regulations had very limited effectiveness. This was due to the large loopholes left in the regulations, the small size of fines allowed, and the substantial control exerted by factory owners over the local authorities, particularly in the industrial cities.[5]

[5] One example of a loophole provide by Thorsheim (2006) is that the acts regulated "black smoke"

Despite their lack of effectiveness, these public measures demonstrate the public awareness of air pollution as well as the importance of this concern. Troesken & Clay (2010) provide evidence these measures began to bear fruit in London in the 1890s; after that point, they document reductions in foggy days and in respiratory-related mortality.[6] However, in other locations there is less evidence that enforcement of these acts substantially affected pollution levels.

The extent to which the disamenity created by coal-based pollution influenced city size during this period depended on the level of migration flows into and between cities. Existing evidence show that during the period I study England was characterized by high levels of internal migration, as well as substantial emigration. Summarizing our knowledge in this area, Long & Ferrie (2003) states,

> *The British populace of the nineteenth century was highly mobile. England, Wales and Scotland were virtually free of institutional barriers to geographic mobility. Though the Poor Law's provision of a degree of economic security created some disincentive to mobility, it was small compared to the effects of large-scale social welfare programs of the twentieth century...Between 1851 and 1881, approximately one in four people changed their county of residence; more than half moved from one town to another.*

The sentiment is echoed by Baines (1994), who argues that "both the housing and labour markets were more open than today and that migrants were less likely to be deterred by the problems of educating children or looking after relatives." Much of this migration was made up of rural residents moving to the cities. Baines (1985) suggests that, controlling for the age structure of migrants, internal migration accounted for about 40% of the population growth in British cities.

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and that defendants were able to avoid fines by claiming that their smokestacks emitted only dark brown smoke.

[6] My measure of industrial coal use per worker, shown in Figure 5 in the Appendix, shows a pattern consistent with this finding.

3 Framework

As in almost all studies in this area, the framework used in this paper begins with the traditional Rosen-Roback framework.[7] However, it is necessary to modify the basic Rosen-Roback framework in several ways. This section briefly describes this framework, beginning with the demand for labor in the economy.

I begin by considering the demand for labor in the economy. Whereas the simplest version of the Rosen-Roback model assumes that each city produces only one good, it is necessary to incorporate many industries into the city economies in my framework in order to reflect the industry-based approach persued in the empirical analysis. In particular, I assume that there are a fixed number of industries indexed by $i \in I$. It is also important to incorporate coal as an input to production. Thus, I modify the inputs used in production to incorporate two new inputs: coal and a fixed industry-specific local resource. Production then uses three inputs: labor, coal, and local resources.[8] Coal use in each industry is assumed to be proportional to employment, with a proportion that can vary across industries. This assumption, which is discussed in more detail at the end of this section, is driven by data availability. Local resources may represent natural features, local infrastructure, and local endowments of entrepreneurial ability. Incorporating these resources into production allows the same industry to operate in many different cities, even under conditions of perfect competition. A simple production function for a firm f in industry i in city c that satisfies these requirements is,

$$y_{fic} = A_i N_{fic}^{\alpha} R_{fic}^{1-\alpha} \quad \text{where} \quad N_{fic} = \min(L_{fic}, CU_{fic}/\gamma_i)\,,$$

where A_i is technology in a city-industry, N_{fic} is a composite of labor input L_{fic} and

[7]This theory emerged from Rosen (1979) and Roback (1982). This study draws on the exposition of this model in Moretti (2010).

[8]In some versions of the Rosen-Roback model, land is also included as an input to production. As in Diamond (2012), I omit this element from the model to keep things simple.

coal power input CU_{fic}, R_{fic} is the level of local resources used, and γ_i determines the ratio of coal power to labor in industry i.

Within each industry, I retain the standard Rosen-Roback assumptions: firms are perfectly competitive, technology has constant returns to scale, and goods (including coal) are freely traded across locations.[9] The result is that in each city there is a downward sloping labor demand curve for each industry,

$$L_{ic} = \left(\frac{\alpha p_i A_i}{w_c + \gamma_i q} \right)^{\frac{1}{1-\alpha}} R_{ic}. \tag{1}$$

where p_i is the price of the output of industry i, w_c is the wage in city c and q is the price of coal. This expression shows that the location of the city-industry labor demand curve depends on fixed local resources as well as a set of national-level factors: the national price for the good produced by the industry (p_i), the national coal price q, and the technology level in the industry A_i. These national-level factors – which reflect, among other things, the introduction of new technologies, opening to foreign competition, or shifts in preferences – will shift the local labor demand curves for an industry across all cities. The city labor demand curve is simply the sum over the labor demand curve for each industry in each city.

Next, consider the supply of labor in the economy. Each worker provides one unit of labor that can be used as an input by industries in their city. Workers are freely mobile across cities and choose the city that maximizes their utility. Workers consume housing and a combination of the consumption goods available in the economy. For simplicity, we can think of there being a CES index over these consumption goods, with the price of this index used as the numeraire. The indirect utility for a worker j in city c is,

[9] Note that constant returns to scale technology means that I can sum across firms to obtain the industry employment expression given in Equation 1.

$$V_{jc} = w_c - r_c + a_c$$

where w_c is the wage, r_c is the price of land used for housing, a_c is the amenity value of the city.[10]

While it is traditional to model the construction sector, to keep things brief I simply assume a reduced-form relationship, $r_c = \lambda L_c + z$, between the price of land for housing and the population of a city. This expression is similar to that used in previous work (e.g., Moretti (2010)) except that the elasticity of housing supply λ does not vary across cities. While this would be unrealistic in the modern setting, particularly in the U.S., it is more reasonable in the empirical setting I consider. This is due in part to the lack of land-use regulations in the period I study and in part to the relatively homogeneous geography across English cities (relative to, say, U.S. cities).

The amenity value in a city may be related to many features, but this study emphasizes the role of coal-based pollution in affecting city amenities. Thus, I model the amenity value as $a_c = \delta_c - \beta CP_c$ where CP_c is a measure of coal pollution intensity in the city and δ_c represents the value of all other city amenities.

Finally, there is an outside option indirect utility level $\bar{v}$ which we can think about as representing the level of utility obtained through emigration or by residents in rural areas. This reflects the fact that residents were flowing into and out of the cities we are studying. Together, these features imply the following expression for labor supply in a city:

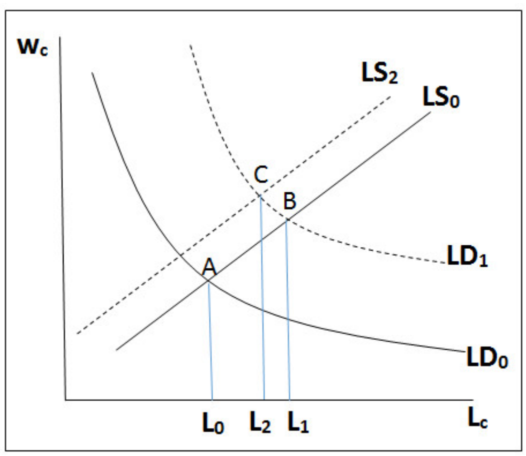
$$L_c = (1/\lambda)\left(w_c - z_c - \beta CP_c + \delta_c - \bar{v}\right) . \tag{2}$$

[10]All of these values are denominated in units of the index of consumption goods.

The solid lines in Figure 1 describes the labor demand and supply curves in a city leading to an equilibrium at point A with city size L_0. Consider a national shock that increase the output price p_i in some industry that produces no pollution ($\gamma_i = 0$). This will shift out the labor demand curve, from LD_0 to LD_1, leading city size to grow to L_1. Note that Equation 1 implies that the size of the increase in employment demand will be larger, the larger is R_{ic}. This is the direct positive effect of industry employment growth on city growth.

Finally, consider a similarly-sized national shock that increases p_i, where industry i is a polluting industry ($\gamma_i > 0$). This will lead to a similar outward shift in the labor demand curve to LD_2. In addition, the increased pollution will reduce amenity levels, causing a leftward shift in the labor supply curve, from LS_0 to LS_2. Overall city size then grows to L_2 rather than L_1, and the gap between these two represents the impact of pollution, acting through the city's amenity value, on city size.

Figure 1: Labor supply and demand within a city



The empirical analysis is motivated by the relationships shown in Figure 1. Specifically, the empirical approach offered in this paper attempts to separately identify the size of the gap $(L_1 - L_0)$, which I call the direct effect of industry employment growth, relative to the gap $(L_1 - L_2)$, which reflects the indirect disamenity effect caused by industrial pollution. In the data, I observe city employment in some base year (L_0), and in some future decade (L_2), but not what city employment would have been in the absence of industrial pollution (L_1). To deal with this, I use each city's initial industrial composition, which depends on R_{ic} in the model, and national industry growth rates, which reflect shifts in p_i, A_i and q in the model, to generate predicted employment levels in each city and predicted pollution levels in each city, following Bartik (1991). Regressing actual city employment on these predicted variables then delivers estimates of $(L_1 - L_2)$ relative to $(L_1 - L_0)$.

To keep things simple, this framework omits several features that one might consider including. One of these is allowing firms to substitute between coal use and labor or other inputs. Doing so would generate an interesting result; cities with more polluting industries, having higher wages, would also have firms that use coal more intensively than firms in the same industry in less polluted cities. This would further exacerbate the pollution issues in these cities. Environmental regulations and the adoption of pollution abatement technologies have also been omitted from my framework because there is limited evidence that they played a substantial role in influencing the location of industry during the period I study. However, if the stringency of regulation was related to the level of coal pollution, then we might expect firms in heavily polluted cities to use less coal per worker than firms in the same industry in less polluted cities. Both of these factors will contribute to measurement error in my estimate of city coal use. The resulting attenuation bias will generally work against finding a strong impact of coal use on city size.

Finally, I have not included the role that coal pollution may have played as a disamenity to production. This impact could occur, for example, by making workers less healthy and therefor less productive, as suggested by Graff Zivin & Neidell (2012). Alternatively, if workers are heterogeneous, pollution could drive away high-skilled workers and thereby reduce human capital spillovers in cities (Rauch (1993), Moretti (2004)). While the impact of consumer and producer amenities will differ when looking at wages, they will have similar implications for employment, the outcome of interest in this study. Thus, the empirical analysis in this paper will pick up the net impact of coal pollution as both a consumer and a producer disamenity, but will not separate these two channels.

4 Data

The data used in this study are drawn from three main sources: the British Census of Production, the Census of Population, and the Registrar General's reports. Data from the Census of Production and the Registrar's General's reports were digitized from original sources, while the Census of Population data have been used in previous work. This section briefly describes each of these data sets.

One necessary piece of information for this study is a measure of the amount of coal used in each industry. This information is drawn from the first British Census of Production, which was completed in 1907. While these data come from near the end of our study period, it is the earliest available consistent source for this information.

Because of the central role coal played in the British economy, this Census collected detailed information on the amount of coal and coke used in each industry, as well as employment in each industry.[11] This allows me to construct a measure of coal use per worker in each industry. Table 1 describes the amount of coal used in each industry, industry employment, and coal use per worker, based on the 1907 census figures. In this table, industries have been collapsed to match the set available in the city-industry database.

The most intensive industrial users of coal were Chemical & Drug Manufacturing, Metal & Machinery Manufacturing, Earthenware & Brick Manufacturing, and Water & Gas Service. However, because of the size of industry, the largest overall user by far

[11]Coal and coke are combined in this study. In practice, coke consumption is small relative to coal.

was Metal & Machinery Manufacturing, principally iron and steel production. Mining related activities were also major coal burners, but would have been less important in the urban economies considered in this study. Textile production, while using coal less intensively per worker, was also a major overall burner of coal due to the size of the industry and would have been an important urban industrial pollution source.

Table 1: Industry coal use, employment, and coal use per worker in 1907

Industry	Workers	Industry coal use	Coal use per worker
Art, theatre, music, equipment	3,406	7,335	2.2
Chemical and drug manufacturing	61,442	3,869,153	63.0
Dress	243,968	385,597	1.6
Sea and canal transport	6,291	48,091	7.6
Messengers, porters, warehousing, e	17,221	39,698	2.3
Vehical production	53,902	140,155	2.6
Shipbuilding	169,770	1,037,548	6.1
Building	371,726	591,601	1.6
Food processing	220,860	2,649,016	12.0
Oil, soap, etc. production	54,751	1,131,530	20.7
Leather, hair goods production	27,146	327,184	12.1
Beverage production	100,821	1,960,803	19.4
Tobacco production	35,258	38,256	1.1
Wood furniture, etc., production	114,014	619,265	5.4
Basket, etc. production	6,264	11,152	1.8
Textile production	1,066,735	10,800,000	10.1
Paper and publishing	226,894	2,205,660	9.7
Mining related	653,359	18,900,000	28.9
Earthenware, bricks, etc	135,214	6,610,012	48.9
Water and gas service	119,618	6,442,476	53.9
Instruments, jewelry, etc	43,296	86,060	2.0
Metal and engine manufacturing	894,159	39,100,000	43.7
Employment-weighted average:			21.0

The 1907 Census of Manufacturing also provides counts of employment in each industry divided into salaried workers and wage earners. The share of salaried workers in each industry constructed from these data will provide a measure of industry skill intensity.

To translate coal use by each industry into the amount of industrial coal burned in each city, we need information on the size of each industry in each city over time. These data come from the Census of Population, which collected the occupation of each person at each ten-year census interval. These occupational categories generally correspond to industries, such as “Cotton spinner” or ”Steel manufacture”. Consistent city-industry series have been constructed for the period 1851-1911 by combining occupational categories from the various censuses. The resulting British city-industry database covers 25 cities and 27 industries, spanning nearly the entire private-sector economy.[12] Figure 4 in the Appendix. shows the location of the cities included in this database.

The last set of data used in the analysis are mortality data drawn from the Registrar General’s reports. These data were taken from the summaries produced each decade starting in 1870, which report mortality in each location over the preceding decade, a breakdown of mortality by cause, and the average population in the location over that period. From these reports, I have collected data on overall mortality, mortality from respiratory causes, and moretality due to heart/circulatory causes. The geographic unit used in these reports is the registration district, which is not an exact match for the town boundaries used in the city-industry data, but we can use mortality rates in these districts as an indicator of mortality rates in the corresponding towns.

[12]Further information on these data can be found in the Data Appendix to Hanlon & Miscio (2014).

5 Analysis

I begin the analysis by describing how the measure of industrial coal use in cities is constructed. Next, I document the relationship between these coal use estimates and city mortality rates. This provides evidence that my measure of industrial coal use is capturing an important city disamenity. In the heart of the analysis, I investigate the long-run impact of industrial coal use on city size. Finally, to better understand the forces driving these effects I look at how impacts differ across industries.

5.1 Measuring industrial coal use in cities

To construct a measure of industrial coal use in cities, I combine data on coal use per worker in each industry from the 1907 Census of Production with data on city industry employment. Let $COALperEMP_i$ represent the coal used per worker in sector i. From the city-industry database we have employment in each city and industry for 1851-1911, denoted EMP_{ict}. Then city coal use is measured as,

$$COAL_{ct} = \sum_i \left(EMP_{ict} * COALperEMP_i \right) .$$

There are two assumptions implicit in this approach. First, it assumes that coal use per worker in an industry is relatively similar across cities. Second, there is an assumption that industry coal use per worker does not change too much over time.

Table 2 describes the estimates of city industrial coal use per private sector worker that I obtain. These figures reveal several interesting patterns. First, there is substantial variation across cities in the expected level of coal use per worker. Cities specializing in heavy industry, such as Birmingham, Sheffield and Wolverhampton show levels of coal use per worker that are nearly double the national average. Textile manufacturing towns, such as Manchester, Bolton, Halifax and Leeds, show moderate levels, near the national average. Many of the port cities, such as Bath, Brighton and

Bristol, are among the least coal-intensive cities. Despite its reputation for pollution, London is not an outlier and shows relatively modest levels of industrial coal use per worker with little increase over time.

A second pattern to note in these data is that the city economies were shifting towards more coal-intensive industries. This is reflected in consistent growth in the average level of estimated coal use per worker. At the same time, the fall in the standard deviation of estimated coal use across cities suggests that polluting industries were spreading more evenly across locations over time. Cities with initially heavy coal use, such as Wolverhampton, Sheffield and Birmingham, show either slow growth or decline in coal use per worker over the study period. Some of the largest increases were in cities with initially low levels of coal use per worker, including Bath, Leicester and Portsmouth. A third pattern is that the variation in coal use across cities is much larger than variation across time within a city.

Overall industrial coal use in a city is correlated with overall city population, as shown in Figure 3, which describes the relationship between the log of total population in each town and the log measure of industrial pollution (in tons). While we can see that these values are correlated, this figure also demonstrates that there is substantial variation in pollution levels within similarly sized cities. Consider, for example, Sheffield, Bradford, and Bristol, three cities with relatively similar populations in 1851. Industrial coal use in Sheffield, a major producer of iron, steel, and machinery, is more than one-half log-point larger than in Bradford, where the main industry was textile production, and more than a full log-point larger than in Bristol, a port city.

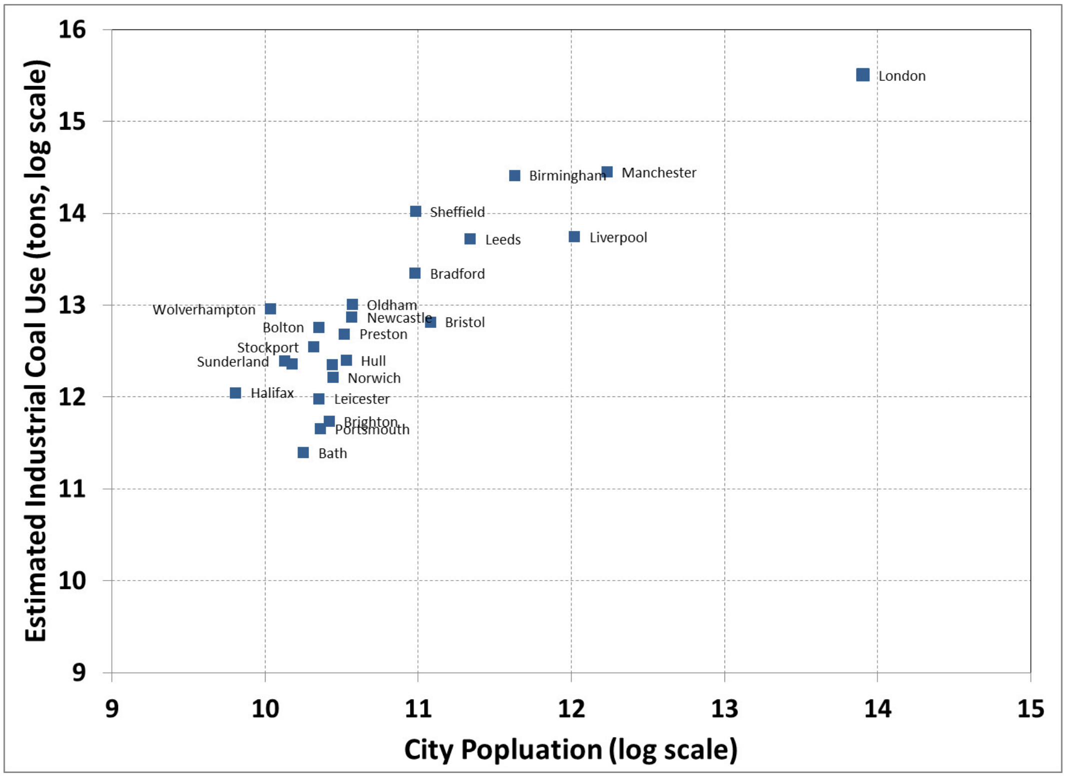
Table 2: Estimated city industrial coal use per private sector worker

City	1861	1871	1881	1891	1901	1911	Average	Std. Dev.	Growth 1861-1911
Leicester	8.1	8.6	7.3	6.8	8.9	10.3	8.3	1.3	2.3
Bath	8.7	9.6	9.2	10.2	10.0	10.5	9.7	0.7	1.8
Norwich	9.5	10.5	10.6	10.4	10.5	10.4	10.3	0.4	0.9
Portsmouth	9.7	10.6	11.5	11.6	12.2	12.3	11.3	1.0	2.6
Nottingham	10.0	10.9	12.7	13.0	13.7	14.0	12.4	1.6	4.0
Brighton	10.4	11.0	10.9	11.6	11.8	12.0	11.3	0.6	1.6
London	10.6	11.2	11.2	12.1	12.2	12.1	11.6	0.6	1.4
Liverpool	11.0	11.6	12.3	12.4	13.0	13.1	12.2	0.8	2.1
Bristol	11.4	11.7	11.4	11.6	12.3	12.7	11.8	0.5	1.3
Blackburn	11.6	11.9	12.3	12.4	12.9	13.2	12.4	0.6	1.7
Stockport	11.8	11.7	11.8	11.1	11.6	13.3	11.9	0.7	1.4
Preston	12.2	12.4	12.6	12.4	12.7	12.6	12.5	0.2	0.5
Hull	12.2	13.9	13.7	14.6	15.7	16.8	14.5	1.6	4.6
Huddersfield	12.6	12.5	13.4	13.5	14.0	14.2	13.3	0.7	1.6
Halifax	12.7	14.7	15.3	15.4	16.1	16.9	15.2	1.4	4.2
Bradford	13.9	13.5	13.7	13.1	13.5	13.5	13.5	0.3	-0.4
Manchester	13.9	14.1	14.4	15.2	15.3	15.6	14.7	0.7	1.6
Sunderland	14.9	17.2	16.8	16.2	16.8	17.1	16.5	0.9	2.2
Bolton	15.9	15.6	15.6	15.9	16.3	16.5	16.0	0.4	0.6
Oldham	16.2	15.0	16.0	17.4	17.7	17.4	16.6	1.1	1.3
Leeds	16.8	17.8	17.3	16.2	16.6	17.1	17.0	0.5	0.3
Newcastle-upon-Tyne	18.1	18.9	17.8	19.2	19.6	19.6	18.9	0.8	1.5
Birmingham	22.7	22.2	22.9	23.3	22.6	21.9	22.6	0.5	-0.7
Wolverhampton	26.9	27.6	27.0	25.6	23.9	23.9	25.8	1.6	-3.0
Sheffield	28.1	28.7	27.9	27.8	27.6	28.8	28.2	0.5	0.7
Average	14.0	14.5	14.6	14.8	15.1	15.4	14.7	0.8	1.5
Std. Dev.	5.2	5.2	5.0	4.9	4.5	4.4			

Values are in tons per worker per year. Only private sector workers in the analysis industries are included.

The correlation between overall industrial coal usage and city population is potentially a concern because city size can generate disamenities other than through coal pollution. These may include factors affecting health, such as poor water or the transmission of communicable diseases, or other congestion forces, such as high house prices. Thus, it will be important to control for city size in our regressions and rely on the substantial variation in industrial pollution levels in similarly-sized cities for identification. This is done either by directly including city size or using city fixed effects.

Table 3: City population and estimated coal use, 1851



In addition to the measure of industrial coal use based on current city employment patterns, it will also be helpful to construct a predicted level of city industrial coal use based only on city-industry employment patters in the first observed year, 1851, and the national growth rate of industry. The advantage of this measure is that it will be uncorrelated with idiosyncratic shocks affecting the city economy in a particular decade, which could cause bias in the estimation results. Predicted coal-use is constructed as,

$$PredCOAL_{ct} = \sum_i \Big(EMP_{ic,1851} * GREMP^{natl}_{it,1851} * COALperEMP_i\Big)$$

where $EMP_{ic,1851}$ is city-industry employment in 1851 and $GREMP_{it,1851}^{natl}$ is 1 plus the national growth rate in industry i between 1851 and year t. The correlation between $PredCOAL_{ct}$ and $COAL_{ct}$ is 0.995 in levels and 0.959 in logs.

5.2 Industrial coal use and mortality

The next order of business is to assess the extent to which the estimated industrial coal use figures are reflecting a meaningful city disamenity. To do this, I run cross-sectional comparisons of industrial coal use and mortality data.[13] I interpret these as providing evidence that the industrial coal use measure is capturing a meaningful city disamenity, but I do not claim that these results as causal. The specification is,

$$MORT_c = \alpha_0 + \alpha_1 \ln(COAL_c) + \alpha_2 \ln(TOTPOP_c) + e_c \tag{3}$$

where $MORT_c$ is the mortality rate in a registration district c over a ten year period (e.g., 1870-1879) relative to the average population of the district over that period, $COAL_c$ is estimated industrial coal use for the city in registration district c near the beginning of the period (e.g., 1871 when looking at mortality from 1870-1879), and $TOTPOP_c$ is the total population of the city near the beginning of the period (e.g., 1871 when looking at mortality from 1870-1879). The total population term is included to allow mortality rates to vary with city size.

Before proceeding, it is worth pausing to consider the functional form for the impact of coal use used in Equation 3, which will also be applied in later regressions. In Equation 3, the impact depends on the logarithm of coal use. Thus, a given increase in coal use depends on the initial level of coal burning in the city. In a city with a

[13]While full panels are available for both the mortality data and the industrial coal use figures for 1871-1901, most of the mortality variation occurs in the cross-section. Thus, identifying on time-series variation only would throw out most of the relevant variation and make the estimates more prone to measurement error issues. This concern is made worse by the possibility that mortality rates may lag pollution levels, and that factors such as improved medical care may be changing the relationship between mortality and pollution over time.

high level of initial coal use, a larger increase in coal use is required to generate the equivalent effect, in terms of percentage growth in city size, as would be required in a city with a low level of initial coal use. Because of the strong correlation between the level of coal burnt and city size, this essentially means that in a larger city, a greater increase in coal use is required to generate the same disamenity effect.

We can compare this functional form to two natural alternatives. One alternative is to simply use the overall level of coal burnt in a city as the key explanatory variable, rather than the log level. In this case, an additional ton of coal burnt would generate the same disamenity effect regardless of city size or initial coal use. Thus, an increase in coal use of, say, 1000 tons, should generate the same effect, in percent of initial city size, in a city of one million as in a city of 50,000. This seems fairly unreasonable. Another alternative is to use coal use per capita as the key explanatory variable. This has the advantage of explicitly incorporating city size. However, it also means that, holding the level of industrial coal use fixed, adding additional residents to a city reduces the disamenity value of the coal smoke. This seems unreasonable, particularly since additional residents means additional residential coal use, which may exacerbate the negative effects of industrial coal burning.

The results are presented in Table 4. The first panel presents results for overall mortality. The second panel shows results for mortality due to respiratory system causes, which are most closely related to air pollution. For comparison, the third panel presents results for mortality due to the heart and circulatory system, which is less directly related to air pollution levels.

Several patterns are visible in these results. First, it is clear that the estimates of industrial coal use in each city can help predict overall mortality rates and is a particularly strong predictor of mortality due to respiratory system failure. However, the results in the bottom panel suggest that there is no strong relationship between this measure and mortality from causes that are less directly related to air pollution. This provides some comfort that the relationship between industrial pollution and mortality due to respiratory system failure is not driven by higher mortality rates of all types in cities with more industrial pollution. The relationship between industrial coal use and mortality does not seems to be weakening over the study period.[14]

Table 4: Industrial coal use and mortality using current city-industry employment

DV: Overall city mortality rate				
	1871	**1881**	**1891**	**1901**
$Ln(COAL_{ct})$	0.0349***	0.0358***	0.0348***	0.0378***
	(0.00911)	(0.00735)	(0.00780)	(0.00809)
$Ln(TOTPOP_c)$	-0.0258**	-0.0322***	-0.0330***	-0.0392***
	(0.0122)	(0.00942)	(0.00987)	(0.0108)
DV: Mortality rate due to respiratory system				
	1871	**1881**	**1891**	**1901**
$Ln(COAL_{ct})$	0.00796	0.0101***	0.0111***	0.0120***
	(0.00498)	(0.00260)	(0.00320)	(0.00288)
$Ln(TOTPOP_c)$	-0.00408	-0.00685*	-0.00849**	-0.0108***
	(0.00667)	(0.00333)	(0.00405)	(0.00383)
DV: Mortality rate due to heart/circulatory system				
	1871	**1881**	**1891**	**1901**
$Ln(COAL_{ct})$	0.000766	-0.000166	0.000860	0.00139
	(0.000557)	(0.000871)	(0.000794)	(0.000962)
$Ln(TOTPOP_c)$	-0.00105	-0.000770	-0.00190*	-0.00276**
	(0.000745)	(0.00112)	(0.00101)	(0.00128)
Observations	25	25	25	25

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Additional results, available in Appendix A.2, show that similar patterns are obtained when $PredCOAL_{ct}$ is used in place of $COAL_{ct}$ in similar regressions. This is not surprising given the high correlation between these two variables. Overall, these results show that industrial coal use was closely related to city mortality, and particularly to mortality due to respiratory related causes. This suggests that my industrial coal use measure is capturing an important city disamenity. Next, I consider the

[14] This contrasts somewhat with the results from Troesken & Clay (2010), which focuses only on London. However, this does not contradict their finding regarding an early environmental Kuznets curve, since London was likely wealthier than other cities, which would place it on a different part of the Kuznets curve during this period.

impact of this disamenity on overall city growth.

5.3 Industrial coal use and city size

We now come to the heart of the analysis; an investigation of the relationship between industrial coal use and city size. Three ingredients are used in constructing the empirical specification:

$$\begin{aligned}
WORKPOP_{ct} &= \textstyle\sum_i EMP_{ict} \\
PredWORKPOP_{ct} &= \textstyle\sum_i (EMP_{ci,1851} * GREMP^{natl}_{it,1851}) \\
PredCOAL_{ct} &= \textstyle\sum_i \left(EMP_{ic,1851} * GREMP^{natl}_{it,1851} * COALperEMP_i\right)
\end{aligned}$$

The first ingredient, $WORKPOP_{ct}$ is the working population of a city, which is just the sum of employment in all industries in that city. In this case the working population will cover only private sector workers in the industries contained in the city-industry database. The second ingredient is the predicted level of working population in a city, $PredWORKPOP_{ct}$. This is constructed by taking employment in each industry in the city in the earliest available year (1851) and multiplying it by the national growth rate in that industry over the period from 1851 to t. Finally, we have the $PredCOAL_{ct}$ variable discussed previously.

Notice that $PredCOAL_{ct}$ includes the $PredWORKPOP_{ct}$ variable. This means that, if we were to run a regression of $WORKPOP_{ct}$ on $PredCOAL_{ct}$ while excluding $PredWORKPOP_{ct}$, then the coefficient on $PredCOAL_{ct}$ will capture both the negative effects of pollution on city growth as well as the positive direct effect of industry growth. However, if $PredWORKPOP_{ct}$ is included in the regression, the remaining variation in $PredCOAL_{ct}$ will come only from variation in coal use across industries, while $PredWORKPOP_{ct}$ will capture the direct effect of predicted industry growth on city growth. This also highlights why it is necessary to use $PredCOAL_{ct}$ in these regressions rather than $COAL_{ct}$, since the latter will include direct effects of industry size on city size that are not perfectly captured by $PredWORKPOP_{ct}$.

Putting these ingredients together, the regression specification is,

$$\begin{aligned} \ln(WORKPOP_{ct}) = \beta_0 &+ \beta_1 \ln(PredWORKPOP_{ct}) \\ &+ \beta_2 \ln(PredCOAL_{ct}) \\ &+ \beta_3 \ln(INITPOP_{ct}) + \epsilon_{ct} , \end{aligned} \tag{4}$$

where $INITPOP_{ct}$ is the working population of the city in 1851. In effect, the $PredWORKPOP_{ct}$ term models the direct effect of industry growth on the growth of a city's working population, while $PredCOAL_{ct}$ represents the indirect effect related to the amount of industrial coal burnt in a city. Including the $INITPOP_{ct}$ term allows me to control for the impact of the initial city size. Note that this specification takes advantage of both variation across cities and variation over time. Later I will explore how the results change when fixed effects are added.

On advantage of the approach described in Equation 4 is that it provides a natural check on the functional form assumption through the coefficient on the $\ln(PredWORKPOP_{ct})$ variable. My prior is that the coefficient on this variable should be close to one, or, in the presence of a local multiplier effect, somewhat above one. A functional form that delivers a coefficient on this term that differs substantially from this prior is likely to be incorrect.

Equation 4 reflects a reduced-form regression approach. Alternatively, one might consider an instrumental variables regression in which $\ln(PredCOAL_{ct})$ is used as an instrument for $\ln(COAL_{ct})$. However, note that $\ln(COAL_{ct})$ is itself a proxy for actual coal use in a city and that both of these variables are constructed using the common underlying input $COALperEMP_i$. In an IV regression This will result in estimating a misleadingly strong first-stage. For this reason, the reduced-form approach is likely to be more appropriate in this context.

In estimating Equation 4 we may be concerned about both spatial and serial correlation. Spatial correlation is a particular concern in this context because coal smoke from one city may affect other nearby cities. Serial correlation is less of a concern in this context because the data have a relatively short time dimension (Bertrand *et al.* (2004)), but this is still an issue that should be considered. To deal with these concerns I allow spatial and serial correlation of standard errors following Newey & West (1987) and Conley (1999) using the implementation from Hsiang (2010). Specifically, I allow for spatially correlated errors between any pair of cities within 100km of each other. The error terms on observations for a city are allowed to be correlated with error terms one decade before and one decade after. It is worth noting that allowing correlated standard errors often reduces the confidence intervals because errors are generally negatively correlated.

Table 5 presents baseline results obtained using data from 1861-1911 with predicted values based on city-industry employment in 1851. Columns 1-2 undertake some preliminary regressions. In column 1, only the $\ln(PredWORKPOP_{ct})$ variable is included, so there is no adjustment made for coal use in a city. The result shows a coefficient that is significantly below one. Taken at face value, this suggests that generating one new job in a city actually crowds out a fraction of an existing job. Column 2 conducts a similar exercise using only the $\ln(PredCOAL_{ct})$ variable, which yields an even lower coefficient.

The main regression results begin in Column 3, where both the $\ln(PredWORKPOP_{ct})$ and $\ln(PredCOAL_{ct})$ variables are included. Here I observe a coefficient on predicted city employment that is above, but not statistically different from, one. In addition, I observe that predicted city coal use exerts a statistically significant negative effect on city size equal to about 7% of the positive direct effect. Column 4 presents results from a similar regression that also includes the log of initial city population. Column

5 allows this initial city-size effect to vary over time.

Table 5: Impact of coal use on city working population – baseline results

	DV: Log of city working population in analysis industries				
	(1)	(2)	(3)	(4)	(5)
$\ln(PredWORKPOP_{ct})$	0.946***		1.026***	1.071***	1.016***
	(0.0144)		(0.0454)	(0.107)	(0.0508)
$\ln(PredCOAL_{ct})$		0.803***	-0.0746**	-0.0813**	-0.0871**
		(0.0242)	(0.0335)	(0.0375)	(0.0386)
$\ln(INITPOP_{ct})$				-0.0407	
				(0.0833)	
$\ln(INITPOP_{ct})$					0.00585
x 1871					(0.00704)
$\ln(INITPOP_{ct})$					0.00864
x 1881					(0.00636)
$\ln(INITPOP_{ct})$					0.0118
x 1891					(0.00816)
$\ln(INITPOP_{ct})$					0.0145*
x 1901					(0.00772)
$\ln(INITPOP_{ct})$					0.0176*
x 1911					(0.00896)
Constant	0.654***	0.0999	0.794***	0.824***	0.972***
	(0.173)	(0.336)	(0.139)	(0.123)	(0.151)
Observations	150	150	150	150	150
Cities	25	25	25	25	25

*** p<0.01, ** p<0.05, * p<0.1. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. HAC standard errors, shown in parenthesis, allow for spatially correlated errors across cities within 100km of each other and serial correlation among standard errors within a city one decade before and after.

The results in Table 5 suggest that industrial coal use exerts a substantial negative effect on city population. Using the estimates from Column 5, these results suggest that a 1% increase in employment in a non-polluting industry increases city employment by 1.016%, suggesting a very mild local multiplier. However, a 1% increase in employment in a polluting industry that also increase industrial coal use by 1% only increases city employment by 0.94%. Thus, in an industry that uses coal in proportion to its contribution to city employment, the disamenity value of coal use shaves about 8% off of the impact of increased employment on overall city employment. In industries such as Chemicals and Metal & Machinery, which use 2-3 times the avereage level of coal per worker, these negative effects would be substantial.

The baseline specification in Equation 4 does not include either city or decade fixed effects. Incorporating these additional controls is possible given the structure of the data, though there are also drawbacks in introducing additional controls when using a relatively small dataset. Nevertheless, in Table 6 I explore how the results change when fixed effects are incorporated. Column 1 includes a full set of decade indicator variables. These results are very similar, if slightly larger, than those obtained in Table 5. Column 2 introduces city fixed effects. These estimates are now identified only using time variation with cities. We can see that this changes the results substantially, suggesting a much larger negative impact of coal use on city size. However, the inclusion of these additional controls has led to a substantial increase in the standard errors making these results less precise than those in Table 5. Finally, Column 3 includes both decade and city effects. This regression suggests an even larger negative effect from coal use, which is now statistically significant despite the fact that the estimates are much less precise. The estimated effect in Column 3 are quite large. If one ignores the large errors and takes the coefficients seriously, they would suggest that increases in employment in some heavily polluting industries would lead to a net loss of employment in the city overall.

It is interesting to note that the results generated using primarily cross-sectional variation (e.g., Column 1 of Table 6) are much smaller than those obtained when relying on time-series variation (e.g., Column 2 of Table 6). This suggests that there are strong selection forces at work. To see why, suppose that there are some workers or some firms that are more willing, or more able, to deal with high levels of local pollution. In the cross section, we expect that these workers or firms will sort so that more tolerant firms or workers are in more polluted cities. This selection will act to reduce the impact of coal pollution. On the other hand, when results are identified using primarily time-series variation, this is akin to asking what the impact of an increase in pollution will be given the set of workers and firms in a location. There will be less room for selection to reduce the negative effects of pollution in this case. Taken to the extreme, if pollution increases at an equal rate in all cities, then there is no room for selection to reduce the impact of increased pollution. From a policy perspective, both of these impact measures are potentially interesting. However, to be conservative, in discussing my results I will generally focus on the results described in Table 5, which I will think of as a providing a lower bound for the impact of industrial coal use on city size.

Table 6: Impact of coal use on city working population – with fixed effects

DV: Log of city working population in analysis industries			
	Decade FEs	City FEs	City & Decade FEs
	(1)	(2)	(3)
$\ln(PredWORKPOP_{ct})$	1.027***	1.952*	1.303
	(0.0495)	(1.073)	(1.074)
$\ln(PredCOAL_{ct})$	-0.0885**	-0.686	-1.842**
	(0.0385)	(0.936)	(0.773)
City FEs	No	Yes	Yes
Decade effects Yes	No	Yes	
Observations	150	150	150
Cities	25	25	25

*** p<0.01, ** p<0.05, * p<0.1. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. Column 1 includes a full set of decade indicator variables. Column 2 includes a full set of city fixed effects. Column 3 includes both city and decade effects. HAC standard errors, shown in parenthesis, allow for spatially correlated errors across cities within 100km of each other and serial correlation among standard errors within a city one decade before and after.

All of the results presented thus far focus on the impact of coal use on working population in the analysis industries.[15] Next, I consider the impact on two other outcome populations. First, I look at the impact of coal use on the working population across all industries, which includes government workers and some miscellaneous

[15]The main reason for focusing first only the working population in the analysis industries is that there is a direct link between the actual working population in the analysis industries in a city and the predicted working population $\ln(PredWORKPOP_{ct})$, since the prediction is based on the employment in the analysis industries. One advantage of this direct connection is that it allowed a natural specification test on the relationship between actual and predicted working populations. Such a direct test is not possible when the dependent variable includes population outside of the analysis industries.

workers not classified into one of the analysis industries. Table 7 presents these results. Second, in Table 8 I calculate results in which total city population is used as the dependent variable.

Both sets of results show that coal use had strong and statistically significant negative impact on city size. Moreover, both the positive direct effect of industry growth and the negative impacts of coal use are larger than the coefficients estimated in table 5. The larger impacts on working population across all sectors, shown in Table 7, suggest that local multipliers are larger when one accounts for all types of work, including public sector employment. The larger impacts on total population also make sense. The gain or loss of workers in an analysis industry is likely to mean a larger gain or loss of total population, since worker movements will also imply movement of nonworking children or elderly parents.

Table 7: Impact of coal use on total city working population in all sectors

	DV: Log of city working population in all sectors				
	(1)	(2)	(3)	(4)	(5)
$\ln(PredWORKPOP_{ct})$	1.226***	1.143***	1.216***	1.228***	1.427
	(0.0577)	(0.112)	(0.0257)	(0.0202)	(0.989)
$\ln(PredCOAL_{ct})$	-0.261***	-0.243***	-0.270***	-0.272***	-2.357***
	(0.0541)	(0.0523)	(0.00925)	(0.00474)	(0.711)
$\ln(INITPOP_{ct})$		0.0679			
		(0.0854)			
City FEs	No	No	Yes	No	Yes
Decade effects	No	No	No	Yes	Yes
Observations	150	150	150	150	150
Cities	25	25	25	25	25

*** p<0.01, ** p<0.05, * p<0.1. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. Columns 1-2 use HAC standard errors that allow for spatially correlated errors across cities within 100km. Serial correlation is not included in these specifications because I run into difficulties with matrix inversion. Columns 3-5 use HAC standard errors that allow for both spatially correlated errors across cities within 100km of each other and serial correlation among standard errors within a city one decade before and after.

Table 8: Impact of coal use on total city population

	DV: Log of city total population				
	(1)	(2)	(3)	(4)	(5)
$\ln(PredWORKPOP_{ct})$	1.139***	0.872***	1.124***	1.140***	0.255
	(0.0633)	(0.129)	(0.0396)	(0.0352)	(0.835)
$\ln(PredCOAL_{ct})$	-0.167***	-0.107*	-0.179***	-0.181***	-1.475**
	(0.0631)	(0.0564)	(0.0334)	(0.0316)	(0.593)
$\ln(INITPOP_{ct})$		0.219**			
		(0.0912)			
City FEs	No	No	Yes	No	Yes
Decade effects	No	No	No	Yes	Yes
Observations	150	150	150	150	150
Cities	25	25	25	25	25

*** p<0.01, ** p<0.05, * p<0.1. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. Columns 1-2 use HAC standard errors that allow for spatially correlated errors across cities within 100km. Serial correlation is not included in these specifications because I run into difficulties with matrix inversion. Columns 3-5 use HAC standard errors that allow for both spatially correlated errors across cities within 100km of each other and serial correlation among standard errors within a city one decade before and after.

Some additional robustness checks related to the results presented in this section are available in the Appendix. In one set of results, I consider the impact of dropping London, which stands as an outlier in terms of overall city size, though not in terms of industrial coal use. I find that this has essentially no impact on the results reported in Table 5. I also consider some alternatives for the functional form for the impact of industrial coal use on city size. I find results that are qualitatively similar to those reported above using either total coal use in a city, or coal use per capita, as the key explanatory variable, but these results are often not statistically significant. These specifications often fail the functional form test by delivering coefficients on the $\ln(PredWORKPOP_{ct})$ variable that are significantly below one.

5.4 Industry-specific impacts of city coal pollution

To better understand the factors generating these city-size effects, I now estimate the impact of overall city coal use on individual industries. The specification is,

$$\ln(EMP_{ict}) = \alpha_0 + \alpha_1 \ln(PredEMP_{ict}) + \sum_i \alpha^i \ln(PredCOAL_{ct}) + \delta_{ic} + \phi_{it} + \eta_{ct} + e_{ict} \,, \quad (5)$$

where EMP_{ict} is employment in industry i in city c and year t, $PredEMP_{ict}$ is predicted employment in that city-industry and $PredCOAL_{ct}$ is the predicted level of city coal use. The $PredEMP_{ict}$ variable is calculated using the initial size of industry i in city c in 1851 multiplied by the national growth rate of industry i from 1851 to year t. Thus, this plays the same role as the $\ln(PredWORKPOP_{ct})$ variable used for the city-size effects. The model also includes a full set of city-industry effects, δ_{ic}, industry-time effects, ϕ_{it} , and city-time effects, η_{ct}. These control for local factors that affect all industries equally, shocks to industry employment over time, and initial city features that influence the size of an industry in a particular location. In this regression, we may be worried about correlated errors across industries within the same city, across time within the same city-industry, and within the same industry across space. To deal with this, I follow Hanlon & Miscio (2014) and apply the multi-way clustering (Cameron *et al.* (2011)). Errors are clustered by city-industry, to allow for serial correlation, by city-year, to allow correlated errors across industries within the same city and year, and by industry-year, to allow correlated errors across space for the same industry within a year.

Table 9 presents the estimated α^i coefficients and standard errors generated with this approach. We can see that a number of industries show negative effects that are statistically significant at either the 90% or 95% level.

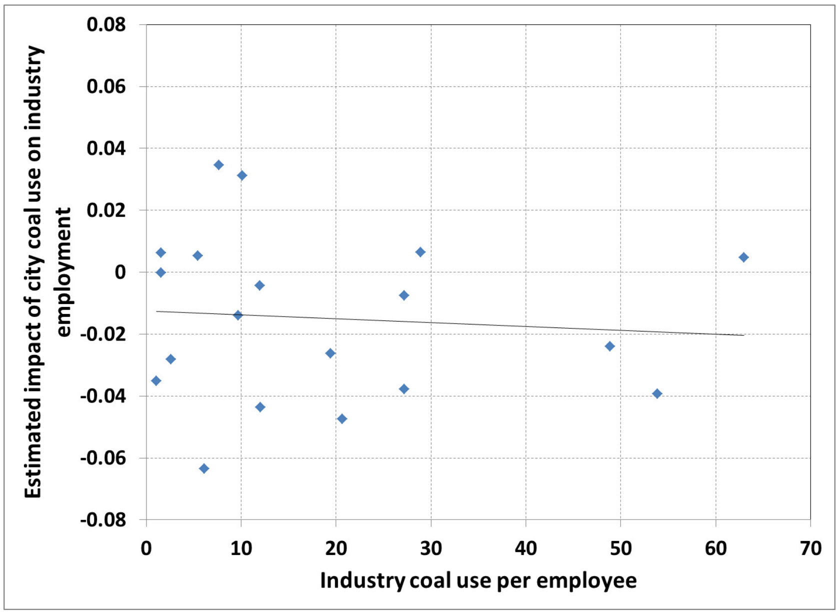
Table 9: Industry-specific city coal use effects

Industry	Coef.	SE
Chemicals & drugs	0.0047	(0.0222)
Dress	-0.0002	(0.0232)
Railway transport	-0.0075	(0.0199)
Road transport	-0.0378*	(0.0223)
Sea & canal transport	0.0347	(0.0220)
Vehicles	-0.0282	(0.0231)
Shipbuilding	-0.0634**	(0.0258)
Construction	0.0062	(0.0216)
Food	-0.0044	(0.0218)
Oils, soaps, etc	-0.0474*	(0.0246)
Leather & hair goods	-0.0436**	(0.0220)
Drinks	-0.0262	(0.0227)
Tobacco	-0.0352	(0.0242)
Wood furniture	0.0053	(0.0219)
Textiles	0.0312	(0.0197)
Paper & publishing	-0.0139	(0.0215)
Mining related	0.0065	(0.0220)
Earthenware & bricks	-0.0240	(0.0233)
Water & gas service	-0.0393*	(0.0235)
Instruments & jewelry	-0.0332	(0.0222)
Metal manufactures	-0.0110	(0.0211)
Log(PredEMP)	0.9484***	0.0396
Observations	3,281	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. Standard errors are clustered by city-industry, city-year, and industry-year. The data set contains 22 industries, 25 cities and 6 decades, with a small number of missing observations due to city-industries with zero employment. Eight of the missing observations are in the Shipbuilding industry and one is in Tobacco.

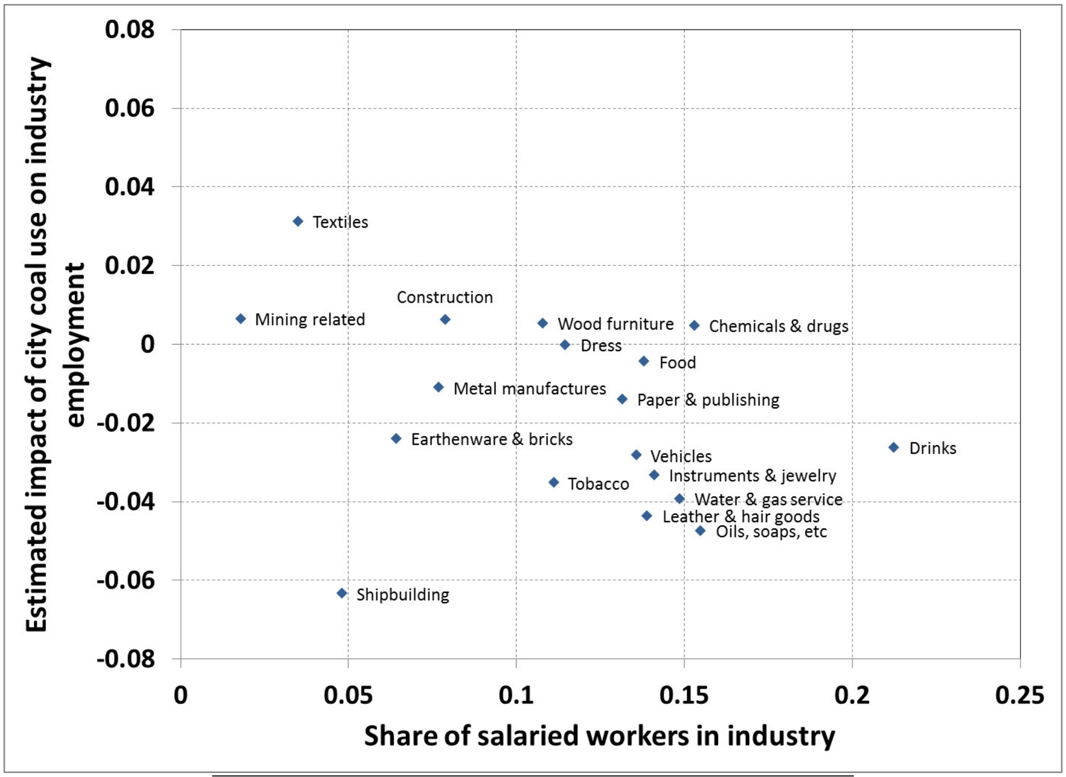
To make some sense of these estimates, it is useful to compare them to available data on industry characteristics. One interesting comparison, shown in Figure 2, is between coal use per worker in an industry and the estimated impact of city coal use on industry employment. If anti-smoke regulations had an important impact on industry employment, and if these regulations were stricter in more polluted cities, then we would expect to observe a negative relationship between city coal use and employment in coal-intensive industries. No such relationship appears in Figure 2.

Figure 2: Industry-specific effects compared to industry coal intensity



Another interesting industry characteristic to look at is the share of skilled workers employed. This share can calculated using the data on employment of salaried and wage laborers in each industry reported in the 1907 Census of Production. Figure 3 graphs the skilled worker share of each industry against the estimated impact of city coal use on that industry. The figure reveals a fairly clear negative relationship, suggesting that industries that were more reliant on skilled workers suffered more from high levels of industrial coal use in a city. The main outlier to this pattern is shipbuilding, which is a peculiar industry in that it is either nonexistent or very small in many of the cities in the sample. Below the figure I present regression results describing the relationship. When shipbuilding is omitted, I find strong evidence of a negative relationship between industry skill intensity and the impact of industrial coal use in a city.

Figure 3: Industry-specific effects compared to industry skilled-worker share



	With shipbuilding	Without shipbuilding
Industry skilled worker share	-0.1649 (0.1154)	-0.2661*** (0.09567)
Observations	18	17

This pattern is consistent with contemporary evidence suggesting that the better-off residents were fleeing the polluted British cities during this period. Thorsheim (2006) reviews a number of contemporary sources discussing the potential negative effects of this pattern. For example, an article in *Chambers's Journal* in 1855 states, "it is not merely that a smoke-charged atmosphere is a blemish to everything...it send away the rich to dwell apart from the poor." Later, Thorsheim (2006) (p. 44) describes a deputation visiting the lord mayor of Manchester in 1877. He writes that they,

> *...urged him to do more to control smoke. They argued that "the well-to-do inhabitants" were moving out of the city, leading to "apathy on their part towards the condition of the lower classes. Indeed the depressing effects of our impure air may fairly be considered as a powerful factor in retarding efforts at social reform."*

This evidence suggests that the coal smoke exerted a particularly strong effect on the skilled and wealthier classes, making it particularly difficult for skill-intensive industries to survive in these locations. It also calls to mind work by Rauch (1993) and Moretti (2004) suggesting that the presence of high-skilled workers generates positive local productivity spillovers and work by Diamond (2012) suggesting that their presence may also generate positive consumption amenities. The estimates I have generated for the impact of coal use on city size will reflect the combined impact of all of these possible effects.

6 Conclusion

This study shows that the endogenous disamenity value of coal-based industrial pollution had a substantial effect on the size of British cities in the late 19th and early 20th centuries. These results show how a city's industrial composition can be an important determinant of its amenity value, and how we can empirically identify this contribution. Thus, they contribute to existing work which has highlighted the impact of the characteristics of residents on endogenous amenities (Diamond (2012)). These two factors – industrial composition and resident composition – will also influence one-another. Understanding the role of these interconnections in generating endogenous city-amenities is an interesting direction for future work.

These findings have implications for local policies aimed at fostering industrial growth in cities. Often, these policies focus on the easily observable direct effects of industry growth, particularly jobs. Yet I find evidence that, for polluting industries, the negative indirect effect of through pollution can be substantial. Policymaker should be cognizant of these potential indirect costs when considering encouraging the growth of polluting industries.

My results contribute to our understanding of the importance of pollution in British cities during the 19th century. Williamson (1981) has argued that the aggregate impact of this disamenity was "trivial". In contrast, by using more detailed data I show that pollution had a substantial aggregate impact. My results also provide support for the idea that an environmental Kuznets curve developed in London in the late 19th century, as suggested by Troesken & Clay (2010).

Finally, this study shows that much can be learned about the impact of pollution on cities, even in a relatively data-sparse environment. The approach I use requires only data on employment in cities and on the use of polluting inputs by industries. These techniques may be useful in places, such as cities in developing countries, where direct measures of environmental quality may be unavailable.

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A Appendix

A.1 Further details on the empirical setting

Table 10: History of British air pollution regulation, 1851-1911

1853-6	Smoke abatement acts relating to the Metropolitan area
1866	The Sanitary Act empowered sanitary authorities to take action in cases of smoke nuisances
1875	The Public Health Act containing a smoke abatement section on which legislation to the present day has been based
1881	Smoke abatement exhibition at South Kensington organized by the Public Health and Kyrle Societies
1882	Formation of the National smoke abatement institution
1891	The Public Health (London) Act
1899	Formation of the Coal Smoke Abatement Society
1909	Sheffield smoke abatement exhibition, at which was set up the Smoke Abatement League of Great Britain (mainly for the provinces and centered later in Manchester and Glasgow).

Sourche: The Glasgow Herald (Sept. 24, 1958)

Figure 4: English cities included in the study

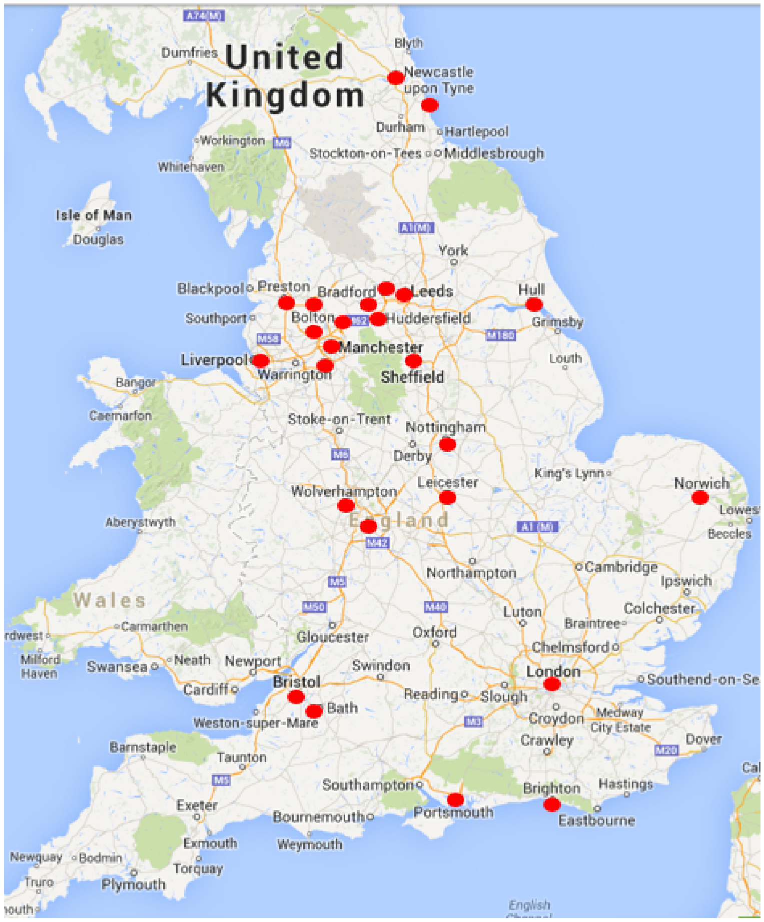
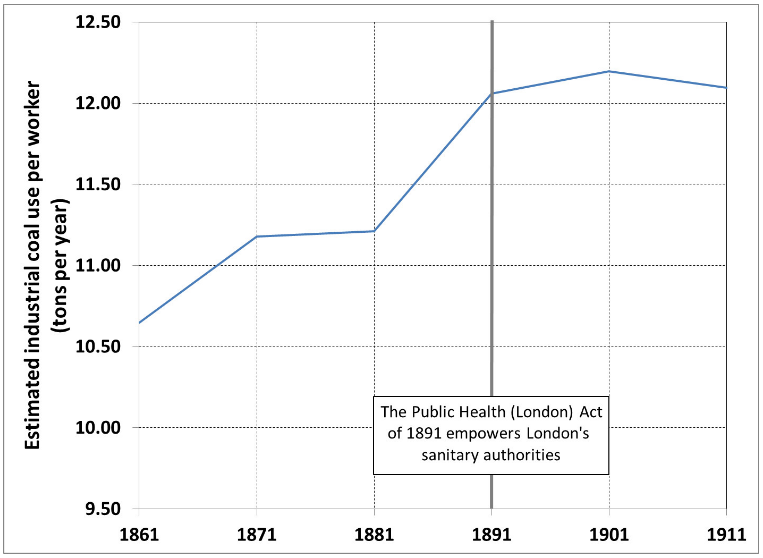


Figure 5: Estimated coal use in London based on industry composition, 1851-1911



A.2 Additional mortality results

Table 11 shows that similar results are obtained when using the $PredCOAL_{ct}$ variable, predicted based on a city's 1851 industrial composition, in place of the $COAL_{ct}$ variable. The advantage of this approach is that the predicted level of industrial coal use will not be affected by shocks that affect a particular city in a particular year, such as a recession or a disease outbreak, that may affect both the level of current industrial activity and the mortality rate.

Table 11: Industrial coal use and mortality using predicted city-industry employment

DV: Overall city mortality rate				
	1871	**1881**	**1891**	**1901**
$Ln(PredCOAL_{ct})$	0.0341***	0.0298***	0.0276***	0.0337***
	(0.00934)	(0.00711)	(0.00709)	(0.00644)
$Ln(TOTPOP_c)$	-0.0253*	-0.0262**	-0.0253**	-0.0334***
	(0.0125)	(0.00950)	(0.00946)	(0.00900)
DV: Mortality rate due to respiratory system				
	1871	**1881**	**1891**	**1901**
$Ln(PredCOAL_{ct})$	0.00643	0.00819***	0.00843***	0.00988***
	(0.00511)	(0.00249)	(0.00290)	(0.00248)
$Ln(TOTPOP_c)$	-0.00255	-0.00487	-0.00562	-0.00824**
	(0.00686)	(0.00333)	(0.00387)	(0.00346)
DV: Mortality rate due to heart/circulatory system				
	1871	**1881**	**1891**	**1901**
$Ln(PredCOAL_{ct})$	0.000833	0.000422	0.00122*	0.00163**
	(0.000556)	(0.000779)	(0.000648)	(0.000777)
$Ln(TOTPOP_c)$	-0.00112	-0.00137	-0.00222**	-0.00294**
	(0.000746)	(0.00104)	(0.000865)	(0.00109)
Observations	25	25	25	25

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A.3 Robustness exercises

The first two tables in this section show results when London is dropped from the data set. The third and fourth tables consider alternative ways of modeling the impact of coal use on cities. Tables 12 and 13 show that excluding London has very little effect on the results.

Table 12: Impact of coal use on city working population excluding London – baseline results

	DV: Log of city working population in analysis industries				
	(1)	(2)	(3)	(4)	(5)
$\ln(PredWORKPOP_{ct})$	0.947***		1.042***	1.093***	1.005***
	(0.0213)		(0.0677)	(0.119)	(0.0736)
$\ln(PredCOAL_{ct})$		0.714***	-0.0823*	-0.0889*	-0.0822*
		(0.0213)	(0.0439)	(0.0483)	(0.0487)
$\ln(INITPOP_{ct})$				-0.0490	
				(0.0798)	
$\ln(INITPOP_{ct})$					0.00641
x 1871					(0.00788)
$\ln(INITPOP_{ct})$					0.00943
x 1881					(0.00717)
$\ln(INITPOP_{ct})$					0.0130
x 1891					(0.00898)
$\ln(INITPOP_{ct})$					0.0162*
x 1901					(0.00833)
$\ln(INITPOP_{ct})$					0.0198**
x 1911					(0.00943)
Observations	144	144	144	144	144
Cities	24	24	24	24	24

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. HAC standard errors, shown in parenthesis, allow for spatially correlated errors across cities within 100km of each other and serial correlation among standard errors within a city one decade before and after.

Table 13: Impact of coal use on city working population excluding London – with fixed effects

	DV: Log of city working population in analysis industries		
	Decade FEs	City FEs	City & Decade FEs
	(1)	(2)	(3)
$\ln(PredWORKPOP_{ct})$	1.018***	1.861*	1.299
	(0.0714)	(1.083)	(1.080)
$\ln(PredCOAL_{ct})$	-0.0838*	-0.589	-1.841**
	(0.0486)	(0.944)	(0.778)
City FEs	No	Yes	Yes
Decade effects Yes	No	Yes	
Observations	144	144	144
Cities	24	24	24

*** p<0.01, ** p<0.05, * p<0.1. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. Column 1 includes a full set of decade indicator variables. Column 2 includes a full set of city fixed effects. Column 3 includes both city and decade effects. HAC standard errors, shown in parenthesis, allow for spatially correlated errors across cities within 100km of each other and serial correlation among standard errors within a city one decade before and after.

Next, I consider two alternative ways of modeling the impact of coal use on cities. First, Table 14 presents results where the predicted level of coal per capita is used in place of the log of predicted coal as an explanatory variable. As in the baseline results, this specification suggests a negative relationship between coal use per capita and city growth, but this finding is generally not statistically significant. Moreover, several of the specifications show coefficients on the predicted workers term that are below 1, which casts doubt on the validity of this functional form.

Table 15 presents results where total coal use in a city, in millions of tons, is the key explanatory variable. Again, the results suggest a negative relationship between coal use and the working population of a city. These results are statistically significant in only some cases. Also, the coefficients on the predicted employment term are often less than one, suggesting that this is also unlikely to be the correct specification.

Table 14: Results using coal use per capita

DV: Log of city working population in analysis industries					
	(1)	(2)	(3)	(4)	(5)
$\ln(PredWORKPOP_{ct})$	0.952***	0.995***	0.938***	1.323***	-0.590*
	(0.0250)	(0.142)	(0.0275)	(0.0961)	(0.355)
$PredCoalperWorker_{ct}$	-0.00538	-0.00584	-0.00592	-0.0822	-0.230***
	(0.00368)	(0.00451)	(0.00404)	(0.0538)	(0.0593)
$\ln(INITPOP_{ct})$		-0.0469			
		(0.155)			
City FEs	No	No	Yes	No	Yes
Decade effects	No	No	No	Yes	Yes
Observations	150	150	150	150	150
Cities	25	25	25	25	25

*** p<0.01, ** p<0.05, * p<0.1. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. Columns 1-3 show HAC standard errors that allow for spatially correlated errors across cities within 100km of each other but do not allow for serially correlated standard errors. Columns 4-5 show HAC standard errors that allow for both spatial correlation within 100km and serial correlation across one decade.

Table 15: Results using total coal use in a city

DV: Log of city working population in analysis industries					
	(1)	(2)	(3)	(4)	(5)
$\ln(PredWORKPOP_{ct})$	0.972***	0.986***	0.949***	1.219***	-0.432*
	(0.0298)	(0.0881)	(0.0291)	(0.0693)	(0.226)
$PredCoal_{ct}$	-0.0105*	-0.0105*	-0.00678	-0.0343***	-0.0125
	(0.00583)	(0.00572)	(0.00561)	(0.00944)	(0.00757)
$\ln(INITPOP_{ct})$		-0.0153			
		(0.0723)			
City FEs	No	No	Yes	No	Yes
Decade effects	No	No	No	Yes	Yes
Observations	150	150	150	150	150
Cities	25	25	25	25	25

*** p<0.01, ** p<0.05, * p<0.1. The estimates use data from 1861-1911, with 1851 values used to construct the explanatory variables. HAC standard errors, shown in parenthesis, allow for spatially correlated errors across cities within 100km of each other and serially correlation among standard errors within a city one decade before and after.