The Hidden Cost of Industrial Pollution: Environmental Amenities and the Location of Service Jobs

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Preliminary and Incomplete †

December 22, 2018

Abstract

This paper presents theory and evidence on the role of environmental amenities in shaping the competitiveness of post-industrial cities. I assemble a rich database at a fine spatial scale to examine the impacts of historical pollution on employment outcomes within cities. I find census tracts that are downwind to highly polluted historical industrial sites are associated with lower housing price and share of skilled employment 40 years later, and the pattern has been reinforcing itself during 1980-2010. These findings suggest the presence of skill sorting around environmental amenities and strong subsequent agglomeration effects. To quantify the contribution of different mechanisms, I build and estimate a spatial equilibrium framework where workers in different sectors value local amenities differently and the initial divergence in environmental amenities put cities into different growth path through attracting workers of different skills. Consistent with the reduced form patterns, the estimated quality-of-life perceived by high-skilled workers is more responsive to local environmental amenities, most notably pollution. Moreover, cities with a higher proportion of industrial land near central business district display a larger misalignment of productivity and amenity and are consequently more susceptible to suburbanization. Counterfactual analyses illustrate the quantitative implications of skill sorting around environmental amenities and the presence of production and residential externalities on cross-city skill distribution and city growth.

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1 Introduction

The comparative advantages of cities evolve slowly over time: during the industrial era, cities serve as production agglomerates where firms benefit from proximity to natural resources, shared infrastructure, and pooled labor market. More recently, cities are increasingly reshaping themselves into innovation hubs and consumption centers. During this transition, while some cities and towns have managed to adapt by shifting focus towards services, others have not fared as well, witnessing declining population and deteriorating economic conditions. Urban decline associated with structural transformation is commonplace in many countries: from Northeast England in the first half of the twentieth century, to the Rust Belt in the past few decades, to North China heavy industrial cities today. Drawing lessons from the experiences of early industrialized cities in the developed world can be essential for policy-makers in recently industrialized countries that start to feel the pressure of urban industrial pollution.

On the quest of the reasons behind industrial city decline, a central puzzle is why they fail to attract new service industries at the wake of manufacture decline with their convenient location, advanced infrastructure, existing agglomerates and declining land value. Among the many proposed explanations of this failed transition, including the structural mismatch of jobs and workers, a lack of entrepreneurship spirit due to the dominance of large corporations and misplaced public policies that attempted to subsidize the failing manufacture sector, an especially interesting one is how the byproducts of their previous successes in the industrial era, industrial pollution, significantly undermines the attractiveness of these cities. In a new era when the appreciation of local amenities plays an increasingly important role in the location choice of skilled workers, and the agglomeration forces are increasingly shaped by the interaction of skilled workers and residents (Glaeser et al. 2004 [31]; Moretti 2012 [40]), the cost of industrial activities quickly outweighs their benefits.

In this paper, I assemble a comprehensive database of census tract level outcomes and historical industrial pollution in U.S. metropolitan areas to document several motivating empirical patterns. I find that census tracts that are closer to early industrial areas, especially to the ones that are heavily polluted in the 1970s, are shown to be occupied by less educated residents and less skill-intensive industries; and experience lower subsequent growth in employment and housing value. To be certain that the results are not purely driven by selection bias or economic linkages to industrial areas, I exploit the variation in historical pollution levels due to prevailing wind patterns and elevation differences for tracts equidistant to historical industrial areas. Equidistant tracts presumably established similar economic links to the nearby industrial areas and experienced similar labor market shocks when these areas deindustrialize. In practice, I estimate the interaction terms of distance buffers to 1970 industrial zones with wind exposure and elevation gap to these areas for each tract, with historical pollution, current pollution and current economic outcomes at the dependent variables. I find wind direction and topography conditions play important roles in accounting for variation in historical pollution, but not so much in current pollution. However, they appear to be important in determining both current economic outcomes and their evolution from 1980 to 2000. I find the tracts that are close and downwind or at the same elevation to nearby industrial areas in the 1970s, and as a result more exposed to historical pollution, are less skilled and have lower housing value in 2000, and has experienced declining housing price, wage and share of skilled employment since 1980. The adverse effects of early industrial pollution are much stronger for tracts near CBD. These findings are highly suggestive of strong production and/or residential agglomeration effects that set cities to diverging development paths.

To quantify how different mechanisms contribute to this pollution-driven urban blight phenomenon, the major difficulty is to separate the amenity impacts of industrial activities from the productivity ones, and to separate the subsequent agglomeration effects from the initial impacts. To deal with both identification challenges, I first estimate a structural spatial equilibrium model that allows me to identify sector-specific productivity and amenity parameters. I then decompose them into exogenous ones driven by fundamentals and endogenous ones determined by agglomeration forces under different assumptions on production and residential externalities. Finally, I examine how the-the changes in pollution driven by EPA regulation affect local productivity amenities both directly and indirectly through the re-sorting of skilled workers and residential externalities.

The spatial general equilibrium model, based on Ahlfeldt, Redding, Sturm, and Wolf (2015) [1], features the internal structure of cities, introduces heterogeneity in people's valuation of local amenities, and allows the initial sorting of sectors based on tastes for amenities to be magnified by production and residential externalities. These features allow me to separately estimate sector-specific productivity and amenity parameters using rich information on census tract level sectoral employment and wage observed at both place of work and place of residence, tract-to-tract commuting patterns and cost, and housing value from 1990 to 2010. With these estimates, we can tell to what extent a tract is more valued by firms in IT sector than those in the construction business as a productive place to locate, and is appreciated by workers from finance sector than those from manufacture as a pleasant place to live. Preliminary results from the structural estimation suggest that the perceived amenities of workers from high-skilled industries, such as FIRE, IT, professional services, education and medical services, are more responsive to the same local amenities such as clean air, safety, public schools and access to natural amenities. In the meantime, these high-skilled sectors benefit more from central city locations in productivity. These two facts together indicate that industrial pollution near city center can be especially damaging as it exacerbates the misalignment of productivity and amenities of high-skilled sectors.

To disentangle the contribution of local fundamentals and residential externalities to estimated local productivity and amenities, I define residential externalities as an increasing function of the residential density of surrounding tracts and the skill-mix (the ratio of college graduates) of these tracts. The elasticity of residential externalities to local skill mix is identified using local demand shocks driven by the industry composition of each tract. Variation in productivity changes across industries differentially impacts each tract's local labor demand for high and low skill workers based on the industrial composition of it (Bartik (1991) [7] and Diamond (2015) [20]). The estimated parameters on the extent of residential externalities for workers from different sectors allow me to decompose the impacts of improved air quality on local perceived amenities into an exogenous and endogenous parts, and the later explains at least 20% of the total effects. On the production side, I borrow estimates on the significance of production externalities and the rate of spatial decay from Ahlfeldt et al. (2015) [1]. I also adopt more flexible specifications by allowing the productivity of a particular sector to depend on the employment density of different sectors according to the industrial linkages across sectors [23].

By checking the correlation between early pollution exposure and estimated productivity and amenity parameters, I show that controlling for current pollution, tracts that are exposed to historical pollution due to downwind position to industrial areas have both lower productivity and amenity in 2000, and the negative effects are stronger for productivity, skill-intensive sectors and central tracts. Accounting for standard agglomeration effects following the literature explains away about 30% and 50% of the variation in aggregate productivity and amenity estimates.

To accurately account for the impacts of industrial pollution on both exogenous and endogenous parts of the estimated sector-specific amenity for counterfactual analysis, I again exploit the quasi-experimental reductions in Particle Matters (PM10) concentrations from 2000 to 2010 induced by differential local regulator responses to the Clean Air Act Amendments (CAAA), studied in Auffhammer, Bento and Lowe (2009) [5] and Bento, Freedman and Lang (2015) [10]. In an instrumental variable specification, I show that changes in perceived amenity by workers from different sectors respond to the evolution in PM10 concentration level in a way that mirrors the responses from the cross-sectional estimation. The elasticity of people's differential valuation to environmental quality is used to simulate the impacts of industrial pollution reduction in the 1970s in my counterfactual analysis.

The fully calibrated model can be used to undertake several counterfactual exercises. Specifically, I examine how the cut in pollution level induced by Clean Air Act Amendments (CAAA) in the 1970s leads to changes in housing value and employment composition across different sectors, with and without agglomeration forces, and compare the results to the reduced-form evidence. To account for the differences in the cost and benefits of pollution abatement across time and space, I consider an alternative counterfactual exercise of cutting pollution level in central cities while increasing pollution level by the same amount in the suburbs to check if a relocation of industrial activities within industrial cities bring about overall welfare improvement.

2 Related Literature

The paper is related to a long history of literature examining the geographic sorting of different types of households (Tiebout, 1956 [44]; Epple and Sieg, 1998 [24]). Among which a small literature specifically deal with the sorting of households by environmental amenities, such as Wu (2006) [46], Banzhaf et al. (2008) [6] and Bayer et al. (2009) [9]. Heblich et al.(2015) [35] in particular document the sorting response to pollution in the 19th century that persist today in British cities. My contribution is to embed this mechanism in a general equilibrium setting where the initial sorting of skilled labor around environmental amenities gets magnified by agglomeration forces, which makes the distribution of industrial pollution around a city as important as the sheer amount of it. My method allows me to disentangle effects on productivity from those on amenity, as well as subsequent agglomeration effects from the initial impacts.

This paper also contributes to the literature on measuring the quality of life in cities (Blomquist et al. 1988 [11]; Albouy, 2012 [2]). To my knowledge, this paper is one of the first attempts to measure the quality of life at a highly disaggregated level. It is also one of the first to directly measure locational quality-of-life perceived by workers with different characteristics. I find the variation in measured quality of life within cities is much more than that across them, and the alignment between amenity and productivity within a city could prove to be vital to its overall competitiveness.

Third, there is a large body of literature on changes in the internal structure of cities, including the ones on post-war decentralization of American cities and recent gentrification of inner cities (Fee and Hartley, 2003; [25] Couture and Handbury, 2015 [18]). My paper extends this literature by listing central city industrial pollution as a particular contributor to the excessive decentralization of post-war industrial cities and examining to what extent could the cleanup of inner city pollution bring the revival of city cores, in spite of agglomeration forces working against it. My preliminary results suggest that central city amenities perceived by high-skilled workers improve disproportionately from 2000 to 2010, which is consistent with the results presented in Couture and Handbury (2015) [18]. In addition, this paper integrates the internal structures of cities into a system of cities to examine how the distribution of industrial land use within a city, and consequently the alignment of amenity and productivity of high-skilled workers within this city, affects its overall attractiveness and competitiveness, which contributes to the literature examining within city land use (Allen, Arkolakis and Li (2015) [4], Turner et al. (2014) [45], Duranton and Puga (2015) [21] as a review.

Another strand of literature studies endogenous productivity and amenities changes in response to the density and composition of an area's residents. Moretti (2004a) [39] and Ciccione and Perri (2006) [17] look at how the productivity of a city respond to its skill-mix, while Bayer et al. (2009) [9], Guerrieri et al.(2013) [33] and Diamond (2015) [20] study residential sorting based on neighborhood characteristics and the endogenous supply of amenities to city level skill-mix. I find the in-migration of college-educated residents to be an important mechanism through which improved air quality raise the perceived amenities of high-skilled workers, and it explains away 30% to the total effects under reasonable assumptions on key parameters.

My findings also relate to the literature studying the structural transformation of cities from manufacture agglomerates to innovation clusters and consumption centers, with high-skilled labor playing an increasingly important role (Glaeser Kolko and Saiz, 2001; Glaeser et al. 2004 [31]; Moretti, 2012 [40]; Diamond, 2015 [20]). In my paper, I take this structural shift as given and look at how it magnifies the importance of environmental amenities in determining a city's growing potentials.

Finally, this paper also contributes to the literature on the causes and consequences of the decline of the Rust Belt. Most importantly, technological change and economic globalization had a profound impact on regions oriented towards goods-production, especially in the Rust Belt (Feyrer et al., 2007 [26]). Glaeser and Ponzetto (2007) [29] argues that the Rust Belt's location-specific advantage, which stemmed from easier access to waterways and railroads, decreased over time. Alder, Lagakos, and Ohanian (2014) [3] cites the lack of competition in both output and factor markets as a key element in Rust Belt decline from a macroeconomics perspective. Glaeser, Kerr, and Kerr (2015) [30] further suggests that proximity to old mines lead to specialization in heavy industries, the dominance of big firms, and subsequently dampened entrepreneurial human capital across several generations.

3 Data

To establish the stylized facts on the relationship between historical industrial pollution and contemporary distribution of skilled labor within and across cities, I assemble a database of tract level outcomes from 1940 to 2010. I draw my data from three main sources: census outcomes from 1940 to 2000, matched across year using according to the Longitudinal Tract Data Base (LTDB); USGS land use data in the 1970s, and EPA pollutants ambient concentration data collected at each monitoring sites from the 1950s.

3.1 Workplace and Residence location choices

The main outcome variables I use are obtained from the Census Transportation Planning Package (CTPP) of the Bureau of Transportation (BTS). The CTPP includes three parts: tabulations by place of residence, tabulations by workplace, and flows from residence to workplace, all at census tract level. It provides detailed information on the counts of employed population by gender (2), industry (15), occupation (25) and race (4) who live or work in certain census tracts, the median earning by industry of people who live or work in these tracts, the number of people who commute between any census tract pairs, and the average travel time by four modes of transportation[1] between any census tract pairs. The CTPP data are available at census tract level for only a few cities in 1990 and all the metropolitan areas in 2000 and 2010. To bilateral travel cost across tracts, I obtain estimated car and public-transit times between the centroids of census tracts from the OpenStreetMap.

I complement the CTPP data with decennial tract level information on employment, skill composition housing value and quality at residence from 1970 to 2010. To normalize the NHGIS and CTPP data to 2010 census tract boundaries, I use the Longitudinal Tract Database (LTDB) (Logan, Xu, and Stults, 2014) [37]. I end up with an unbalanced panel of census tracts from 1970 to 2010, with 52,210 observations in 1970 and 66,438 observations in 2010. I use constant 2010 CBSA boundaries. CBD is defined according to the CTPP 1990 Urban Geographic Data. [2]

Industry-level employment and earning data by both place of work and place of residence are essential for me to separately identify the amenity and productivity parameters in my structural model. More specifically, earning by industry, partialling out educational attainment, gender, race, and occupation, serves as a measure of labor productivity of each industry at the tract level. Tract level quality-of-life perceived by people from different in-

[1] Automobiles, public transportation, walking or cycling, other

[2] `http://www.transtats.bts.gov/TableInfo.asp?Table_ID=1279&DB_Short_Name=CTPP%201990&Info_Only=1`

dustries is backed out using information on the counts of employed population by industry, local housing value and their access to job opportunities within this industry, measured as industrial productivity of nearby tracts inversely weighted by travel cost.

3.2 Historical land use and pollution data

I obtain information on the location of historical industrial areas from the Enhanced Historical Land-Use and Land-Cover Datasets of the U.S. Geological Survey (USGS). This dataset depicts land use and land cover from the 1970s and 1980s and has been previously published by the U.S. Geological Survey (USGS) in other file formats. The basic sources of land use compilation data are NASA high-altitude aerial photographs, and National High-Altitude Photography (NHAP) program photographs. Urban or built-up land use is classified as residential, commercial, industrial, transportation, communications and utilities, industrial and commercial complexes, or mixed urban land use.

The contemporary and historical air pollution data are drawn from the Environmental Protection Agency (EPA) airdata. The EPA monitors different air pollutants over time and their earliest data date back to 1950. The data is available at monitor level, and I match the monitors to census tracts according to their coordinates. In this paper, I focus my attention on Total Suspended Particles (TSP) or Particulate Matter (PM10) because there are more TSP/PM10 monitors than those of other pollutants and they closely related to industrial pollution. Before 1990, the EPA mostly monitored TSPs, during the 1990s the EPA mostly monitored PM10[3].

A major shortcoming of using the actual air pollution data is that they are only available for a small subset of census tracts: only 1755 and 1363 census tracts contain TSP/PM10 monitor(s). Therefore, I need to extrapolate about the air pollution level of other tracts. First, I assign the pollution reading from the closest monitor to tracts that are within one mile to the closest monitor. Second, for the remaining tracts that are within 3 miles of two or more monitors, I assign the geometric mean of the readings of these monitors to the tracts. Finally, for the remaining I estimate an empirical model of local pollution determination where TSP level at each tract is determined by its distance to the CBD, industrial zones, transportation lines, water body and coastal lines, altitude, population density and MSA fixed effects. I then assign the predicted TSP/PM10 value to the remaining tracts. [4]

[3] In 1987, EPA replaced the earlier Total Suspended Particulate (TSP) air quality standard with a PM-10 standard. The new standard focuses on smaller particles that are likely responsible for adverse health effects because of their ability to reach the lower regions of the respiratory tract. To make a sensible comparison across the TSP readings in the 1950s and PM10 after 1990, I compare TSP and PM10 readings at the same monitor during the 1980s and normalize the earlier TSP readings to the PM10 level.

[4] Details are reported in the Appendix. The validity of this kind of extrapolation largely depends on the

3.3 Wind patterns and elevation

In my empirical analysis, I leverage the quasi-experimental variation in wind direction and elevation differences in distributing pollution from industrial sources. I draw the information on local wind conditions from NOAA's Quality Controlled Local Climatological Data (QCLCD). It consists of monthly summaries on wind direction and wind speed for approximately 1,600 U.S. locations, from January 1, 2005 and continue to the present.

Elevation data come from the National Elevation Dataset (NED). NED data are available as one arc-second (approximately 30 meters) for the continental US.

3.4 Amenity data

To examine how my structural amenity parameters respond to actual observable amenities, I have collected a diverse set of data on tract level local amenities, such as public schools and crime rate.

Data on public school are drawn from the National Center for Educational Statistics' Common Core of Data (CCD)[5]. The CCD is NCES' primary census database that includes annual information for the universe of all public elementary and secondary schools, school districts, and other educational administrative and operating units across the U.S. The CCD contains three types of data: descriptive information on school location and type; demographic data on students and staff, and fiscal data on revenues and expenditure. I match school to census tracts using their coordinates, which allows me to infer the number of public schools, average teacher/student ratio, total revenues, and expenditures at census tracts level.

I obtain crime data from National Neighborhood Crime Study (NNCS), 2000[6]. It reports tract-level crime data pertaining to seven of the FBI's crime index offenses for 10,851 census tracts, as well as tract-level information on social disorganization, structural disadvantage, socioeconomic inequality, mortgage lending, and other control variables garnered from the 2000 United States Census of Population and Housing Summary File 3 (SF3) and other publicly available sources.

I also collect information on a variety of natural amenities, following Lee and Lin (2015) [36], including distances to a waterbody, the average slope, the flood hazard risk, the average

selection rule of TSP monitors. According to Chay and Greenstone (2000) [16], the Amendments contain very precise criteria that govern the siting of a monitor. These criteria require that the monitors be placed so that they determine: the highest concentration expected in the area, the representative concentrations in areas of high population density, the impact on ambient pollution levels of significant fixed and mobile categories, and the general background concentration level due to geographic factors.

[5] `https://nces.ed.gov/ccd/pubschuniv.asp`

[6] `http://www.icpsr.umich.edu/icpsrweb/RCMD/studies/27501`

1971–2000 annual precipitation, July maximum temperature, and January minimum temperature.

4 Reduced form evidence

In this section, I estimate the effects of early industrial pollution exposure on subsequent growth and specialization patterns within industrial cities. I start with investigating if areas that are closer to 1970 industrial areas are more polluted in the 1970s and today, with an emphasis on the role of wind and topography conditions in disseminating pollutants. I then proceed to explore the "reduced form" relationship between 1970s industrial activities and contemporary economic outcomes, exploiting variation in wind direction and terrains.

4.1 Proximity to Early Industrial Areas and Local Pollution

4.1.1 Empirical Settings

To check if being closer to industrial areas in the 1970 translates into higher pollution, I adopt the following specification using monitor level pollution data.

$$p_{ic} = \sum \mathrm{I}_{\mathrm{ikm}} \beta_k + X_i' \gamma + \alpha_c + \epsilon_{ic} \tag{1}$$

where $p_{i,1971-1979}$ denotes average pollution level from 1971-1979 recorded by the TSP monitor i, $\mathrm{I}_{\mathrm{ikm}}$ is an indicator variable for whether or not monitor i lies within a distance k from the closest industrial area m in the 1970s; α_c are CBSA fixed effects; X_i is a vector of controls that include the distances to natural amenities, CBD and transportation lines.

To exploit variation in ambient air pollution driven by factors not directly related to industrial activities, I also estimate a model similar to equation (1). where I interact distance buffers to the closest industrial areas with wind direction or elevation. Holding distances to industrial areas to be the same, monitors downwind should capture relatively higher pollution levels. The formal specification is:

$$p_{ic} = \sum \mathrm{I}_{\mathrm{ikm}} * Downwind_{im} \beta_{k_1} + \sum \mathrm{I}_{\mathrm{ikm}} * \beta_{k_2} + \gamma Downwind_{im} + X_i' \delta + \alpha_c + \epsilon_{ic} \tag{2}$$

where $Downwind_{im}$ is an indicator of whether or not monitor i is downwind to its closest industrial area m. As the purpose of this paper is to examine the long-run impacts of early industrial pollution on the location choices of residents and firms. Wind direction should only be a concern if the wind it is exposed to is stable enough throughout years. The data

I use for this purpose keep track of monthly wind speed and directions over 1600 weather stations from 2005 to 2010. Instead of pooling monthly observations together to get an annual average of wind direction, I define seasonal wind coverage ranges in spring-summer (April-September) and autumn-winter (October-March) and only consider a monitor to be downwind to the closest industrial area if it is exposed to this area through the wind in both winter and summer. The lower part of Figure 1 illustrates the way I define these ranges. The winter/summer ranges are defined as the range between the 10th to 90th percentile of all monthly observations on wind directions from 2005 to 2010. I drop observations with monthly wind speed lower than 0.5 m/s and force the downwind dummy to be zero if any of the wind ranges it is exposed to exceed 180 degrees (the 90th and 10th percentiles differ by over 180 degrees). A monitor is considered to be downwind to the closest industrial area if the direction from the industrial area to the tract falls into both ranges. In the end, this definition generates about 6% of the total monitors downwind to its closest industrial area.

Similarly, topography also plays a role in transporting pollutants from the original sources. Significant elevation gaps between the locations of origin and receptor will prevent pollutants from being transported to surrounding areas.

$$p_{ic} = \sum \mathrm{I_{ikm}} * SameElevation_{im}\beta_{k_1} + \sum \mathrm{I_{ikm}} * \beta_{k_2} + \gamma SameElevation_{im} + X_i'\delta + \alpha_c + \epsilon_{ic} \quad (3)$$

where $Sameelevation_{im}$ is an indicator of whether or not the elevations of monitor i and industrial area m are the same. It is noted, however, that the emission of airborne industrial pollutants usually comes from tall smokestacks, so it is essential to account for the height of stacks. In practice, I define $Sameelevation_{im}$ to be one if the monitor is at the same elevation or less than 100 meters higher than the industrial area it is exposed to. Moreover, apart from the elevation difference between monitor and industrial area, the elevation of areas between them also matters. The transportation of pollutants will be blocked if a tract lies in between the pollution source and receptor is higher in elevation than both. To account for this, I draw a straight line between a monitor and its closest industrial area. I force $Sameelevation_{im}$ to be zero if the maximum elevation of areas covered by this straight line exceeds that at both ends.

As a further attempt to link observed pollution to industrial activities, I divide the full sample into two subsets according to the pollution intensity of the industrial areas. The intuition is that areas that are closer to more polluted industrial zones tend to be more polluted, and the additional detrimental effects of downwind position and non-blocked topography will be stronger. To get a pollution intensity measure of each industrial area, I match them to their nearest TSP monitors. The upper graph of Figure 1 maps the location of industrial areas and TSP monitors with at least one year of readings from 1970 to 1979 in Chicago. It is apparent that most of the industrial areas in my sample have a TSP monitor close-by, largely because these monitors are intended to oversee the most polluted parts of the city. I assign average TSP reading from 1970-1979 of the closest monitor to industrial area m to be the pollution intensity of it (TSP_m) and divide the full sample of monitors into two according to whether or not the industrial areas they are closest to have above-median pollution level. I run specifications (1)-(3) on the two subsamples respectively and check if the magnitudes are larger for monitors that are closer to more heavily polluted industrial areas. Another possible approach to exploit both the variation in pollution intensity and wind/topography conditions is a triple difference design, by interacting the distance-to-industrial-areas indicators with the level of historical pollution of these areas and a dummy of downwind/same elevation. I adopt the triple-difference estimation method as a robustness check and have the results reported in Appendix X.

The main purpose of this paper is to explore the long run negative impacts of early industrial pollution.However, it is likely that areas that are more polluted in the 1970s also tend to be more polluted now, making it hard to tell the persistent effects of historical pollution from those of current pollution. To check if pollution has largely reduced in areas with vibrant industrial activities in the 1970s, I estimate similar models as equations (1), (2) and (3), replacing the dependent variable with monitor-level pollution measures of PM10 from 2000 to 2010.

4.1.2 Results

Table 2 reports regression estimates from specifications (1), (2) and (3), where the dependent variable is the average TSP levels measured by each monitor from 1971 to 1979. Each column represents a different regression, where columns (1)-(3) report estimates on a full sample of TSP monitors with at least one reading from 1971 to 1979 and not located within any industrial areas. Columns (4)-(6) report results on a subset of TSP monitors that are close to industrial areas with pollution level above the median, while columns (7)-(9) report regression estimates on the subset of monitors adjacent to below-median polluted industrial areas. Standard errors are clustered at CBSA level. The unit of TSP is $\mu g/m^3$ and the average TSP from 1971 to 1979 is 69 $\mu g/m^3$.

Column (1) indicates that monitors that are close to industrial areas record higher measures of TSPs, and the effects drop as a monitor moves away from industrial areas. Monitors within 1 kilometer to the closest industrial area capture 23.71 units of TSP more, and monitors lie within 3 to 4 kilometer to it capture 7.32 more. Column (2) and (3) include the interaction terms of distance buffers to industrial areas and a dummy of whether or not the monitor is downwind and at the same elevation to the correspondent industrial area. Column (2) suggests that monitors downwind to industrial areas are more exposed to air pollution, but the effects do not move linearly with distance, unlike the uninteracted terms. My estimates show that downwind matters most for tracts that are within 1 kilometer and from 3 to 4 kilometers to the closest industrial area, leading to an extra 7.28 and 11.05 units of TSP measured respectively. Column (3) reports the estimated coefficients of equation (3), which interacts distance buffers with a dummy of whether or not a monitor is at the same elevation or less than 100 meters higher than its closest industrial area, and areas in between are not higher than both ends. It is clear that monitors that are not obstructed from the closest industrial areas due to variation in elevation also report higher TSP readings, but the effects are stronger at mid-to-long distance range. The TSP readings in unobstructed monitors are about 4-5 units higher when they are within 2-4 kilometers away from the closest industrial area than their obstructed counterparts.

The estimation results on the subsample with above-median polluted industrial areas are shown in columns (4)-(6). It is clear that the magnitudes of estimated coefficients for the interaction terms of both downwind and same elevation dummies and distance buffers are larger, which is consistent with our intuition. On the contrary, as shown in columns (7) -(9), the estimated coefficients of both distance buffers and interacted terms are smaller at the subsample with below-median polluted industrial areas. Most coefficients on the interaction terms are not significant. It suggests that the wind only matters in pollution exposure when the industrial area around is heavily polluted. Meanwhile, sharing the elevation with close-by industrial area increases pollution exposure even for less polluted industrial areas, but the interacted effects are not stronger for areas that are at closer ranges to the industrial area.

Table 3 reports estimation results with monitor-level average PM10 levels from 2000 to 2010 as the dependent variable. Similarly, columns (1)-(3) estimates on the full sample, columns (4)-(6) on a subsample of PM10 monitors closest to above-median industrial areas, columns (7)-(9) on a subsample of monitors closest to below-median industrial areas. The average PM10 from 2000 to 2010 is 21 $\mu g/m^3$.

Column (1) shows that monitors that are close to industrial areas also tend to be more polluted after 2000, but the magnitudes are much smaller. PM10 monitors within 1 kilometer to the closest industrial area record an extra 3.2 units of PM10, which is about 15% more, compared to about 33% more TSP recorded in the 1970s. It suggests that areas near historical industrial sites remain more polluted in 2000, but the pollution level has largely been cut since 1970. Column (2) and (3) include the interaction terms of distance buffers to industrial areas and a dummy of whether or not the monitor is downwind and at the same elevation to the correspondent industrial area. All of the coefficients on the interaction terms are small and not statistically significant, which suggests that the roles of wind and topography play little role in accounting for the variation in current pollution, mostly because transmission through these two channels only appears to be important around sufficiently polluted areas.

The estimation results on the subsample with above-median and below-median polluted industrial areas are shown in columns (4)-(6) and columns (7) -(9), respectively. Quite surprisingly, being closer to historically more polluted industrial areas induces less current pollution than being closer to less polluted areas. This suggests that although industrial zones in the 1970s are more likely to be industrial zones today, the pollution intensity of each industrial area changes a lot throughout the recent decades. One explanation is that the most polluted industrial areas were under stricter regulatory oversights after the Clean Air Act, which led to significant industrial relocation. Meanwhile, the coefficients on interaction terms of distance buffers and downwind or same elevation dummies remain small and insignificant in both subsamples. Putting these pieces of evidence together, we are confident to say that the impacts of historical pollution identified through variation in both pollution intensity of industrial areas and wind and topography conditions are not likely to confound with the effects of current pollution.

4.2 Early Industrial Pollution Exposure and Current Economic Outcomes

4.2.1 Empirical Settings

In the previous section I present evidence on the impacts of proximity to industrial areas on local pollution, and the additional roles of wind and topography conditions in disseminating local industrial pollution. In this section, I am going one step further to examine the relationship between historical industrial pollution and current economic outcomes. Do tracts that are dirtier in the 1970s underperform during the post-industrial era? Is it possible they fail to attract skilled workers and residents due to more severe air pollution? To test, I look at the "reduced form" relationship between economic outcomes in 2000 and exposure to 1970 industrial pollution in the following specification:

$$y_{ic} = \sum \mathrm{I_{ikm}} * Downwind_{im}\beta_{k_1} + \sum \mathrm{I_{ikm}} * \beta_{k_2} + \gamma Downwind_{im} + X_i'\delta + \alpha_c + \epsilon_{ic} \tag{4}$$

where y_{ic} denotes economic outcome of interest, which include housing prices, workplace employment, residence employment, college graduates in 2000); α_c are CBSA fixed effects; I_{ikm} is an indicator variable for whether tract i lies within a distance k from the closest industrial area m in 1970s; $Downwind_{im}$ is a dummy variable that takes value one if tract i is located in the downwind of industrial area m; X_i are tract-level characteristics, which include the distances to natural amenities and transportation lines, indicators for different distance buffers to the CBD and route distance buffers to the same industrial area m, 2000 pollution measures (PM10 level, the number of brownfields that require cleanup), 2000 quality of housing measures, and predicted manufacture job growth from 1970 to 2000 based on the industrial composition in 1970.

The coefficients of interest here are β_{k_1}, which tells us the additional effects of being downwind to an industrial area for census tracts that are within a distance buffer k to it. Controlling for CBSA fixed effects limits our analysis to within-city variation. The identification of our main results relies on the assumption that in absence of pollution, tracts that are downwind and upwind to the same industrial areas are similar in housing value and skill composition. However, estimates of β_{k_1} might be inconsistent if downwind to industrial tracts correlates with other geographical features of tracts that are relevant for economic development. For instance, for coastal cities, wind could mostly come from water, which makes coastal tracts more likely to locate in downwind position to industrial tracts. To deal with it, I not only control for the distance to waterbody in all my regressions, but also reexamine my main results in a sample that excludes coastal cities. Another concern is that that the location choice of early industrial sites might take into consideration of its pollution diffusion to nearby neighborhoods driven by wind patterns. More specifically, a potentially heavily polluted plant might avoid wealthy neighborhoods downwind if the latter can exert enough influence. However, before 1970, the public awareness of environmental issues is still in its incipience and probably not strong enough to alter the location decisions of industrial sites, especially because of their indirect environmental implication through wind patterns. I run a set of falsification tests to deal with this concern, reported in Appendix C.

To make use of variation in the pollution intensity of different industrial areas, I split the full sample of census tracts into two according to whether or not the pollution intensity of the closest industrial area from each tract is above the median. Similarly, pollution intensity is defined as the average measure of TSPs ambient concentration at the TSP monitor closest to each industrial area from 1971 to 1979. Only industrial areas that are within 2 kilometers to the closest industrial area are kept in the sample.

I repeat the same analysis using the same elevation dummy to create a different source of variation in pollution that is independent of local industrial activities. The identification assumption is that the differences in economic outcomes between tracts that are at the same elevation as its nearby industrial area and those that are only should only be driven by differences in pollution exposure. A reasonable challenge here is that elevation gaps not only act as an obstacle for the transmission of pollution but also weakens the economic linkages between industrial areas and nearby tracts. Throughout my analysis, I control for route distance buffers to the same industrial area m, and a local ruggedness measure. Furthermore, it appears that route distance does not correlate with the same elevation dummy in my sample.

4.2.2 Results

Table 6 presents regression results on The upper panel reports results on a sample of census tracts whose closest industrial areas are above-median polluted. The outcomes reported are employment density, high-skilled [7] employment share and median wage at the place of work, as well as density, high-skilled employment share, median wage, housing value and college graduates, share at the place of residence. The key coefficients of interests are reported in the first four row, which reports the additional effects of being downwind to 1970 industrial areas within 0-1, 1-2, 2-3 and 3-4 kilometers. It is clear that census tracts that are downwind and close to heavily polluted industrial areas have lower housing price are occupied by less-educated residents who work in less skilled sectors, and earn less. Meanwhile, workers who work in these tracts are also earning less, which is suggestive of negative impacts of historical pollution on current labor productivity.

Estimates from a sample of census tracts closest to below-median industrial areas are reported in the lower panel. It is clear that most of the estimated coefficients on interaction terms of distance buffers and downwind are much smaller and statistically insignificant, which is consistent with the results on TSP. Downwind position only appears to be detrimental to current economic outcomes when the nearby industrial areas are sufficiently polluted because wind direction only significantly affect the pollution concentration around industrial areas that are sufficiently polluted, as reported in Table 2.

Similar results that exploit variation in pollution exposure driven by topography features are shown in Table 5. The patterns are largely consistent with those uncovered using the downwind variation. Census tracts that are exposed to more historical pollution due to similar elevation to the closest industrial areas have lower housing value, college graduates share and median residents income in 2000, and the effects are only statistically significant in a sample with tracts exposed to above-median polluted industrial areas. However, the

[7]"High-skilled" industries are defined as finance, insurance and real estates (FIRE), information, professional service, and educational and health services.

patterns are less clear for workplace employment outcomes. One possible explanation is that the specification that exploits variation in elevation difference still suffers from biases driven by unobservable differential economic linkages to industrial areas. In this case, it is likely that stronger economic links to industrial areas lead to a higher wage, therefore the potential bias work against identifying the full effects of pollution on productivity. Because of this concern, in my subsequent analysis of separating productivity effects from amenity effects, I stick to identification using the wind variation.

I did not directly evaluate the relationship between economic outcomes and measured historical pollution instrumented by proximity to industrial areas and wind direction because only a small proportion of census tracts can be matched to TSP monitors with readings from 1970 to 1979. But we can still compare the magnitudes of coefficients from the "reduced form" estimation to those from the first stage. In Figure 2, I plot the coefficients on the interaction terms of 500 meters distance buffers from each TSP monitor to its closest industrial area with the downwind dummies in regressions with 1970-1979 TSP as dependent variable on the first row. It appears that downwind matters most when the monitor is about 2.5 km and 4 km away from the closest industrial area, especially in the heavily-polluted sample. In Figure 3, I repeat the same exercises using 2000 outcomes as dependent variables. The negative impacts of downwind position on most economic outcomes also appear to matter most when the census tract is about t 2.5 km and 4 km away from its closest industrial area. Similar patterns emerge when we examine the extra effects of same elevation.

4.3 Dynamic effects from 1980-2000

We have established the facts that census tracts that are exposed more to 1970 industrial pollution are poorer and less skilled in 2000. But it is unclear whether or not they have been equally poor in the 1970s, or if they are improving or declining with subdued industrial activities during this period. Without any agglomeration forces, with the de-industrialization trend, these areas should experience an improvement in air quality and a loss of manufacture jobs, both of which lead to a higher ratio of employment in the service sector. However, if agglomeration forces in skill-intensive service sectors are strong enough, then the failure of attracting high-skilled workers at the wake of industrial decline put these areas in a disadvantaged position throughout the whole structural transformation process, and they may end up with an even lower share of service employment in the end.

To explore the evolution of census tracts in post industrial era, I replace outcomes in specification (4) with growth rates of some of the key outcomes from 1980 to 2000, including housing price, median income, share of college graduates and employment of different sectors.

As workplace outcomes are not available before 2000, I only look at the growth of outcomes counted at place of residence.

The estimates identified through variation in wind direction and topography condition are presented in Table 7 and Table 8, respectively. It is apparent from the upper panel of Table 7 that tracts downwind and close to 1970 industrial areas are not only poorer and less skilled in 2000, but also experience slower growth in total employment, median income, housing price and the share of college graduates from 1980 to 2000. Similarly, from the upper panel of Table 8 we can see that tracts that are more exposed to historical pollution because of similar elevation as the nearby industrial areas also experience slower growth in employment, median income and the share of college graduates, although the pattern is less clear for housing price.

4.4 Mechanisms

In the past sections I have shown that census tracts that are more exposed to industrial pollution in the 1970s are poorer and less skilled in 2000, and display lower growth rates in housing price, income and employment from 1980 to 2000. They strongly suggest the relevance of agglomeration forces in shaping the evolution of industrial cities during waves of de-industrialization. But we are still unclear about the nature of the agglomeration effects that operate here. In the rest of this paper, I will approach this issue from two angles. First, in this section, I will check if any observed endogenous amenities such as crime rate or the provision of public schools respond to early industrial pollution. Second, in the following two sections, I will lay out a theoretical framework in order to separately identify the productivity and amenity effects, and further decompose both into exogenous ones driven by fundamentals and endogenous ones determined by agglomeration forces under assumptions on production and residential externalities.

To directly check the existence of residential agglomeration forces, a straightforward way is to examine the relationship between early industrial pollution exposure and observable endogenous amenities, such as crime rates and public schools. Higher crime rate in historically more polluted tracts due to downwind position to 1970 industrial areas could only be an outcome of re-sorting of residents and residential externalities. Housing durability could also play a role here: if housing units constructed at more heavily polluted areas are of poorer quality, and housing stock is persistence, it will as a disamenity especially for high-income residents for a long time.

Table A5 shows the results. The upper panel reports results on the sample of census tracts closest to above-median polluted industrial areas, and the lower panel on that with below-median one. For simplicity I use only one distance dummy (within 4 kilometers) instead of four. The interaction terms of the distance dummy and both downwind and same elevation dummy are positive and significant for violent crime rate in the heavily-polluted sample. It suggests that census tracts that are predicted to more polluted in the 1970s due to wind and topography features end up with higher violent crime rate in 2000. The evidence on the number of public schools per-capita and housing quality is less conclusive. Tracts that are close and downwind to industrial areas have less public schools per resident, but elevation plays little role here. In this exercise, I use the share of housing units without kitchen or plumbing devices as a proxy for housing quality. Neither downwind or elevation difference affects housing quality in 1980 or 2000.

5 Theoretical model

The previous section has summarized several empirical facts that are consistent with (1) Larger negative impacts of pollution on both amenities and productivity; (2) Sorting of workers by sectors according to environmental amenities; (3) Production or residential externalities that fueled further sorting by sectors. To integrate these features into an analytical framework, I develop a multisector model of internal city structure based on Ahlfeldt, Redding, Sturm, and Wolf (2015) [1]. In particular, I extend the framework to allow for systematic sectoral heterogeneity in productivity and amenities at different locations. The main purpose of the model is to help us disentangle the impacts of industrial pollution on local productivity and amenity, and to account for the contribution of agglomeration forced in both channels.

In my model, ex-ante identical workers simultaneously sort across sectors, and choose their places (census tracts in data) to work and live based on the amenity and productivity at these locations. The same local fundamentals, such as clean air, distance to natural resources or distance to the CBD, could be of different production and consumption value for workers from different sectors in a systematic way. Admitting sectoral heterogeneity in both production and amenity valuation enables me to account for the sorting of sectors around both productivity and amenities.

We consider a set of discrete locations or tracts, indexed by $i = 1, ..., P$, exogenously distributed across C discrete cities. The whole economy is populated by H workers, who are perfectly mobile across all the locations, within or across different cities. Firms produce a single costlessly-traded final good, which is chosen as the numeraire.

Locations differ in their final goods productivity, amenities, land supply and access to the transport network. Commuting is allowed across different locations within a city but not across cities.

5.1 Preferences

Worker o from sector s residing in tract i and commuting to tract j derives her utility from consumption of the single final good c_{ijso}, consumption of housing h_{ijso} and local amenities.

$$U_{ijso} = \frac{B_{is} z_{ijso}}{d_{ij}} (\frac{c_{ijso}}{\beta})^{\beta}) (\frac{h_{ijso}}{1-\beta})^{1-\beta} \tag{5}$$

where B_{is} stands for common residential amenities that makes a particular location more or less attractive to live for workers from sector s; d_{ij} captures the disutility from commuting from tract i to j for work ($d_{ij} = e^{\kappa \tau_{ij}} > 1$), where τ_{ij} is the bilateral travel time between tract i and j. Travel time is measured in minutes. z_{ijso} is an idiosyncratic shock specific to individuals. Following Ahlfeldt, Redding, Sturm, and Wolf (2015) [1], I assume heterogeneity in the utility that workers derive from living and working in different parts of the city and allow this idiosyncratic component of utility to be drawn from an independent Frechet distribution. Moreover, in my model, utility derived from living and working in different tracts is allowed to differ across workers' chosen sectors.[8] The heterogeneous utility that a worker o from sector s living in tract i and commuting to work in tract j is:

$$F(z_{ijso}) = e^{-T_{is} E_{js} z_{ijso}^{-\epsilon}} \tag{6}$$

where the scale parameter T_{is} determines the average utility derived from working for sector s and living in tract i; the scale parameter E_{is} determines the average utility derived from working for sector s tract j; and the shape parameter governs the dispersion of idiosyncratic utility.

After observing her realizations for idiosyncratic utility, each worker chooses a sector and locations to live and work to maximize her utility, taking as given residential amenities, wages, goods and housing prices, and the location decisions of other workers and firms.

Using the feature that the maximum of a Frechet distribution is itself Frechet, the probability that a worker chooses to live in tract i, work in tract j and for sector s is:

[8] Since the workers are ex-ante identical in preferences apart from the idiosyncratic component, the differences in amenities valuation across sectors are interpreted as characteristics specific to each sector, including the fixed skills or earning capabilities of workers from different sectors. One could think of it as a simplified version of a model where ex-ante heterogeneous workers sort across sectors first and choose their locations to live and work subsequently, where the systematic differences in utility realization across sectors are partially capturing the sorting of workers across sectors by their inherent characteristics.

$$\pi_{ijs} = \frac{T_{is}E_{js}(d_{ij}q_i^{1-\beta})^{-\epsilon}(B_{is}w_j)^{\epsilon}}{\sum_{o=1}^{O}\sum_{p=1}^{P}\sum_{s=1}^{S}T_{os}E_{ps}(d_{op}q_o^{1-\beta})^{-\epsilon}(B_{os}w_p)^{\epsilon}} \tag{7}$$

We can sum the probabilities across workplaces for a given residence i and sector s, which gives us the probability that a worker from sector s lives in tract i, π_{Rjs}; as well as across residences for a given workplace (j) and sector s, which gives us the probability that a worker from sector s works in tract j.

5.2 Production

The single final good in this model can be produced by different sectors. The productivity is allowed to be different across sectors in the same location and also allowed to be different across different locations for the same sector. The good is the costlessly-traded numeraire that takes common price $p = 1$ across all tracts and cities. I follow Ahlfeldt, Redding, Sturm, and Wolf (2015) [1] and assume the production technology to be Cobb-Douglas, and the final good production function of sector s in tract j to be:

$$y_{js} = A_{js}(H_{Mjs})^{\alpha}(L_{Mjs})^{1-\alpha} \tag{8}$$

where A_{js} is the location-sector specific productivity, H_{Mjs} and L_{Mjs} is the amount of labor and land hired by sector s at location j.

Firms choose a sector to specialize in and a location to produce. They take final goods productivity A_{js}, goods and factor prices, the utility distribution of workers, and the location decisions of other firms as given. Combining the first-order conditions of firms' profit maximization problem and a zero-profit condition, we have:

$$A_{js} = q_j^{1-\alpha}(w_{js})^{\alpha} \tag{9}$$

where q_j is the land price at location j, and w_{js} is the local wage of sector s. It is clear that conditional on local land prices, firms in tracts with higher productivity are able to pay their workers higher wages.

5.3 Land market clearing

In characterizing land market clearing, we assume each tract to be endowed with fixed land supply L_i, among which L_{Mis} is allocated to sector s for production purposes, and L_{Ris} is allocated to workers from sector s as residential land.

Solving for consumers' utility maximization problem yields:

$$(1-\beta)\frac{\mathbb{E}[w_{ps}|i]H_{Ris}}{q_i} = L_{Ris} \tag{10}$$

where $\mathbb{E}[w_{ps}|i]$ is defined as $\sum_{p=1}^{P} \frac{E_{ps}(w_{ps}/d_{ip})^{\epsilon}}{\sum_{r=1}^{P} E_{rs}(w_{rs}/d_{ir})^{\epsilon}}$

Similarly, firms maximization problem yields:

$$(\frac{(1-\alpha)A_{js}}{q_j})^{\frac{1}{\alpha}} H_{Mjs} = L_{Mjs} \tag{11}$$

Land market clearing has $\sum_{s=1}^{S}(L_{Ris} + L_{Mis}) = L_i$.[9]

5.4 Equilibrium

In a competitive general equilibrium, individuals maximize utility; final good producers maximize profits, and both labor and land market clear. I follow Ahlfeldt, Redding, Sturm, and Wolf (2015) [1] by starting with a benchmark of the model with exogenous location characteristics, before introducing agglomeration forces in section 5.1

Definition 5.1. Given the model's parameters $\alpha, \beta, \mu, \epsilon, \kappa$, exogenous location-sector specific characteristics $\mathbf{T}, \mathbf{E}, \mathbf{A}, \mathbf{B}, \mathbf{L}, \tau, H$, the general equilibrium of the model is referenced by vectors $\pi_{Rs}, \pi_{Ms}, L_{Ms}, L_{Rs}, \mathbf{q}, \mathbf{w}$

The equilibrium is characterized by the following equations:

$$\pi_{Ris} = \frac{\sum_{p=1}^{P} T_{is}E_{js}(d_{ij}q_i^{1-\beta})^{-\epsilon}(B_{is}w_j)^{\epsilon}}{\sum_{o=1}^{O}\sum_{p=1}^{P}\sum_{s=1}^{S} T_{os}E_{ps}(d_{op}q_o^{1-\beta})^{-\epsilon}(B_{os}w_p)^{\epsilon}} \tag{12}$$

$$\pi_{Mis} = \frac{\sum_{o=1}^{O} T_{is}E_{js}(d_{ij}q_i^{1-\beta})^{-\epsilon}(B_{is}w_j)^{\epsilon}}{\sum_{o=1}^{O}\sum_{p=1}^{P}\sum_{s=1}^{S} T_{os}E_{ps}(d_{op}q_o^{1-\beta})^{-\epsilon}(B_{os}w_p)^{\epsilon}} \tag{13}$$

$$A_{js} = q_j^{1-\alpha}(w_{js})^{\alpha} \tag{14}$$

$$(1-\beta)\frac{\sum_{p=1}^{P} \frac{E_{ps}(w_{ps}/d_{ip})^{\epsilon}}{\sum_{r=1}^{P} E_{rs}(w_{rs}/d_{ir})^{\epsilon}} H_{Ris}}{q_i} = L_{Ris} \tag{15}$$

$$(\frac{(1-\alpha)A_{js}}{q_j})^{\frac{1}{\alpha}} H_{Mjs} = L_{Mjs} \tag{16}$$

[9] Land is allowed to be allocated entirely to residential or commercial use of a particular sector. I omit the discussion on corner solution in this version.

$$\sum_{s=1}^{S}(L_{Ris} + L_{Mis}) = L_i; \tag{17}$$

6 Model Calibration and Estimation

In Section 4, I have presented empirical results consistent with the sorting of skilled workers around environmental amenities and the magnifying role of endogenous amenities and productivity. The structural estimation of the theoretical framework presented in Section 5 will further guide my empirical analysis in the following aspects:

First, I am able to separately estimate the productivity and perceived amenities by workers from different sectors, and check how they respond to some common local (dis)amenities, such as pollution, crime rate, public school, distance to the CBD, industrial zones, and natural amenities differently. Second, it allows me to quantify the contribution of production and residential externalities in magnifying the impacts of initial amenities differences and the sorting of skilled workers around amenities. Third, I check how the distribution of locational fundamentals matters for the attractiveness of cities. In other words, a city's general competitiveness might be compromised if the locations with high productivity in a sector are unpleasant places to live for the workers of this sector. A possible counterfactual is to look at how the employment patterns look like in Detroit if we move some of its industrial zones out of its central city, keeping or shutting down agglomeration forces.

I calibrate the model's parameters according to Ahlfeldt, Redding, Sturm, and Wolf (2015) [1], reported in Table 11. The calibration of other parts of my model differs slightly from their method because additional data on sectoral median earning are available in my case, which allows me to back out productivity parameters directly from earnings without relying on imputed commuting flows. In addition, as my model features sectoral heterogeneity in both productivity and amenities, I need to back out productivity and amenity parameters by sector.

6.1 Productivity and Production Fundamentals

In the model, firm profit maximization and zero profit conditions imply

$$A_{js} = q_j^{1-\alpha}(w_{js})^{\alpha} \tag{18}$$

Therefore, we are able to back out local industry-specific productivity A_{js} from observed sectoral median earnings and housing value. To minimize possible biases in productivity estimation caused by selection of workers of different earning capabilities, I try to estimate a Mincerian-type wage equation:

$$ln(w_{ijs}) = X'_{ijs}\beta + \mu_{js} + \epsilon_{ij}$$

where i stands for individuals, j and s stands for census tracts and industries; $ln(w_{ijs})$ is log wage of individual i who works in tract j and sector s, X_{ijs} are individual characteristics including gender, race, education attainment and occupation of workers who works in tract j and sector s; μ_{js} are tract level fixed effects that capture tract level industry-specific productivity. Ideally, we could tease out μ_{js} using micro-data (Albouy, 2012 [2]). But US census microdata from the Integrated Public Use Microdata Series (IPUMS) sample only report geographical locations of individuals at the Public Use Microdata Area (PUMA). A PUMA is a geographical unit much larger than a census tract. To get around of this difficulty, I combine tract level aggregate characteristics such as gender (2), race (4), educational attainment (9), occupation (25) composition by industry[10] with the estimated coefficients from a Mincerian model using 5% Integrated Public Use Microdata Series (IPUMS) microdata. In practice, I estimate $ln(w_{ijs}) = X'_{ijs}\beta + \epsilon_{ij}$ in micro sample, get the estimated coefficients $\hat{\beta}$ and calculate μ_{js} as the residuals between the actual and predicted log industry-specific average wage at tract level.

$$A_{js} = \mu_{js} = ln(\bar{w}_{js}) - \bar{X_{js}}'\hat{\beta} \tag{19}$$

The estimated industry-specific productivity can be further decomposed into an exogenous part that reflects local fundamentals and an endogenous part that reflects production side agglomeration forces.

I follow the literature in assuming the productivity externalities to be dependent on the travel-time weighted sum of workplace total employment density. I also assume production externalities to be the same for different industries:

$$A_{js} = a_{js}\Upsilon_j^{\lambda}, \Upsilon_j \equiv \sum_{p=1}^{P} e^{-\delta\tau_{jp}}(\frac{H_{Mp}}{L_p}) \tag{20}$$

[10] All variables apart from educational attainment are measured at place of work for each census tract, and aggregated to census tract-industry level. As we do not have data on within-industry educational attainment composition, I try to impute that using information on tract level aggregate educational attainment composition, tract level industrial composition and CBSA-level skill composition within each industry. Basically I calculate the expected shares of workers with different levels of educational attainment according to the industrial composition of each tract and the skill composition of each industry, and adjust the CBSA skill composition of each industry to census tract level by the discrepancy between actual and expected tract level educational attainment composition, assuming the discrepancy is evenly distributed across industries.

where H_{Mp}/L_p is workplace employment density; τ_{jp} is travel time from tract j to p; δ governs the rate of spatial decay and λ controls the importance of agglomeration effects in determining local productivity.

The specification above implicitly assumes that the access to workers out of one's own industry is equally as important as that to workers within one's own industry. However, in reality, we would imagine agglomeration forces to be much stronger within-industry. Therefore, I consider another specifications of agglomeration effects. As a general case, I consider production externalities of a particular sector s to be dependent on the employment density of both its own density and the density of other industries, but the dependence on the density of other industries is smaller and governed by the similarity between these industries and s. In another word:

$$\Upsilon_{js} \equiv \sum_{p=1}^{P} e^{-\delta\tau_{jp}} (\sum_{r=1}^{S} \frac{Sim_{rs} H_{Mpr}}{L_p})$$

where Sim_{rs} is the weighted[11] average of pairwise labor pool similarity and input-output similarity specified in Ellison, Glaeser and Kerr (2010) [30]. This similarity index is standardized to range from 0 to 1 and $Sim_{ss} = 1$.

6.2 Amenities and Residential Fundamentals

With detailed information on industry-specific productivity at the tract level, we can now proceed to get estimates for industry-specific amenities, with extra information on sectoral employment by place of residence, travel costs around tracts and housing value.

Specifically, adjusted industry specific amenities $\tilde{B_{is}} \equiv B_{is} * T_{is}$ can be recovered from the residential choice probabilities

$$H_{Ris} = \sum_{p=1}^{P} (d_{ips} q_{is}^{1-\beta})^{-\epsilon} (\tilde{B_{is}} \tilde{w_{ps}}) \tag{21}$$

where H_{Ris} are industry-specific employment by place of residence,

Similarly, estimated amenities can also be decomposed into an exogenous part that captures local fundamentals and an endogenous part that captures the benefit from living closer to other people. In my analytical framework, environmental amenities are treated as local

[11] Weight is determined by the contribution of these measures to coagglomeration patterns in Ellison, Glaeser, and Kerr (2010) [30]. I ignore technology similarity because the knowledge spillovers across most service industries that I am studying are not patented, and technology similarity plays a relatively small role in explaining coagglomeration patterns EGK 2010.

fundamentals; they interact with residential externalities in determining the overall attractiveness of locations within and across cities.

I adopt similar specifications of residential externalities as for the production ones. The "standard" one mirrors that of production externalities:

$$\tilde{B_{is}} = \tilde{b_{is}}\Omega_i^{\eta}, \Omega_i \equiv \sum_{p=1}^{P} e^{-\rho\tau_{ip}}(\frac{H_{Rp}}{L_p}) \tag{22}$$

where H_{Rp}/L_p is residence density per unit of land; residential externalities decay with travel time τ_{ip}; the importance of access to surrounding density in determining local amenities is governed by η. It is worth noting that the nature of residential externalities could be very different from agglomeration forces in production. Specifically, the distinction between own-industry and other industry access might not be as important in the residence case. Residents tend to care more about other aspects of their neighbours, such as income or education, than occupation. Therefore apart from the basic specification, I consider an alternative case where the access to higher-educated population is allowed to play an additional role in shaping local amenities apart from the access to total population:

$$\tilde{B_{is}} = \tilde{b_{is}}\Omega_i^{\eta}\Omega_{Hi}^{\nu_s}, \Omega_i \equiv \sum_{p=1}^{P} e^{-\rho\tau_{jp}}(\frac{H_{Rp}}{L_p}), \Omega_{Hi} \equiv \sum_{p=1}^{P} e^{-\rho\tau_{jp}}(\frac{H_{RHp}}{L_p}) \tag{23}$$

where H_{RHp}/L_p is the density of college graduates, here $Omega_i$ captures the access to all the neighbors from tract i, and $Omega_{Hi}$ captures that only to the college-educated neighbors. When $\nu = 0$, it collapses to the standard one. This additional assumption echoes empirical findings on gentrification and neighborhood effects. For instance, Diamond (2015) show that the endogenous supply of amenities such as safety and public school quality depends on the skill mix of cities. Such a specification requires the estimation of the parameters ν_s, which captures the influences of access to high-educated neighbors on amenities perceived by workers from different sectors. For identification, I would need an instrument that correlates with the skill-mix of residents for each tract but not with local amenities. A natural idea is to use productivity shocks that affect local demand for workers with different skills. Here I base my identification on changes in amenities in response to changes in the access to high-educated neighbors from 2000 to 2010. I instrument changes in the access to high-educated neighbors with a Bartik-style predicted shifts in the number of residents with college degrees depending on the industrial employment from 80 industries at each tract in 2000, the skill requirement of each industry, and the national growth of each industry from 2000 to 2010. The predicted change in the number of college graduates living in tract i

between 2000 and 2010 is:

$$\Delta \hat{H}_{RHi} = \sum(\frac{H_{Ris',2000}}{H_{Ri,2000}}) * CollegeShare_{s',2000} * \Delta H_{Rs'}$$

where $H_{Ris',2000}$ is the number of workers over age 25 from sector s' living in tract i in 2000; $H_{Ri,2000}$ is the total number of workers over age 25 who live in tract i in 2000; $CollegeShare_{s',2000}$ is the national share of college graduates for sector s'; and $\Delta H_{Rs'}$ is the national growth in employment in sector s'. Correspondingly, the change in access to college-educated neighbors $\Omega_{Hi} \equiv \sum_{p=1}^{P} e^{-\rho\tau_{jp}}(\frac{H_{RHp}}{L_p})$, can be instrumented by:

$$\hat{\Omega_{Hi}} = \sum_{p=1}^{P} e^{-\rho\tau_{jp}}(\frac{\Delta \hat{H}_{RHp}}{L_p})$$

6.3 Productivity and Amenity estimation results

Table A5 shows the correlation between my estimated aggregate amenities $\tilde{B_{is}}$ by sectors and some observable amenity measures at the tract level. My estimated amenities correlate as expected with these "real-world" measures of amenities, such as the number of public schools, pollution[12], crime rate and access to beaches. Besides, the differences in the valuation of same observable amenities across workers from different sectors are also consistent with our intuition. For example, living in a tract that encompasses an industrial area decreases the subjective utility of FIRE workers by 12.7%, and that of manufacture workers by only 7.22%. In the meantime, access to beach increases the subjective utility of FIRE workers by 11.5%, and that of manufacture workers by only 3.08%. Being closer to the CBD does not seem to bring any extra consumption value, conditional on other covariates.

As a more straightforward presentation of the estimated amenity measures, Figure 1-5 maps amenities perceived by FIRE and manufacture workers to areas around New York, Detroit, San Francisco, Chicago and Pittsburgh. It is clear that considerable heterogeneity exists in perceived amenity within cities. From Figure 6, We observe the stark contrasts in neighborhood desirability between the Upper East Side and East Harlem of New York City. It is also noted that in New York, FIRE workers prefer central Manhattan as a place to live more than manufacture workers, and display weaker preferences over non-central locations. This pattern reverses itself in Detroit, as shown in Figure 7, where FIRE workers exhibit stronger preferences over suburbs than manufacture workers. San Fransisco Bay Area is

[12]Since data on crime rate and direct pollution measures at the census tract level are only available for a subset of tracts, I do not include them in my main specification. Instead, the results are shown in Table A1 and Table A2

overall a much more desirable place to live, and the preferences across different locations within the city do not vary as greatly as in New York, or more so, in Detroit. San Fransisco downtown is a desirable place to live for both types of workers and more for FIRE workers. From these maps, it is observed that one distinctive difference of Detroit from the more successful cities such as New York or San Francisco is its considerably lower urban amenity in downtown, especially for FIRE workers.

It appears to be a piece of evidence consistent with the observed centralized poverty in former industrial towns. As these cities fail to create favorable living conditions for the skilled labor force around locations where the skilled sectors are more productive, they are becoming increasingly unattractive to these sectors.

Table A6 shows the correlation between my estimated aggregate productivity A_{is} by sectors with the same set of covariates. It is clear that being closer to industrial areas does not bring about productivity loss, while being closer to the CBD is positively correlated with the productivity of all the sectors, and the relationship is stronger for high-skilled sectors such as FIRE, IT, education and medical services. Understandably the productivity of these sectors relies much on intensive human interactions, which are more likely to be achieved in dense urban cores where the commuting and interacting costs are relatively low.

The great heterogeneity across amenities and productivity reveals urban form as an important source of a city's competitiveness: a well-organized city usually features stronger correlation between productivity and amenities, especially for the skilled labor. For instance, the correlations between perceived amenity by FIRE workers are 0.6957 and 0.8025 in San Fransisco and New York, compared to 0.3625 and 0.3245 in Buffalo and Detroit.

Several reasons could contribute to the misalignment between productivity and amenities. Industrial areas around central city tend to significantly undermine the livability of areas around the CBD. This effect, combined with the endogenous sorting of workers and residential externalities, leads to central poverty and excessive suburbanization.

To test this mechanism, I plot the pairwise relationship between central city industrial activities, productivity-amenity alignment and urban growth across MSAs in Figure 4. The top panels plot the correlation between productivity and amenities of FIRE and manufacture workers against the percentage of industrialized tracts within central city tracts, defined as top quartile tracts in distance to the CBD. It is clear that cities with a more industrialized center display a weaker correlation between productivity and amenities, and the effect is stronger for FIRE workers. The middle and bottom panels plot employment growth rates of MSAs from 1983 to 2003 against central city industrial tracts share in the 1970s and productivity-amenity correlation in 2000. Cities with limited central city industrial activities and a stronger link between productivity and amenities tend to grow faster in total employment.

It is noted that this is only a documented correlation but has no causal inference. To explore the welfare implications of different configurations of industrial zones, I will implement counterfactual analysis by generating predicted pollution level of all the tracts under different hypothetical configurations of industrial areas, and examine the long-run general equilibrium effects after factoring in both endogenous sorting of skilled labor and production/residential externalities.

6.4 How do estimated productivity and amenity respond to early industrial pollution?

In the previous sections, I back out industry-specific productivity and amenity parameters (A_{js} and $\tilde{B_{is}}$), and manage to isolate parts of the productivity and amenities determined by local fundamentals, a_{js} and $\tilde{b_{is}}$, under several assumptions on the extent and forms of production and residential externalities. In this section, I will check how they correlate with historical pollution exposure driven purely by wind patterns.

In Figure 11 I plot the estimated estimated coefficients of the interaction term of 0-4 km distance buffer to the 1970 industrial areas and a dummy of being downwind to them, where the dependent variables are industry-specific productivity or amenity estimates, in a sample with census tracts that are closest to above-median polluted industrial areas. They give us a basic idea on how the variation in exposure to 1970 industrial pollution as a result of different wind directions leads to estimated productivity and amenity differences in 2000, and how the impacts vary across industries. To make the point that early industrial pollution creates self-fulfilling skill sorting, I plot the estimated coefficients against the skill intensity of each industry, and it is clear that more skilled industries suffer more in productivity as a result of being more exposed to 1970 industrial pollution. To highlight the role of agglomeration effects, I present the estimated coefficients from a sample with only central tracts[13] in the right figure. The effects are three times as large, suggesting that agglomeration forces play an important role in this pattern, since the closer to CBD, the denser are the tracts and the stronger are the agglomeration benefits. In Figure 12, I repeat the exercise with industry-specific amenity parameters ad the outcomes. The patterns are quite similar except for relatively small magnitudes. Employees from more skilled sectors find historically dirtiers tracts less pleasant now, more than employees from other sectors.

In the next step, I try to decompose the estimated productivity and amenity into an endogenous agglomeration term and an exogenous local fundamental term. If we believe

[13]Central tracts are defined as tracts closest to the CBD holding up to 25% of total MSA population.

the impacts of early industrial pollution on contemporary variables are largely driven by agglomeration forces, as the pollution level in US cities has been cut down hugely since 1970, we should observe much smaller coefficients on production and residential fundamentals (a_{js} and $\tilde{b_{is}}$). The results are shown in Figure 13 and 14. If we compare the magnitudes of the estimated impacts on productivity fundamentals shown in 13 to the aggregate productivity estimates in 11, it is clear that accounting for the agglomeration effects explain away about 30% of the variation in the full sample, and about 50% in the central tracts sample. Taking away agglomeration effects also makes the slope of estimated coefficients over sector-specific skill intensity much flatter in central tracts. These facts are clear sign that agglomeration effects play The patterns are similar for amenity fundamentals 13, in the sense that accounting for residential side agglomeration forces explain away 10% to 30% of the variation in estimated effects of early industrial pollution in both samples.

6.5 How do estimated productivity and amenity respond to contemporary industrial pollution?

The natural next step is to conduction counterfactual analysis on cutting pollution at different locations at different points of time. Before that, we would need a set of reliable estimates on the elasticity of sectoral productivity and amenity changes to changes in pollution level.

To uncover the causal impacts of CHANGES in air pollution on local productivity and amenities, I implement a similar identification strategy explored in section 3.2.2, which exploits differential regulation intensity following the Clean Air Act Amendments (CAAA) in the 1990s. Previous work by Auffhammer, Bento and Lowe (2009) [5] and Bento, Freedman and Lang (2015) [10] provides evidence that air quality improvements induced by CAAA were highly localized, as local regulators had incentives to target the areas around nonattainment monitors as a strategy to comply with federal standards in the least costly way.

In 1990, EPA started to regulate PM10 seriously. The regulation under the 1990 CAAA assigns nonattainment status to a county not only when the three-year geometric average of PM10 concentration of each monitor exceeds a certain level but also when the 24-hour average concentration at any monitor exceeds a higher standard. As a response, in counties with more than one monitor, local regulators are likely to allocate a disproportionate amount of efforts in reducing PM10 levels around monitors with pollution readings near or above the federal thresholds. I follow Bento, Freedman and Lang (2015) [10] to use monitor attainment status as an instrument for localized pollution reductions.

The first and second stage of the IV analysis is:

$$\Delta PM10_{ic}^{(}2009-2001)=\delta PM10_{ic,2000-2006}^{\bar{}}+\sigma N_i+X_i'\mu+\alpha_c+\epsilon_i \tag{24}$$

$$\Delta ln(y_{is}^{2010-2000})=\beta\Delta P\hat{M}10_i+X_i'\Gamma+\alpha_c+\epsilon_i \tag{25}$$

where y_{is} is the outcome variable for sector s at tract i that takes the value of A_{is}, or $\tilde{B_{is}}$. $\Delta ln(y_{is})$ measures their log changes from 2000 to 2010. $\Delta PM10_i$ is the change in TSP measures from 2000 to 2010; the instrument N_i is equal to the ratio of nonattainment years during 2001 to 2007; X_i are time-invariant observable tract characteristics and Γ captures changes over time in the premium to these characteristics; α_c are city fixed effects that control for city-wide shocks in productivity and amenities. I only keep the tracts within 2 km to the closest PM10 monitor with reading in year 2000,2002-2007 and 2010.

The upper panel of Table 12 reports the changes of estimated industry-specific amenity parameters from 2000 to 2010 on the reductions of PM10 concentrations, instrumented by monitor level nonattainment. I also include changes in the number of public schools during the same period as a control variable to check if the measured amenity changes are able to pick up changes in other observable amenities.

It is clear that policy-induced pollution cut does lead to growth in amenity, especially in skilled sectors. One unit decrease in PM10 leads a 0.9% appreciation of local amenity perceived by FIRE workers, 1.48% by IT employees, compared to only 0.08% by manufacture workers. In this context, the regulated tracts (tracts with at least one year in nonattainment status) experience 5 units more PM10 cut from 1990 to 2000, which translates into on average 5% increase in local amenity. In the meantime, amenity also responds positively to new public schools. One additional public school makes local FIRE employees 1.95% more appreciative of the tract as an ideal place to reside, compared to 1.16% for manufacture workers.

The lower panel of Table 12 reports similar results on productivity changes. Although the coefficients are not significant for most of the outcomes, their signs are mostly negative, which suggests that a reduction in PM10 level induce a positive but not significant growth in productivity. Figure 15 plot the coefficients from both productivity and amenity regressions on sectoral skill intensity. It is clear that the responsiveness of both industry-specific amenity and productivity increases in the skill intensity of the industry, again

In my counterfactual analysis, I will examine the general equilibrium implications of cutting pollution in some tracts. In light of the model, this cut will be reflected in changes in local production and amenity fundamentals. Although the coefficients reported in Table 12 correspond to elasticity of aggregate productivity and amenity changes to pollution change, under the assumption agglomeration forces are limited within 10 years' time, we can roughly take these to be estimates on the responsiveness of local production and residential fundamentals to pollution cut. One small problem here is that although the coefficients on amenity are negative over the board, they are positive on productivity for a few sectors. Since conceptually we believe pollution is generally detrimental to local productivity, I impose the elasticity to be zero in my counterfactual analysis if the coefficients are positive.

7 Counterfactual Analysis

I use the parametrized model to assess the contribution of environmental disamenities to the differences in employment composition across cities. In particular, the structural model allows me to separately account for the contribution of initial residential sorting and further agglomeration forces to the differences in employment patterns across cities.

In this paper, I consider two main counterfactual analyses. First, I simulate the impact of regulation-induced TSP reduction in the 1970s, holding productivity and amenities at their 1970 level. I calculate the changes in local amenities as a result of CAAA regulation by combining the estimated responsiveness of productivity and amenity to pollution reported in Table 12 with a predicted reduction in TSP level at tracts level. I then reestimate the specification in section 3.2.2 for the impact of CAAA-induced pollution cut using the counterfactual changes in employment across different sectors, and compare them to the reduced-form results.

In the second counterfactual, I examine the welfare implications of relocating industrial areas from the central city to the suburbs. I mimic the industrial relocation by reducing the amount of TSP in central city tracts and increasing the same amount of TSP in suburban tracts with similar estimated manufacture productivity. The TSP reduction is reflected in the changes in amenity and productivity parameters with the elasticity estimated in section 5.4. As briefly discussed in section 5.3, a larger share of industrial areas in the central city is related to a greater misalignment between city productivity and amenities and lower urban growth. Therefore, a potential welfare gain from industry relocation is attracting skilled workers to live closer to where they work. The benefits are potentially larger with agglomeration forces.

One problem here is that the model is calibrated using 2000 data, while I am more interested in examining potential policy implications in the 1970s. Therefore the parameters need to be adjusted in order to reflect realities in the 1970s. Here I make two key assumptions on the evolution of productivity and residential fundamentals from 1970 to 2000. First, the changes in residential fundamentals during this period are assumed to be induced by changes in environmental quality. Second, the only changes in productivity fundamentals over the thirty years correspond to the national growth trends of different sectors. I then combine the assumed fundamental parameters with the observed 1970 data on industry employment at place of residence and housing price as the inputs of my quantitative model to solve for other variables through iteration.

Table **??** reports the simulated changes in key outcomes after proposed industrial relocation in a model without any endogenous agglomeration/sorting forces. It is clear that relocating pollution from central tracts to suburban tracts relocate skilled workers, such as those from FIRE and IT, to the city center as they are more responsive to improvement in air quality. In the meantime, manufacture and construction workers settle more in the suburban tracts. At the aggregate level, there is a tiny increase in total finance and IT workers at national level as the industrial relocation improves the alignment of productivity and amenity of these sectors more than others. The welfare implications are modest under this scenario: at the aggregate level we observe less than 0.2% in average housing price.

(Incomplete, more results to be added)

We have established the facts that census tracts that are exposed more to 1970 industrial pollution are poorer and less skilled in 2000. But it is unclear whether or not they have been equally poor in the 1970s, or if they are improving or declining with subdued industrial activities during this period. Without any agglomeration forces, with the de-industrialization trend, these areas should experience an improvement in air quality and a loss of manufacture jobs, both of which lead to a higher ratio of employment in the service sector. However, if agglomeration forces in skill-intensive service sectors are strong enough, then the failure of attracting high-skilled workers in the wake of industrial decline put these areas in a disadvantaged position throughout the whole structural transformation process, and they may end up with an even lower share of service employment in the end.

Table **??** and Table 7 report results on growth from 1980 to 2000, following the same specifications. It is clear from Table **??** that tracts closer to 1980 industrial areas experience slower growth in total, manufacture, FIRE employment, median income, housing value and the number of college graduates in the subsequent two decades, and from Table 7 that these negative growth effects are stronger if the relevant industrial areas are more polluted prior to 1980, and the tracts are more exposed due to downwind location to them. Since from 1980 onward the air quality around the US is improving greatly, and the improvement is greater in areas that are more heavily polluted initially[14], the negative growth impact is

[14] It is shown in the second column of Table A4 that tracts that are closer to more polluted industrial areas experience larger cut in pollution level from 1980 to 2000.

not caused by worsening air pollution, but more of a result of self-reinforcing agglomeration forces. Tracts that have been able to attract more educated workforce and residents due to better environmental amenities are able to attract more if educated people would like to live and work near other educated people.

To further analyze the dynamics of the agglomeration patterns, I look at the responses of outcomes from 1940 to 2010 to industrial pollution exposure around the 1970s[15].

The results are shown in Table ??. Each cell reports the coefficient of a separate regression with the dependent variables being census outcomes from different years and the independent variable being the triple interaction term of distances to the closest industrial area, its correspondent pollution level and whether or not the tract locates downwind to it. For ease of interpretation, I condense four distance buffers into a single indicator of whether or not a tract is within 4 kilometres to the closest industrial area.

This coefficient is intended to capture the variation in historical industrial pollution independent of the initial industrial composition and socioeconomic characteristics of each tract. It is observed that the estimated coefficients are not only negative and significant for almost all of the outcomes after 1970, but they are getting larger in absolute value, indicating increasingly negative impacts of early industrial pollution over time on housing price, college share and log median household income. The biggest jump in outcomes between two consecutive censuses in adverse impacts of industrial pollution exposure occurs from 1980 to 1990, which is the accelerating period in the structural transformation process, with an astonishing 60% growth in service jobs over the decade [41]. A plausible interpretation is that with massive secular growth in the service sector, small differences in initial conditions could be significantly magnified because it is the period where service-based agglomerates were quickly forming, and the location choices of newly-added service jobs were highly dependent on earlier clustering of skills.

One concern over specification (2) is that the location choice of early industrial sites might take into consideration of its pollution diffusion to nearby neighbourhoods driven by wind patterns. More specifically, a potentially heavily polluted plant might avoid wealthy neighbourhoods downwind if the latter can exert enough influence. However, before 1970, the public awareness of environmental issues is still in its incipience and probably not strong enough to alter the location decisions of industrial sites, especially because of their indirect environmental implication through wind patterns.

To confirm that the placement of early industrial sites does not weigh in the socioeconomic

[15]Census outcomes from 1970 onwards are matched to 2010 tracts according to the Longitudinal Tract Database (LTDB) (Logan, Xu, and Stults, 2014) [37]. So all the distance measures are calculated based on 2010 tracts. Earlier tracts are not easily matched to 2010 tracts, so I calculate their distances to industrial areas/CBD/transportation lines/TSP monitors based on the geography of 1940/1950 tracts.

characteristics of downwind and upwind neighbourhoods with much difference, I run a set of falsification tests, using the outcomes in 1940 and 1950. A problem with running the falsification tests using 1970s industrial areas directly is that some of these industrial sites might have been set up before 1970, or maybe even before 1940, and as a result we might capture partial early treatment effects in this specification. Table A15 present the results. I find tracts that are close to 1970 industrial areas tend to be denser but less educated regarding college graduates share, which could be driven by both selection bias and early partial treatment effects. However, the triple interaction terms of distance buffers with 1970 industrial area pollution level and downwind position are quite small and largely positive for 1950 median income and college share.

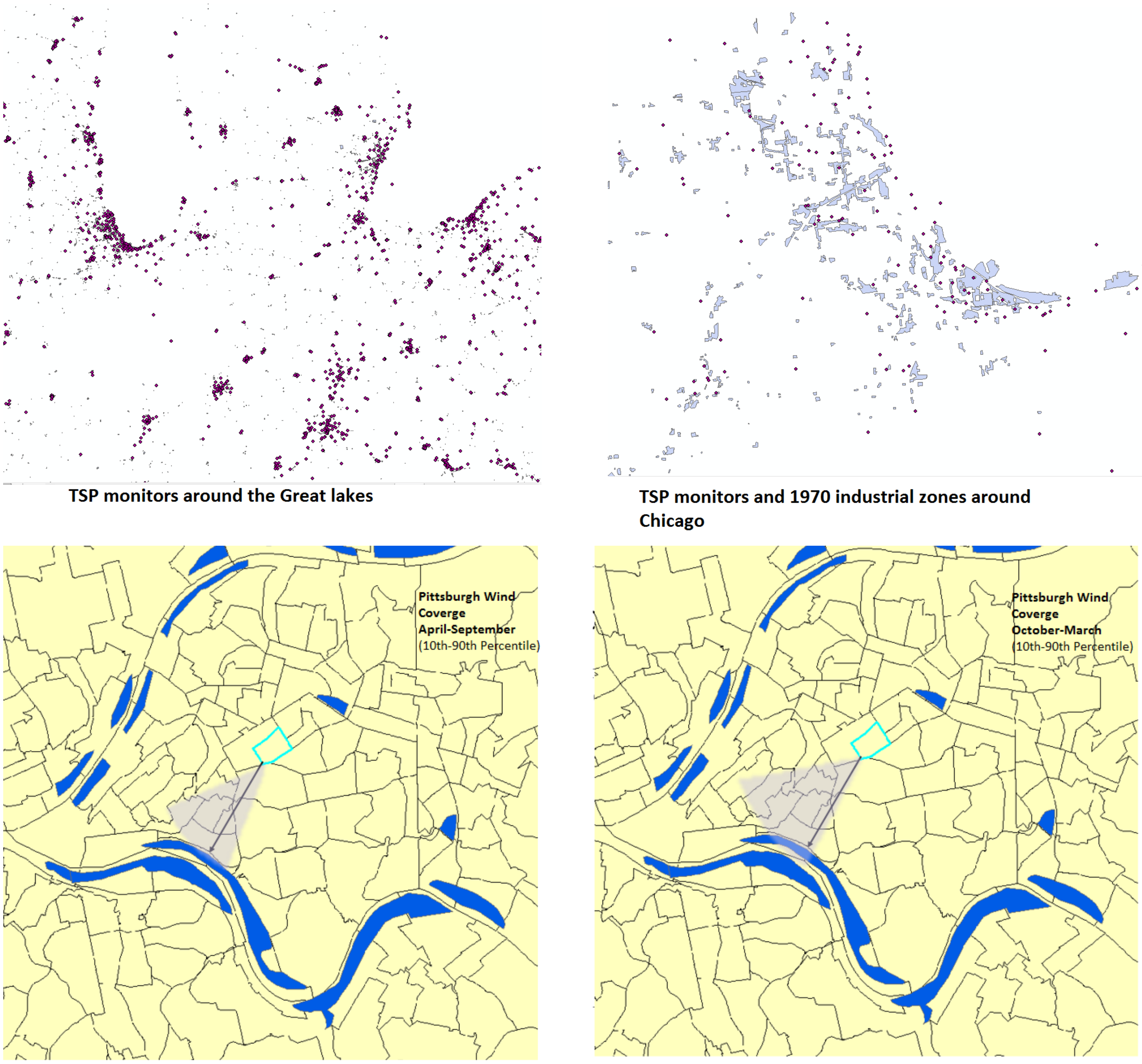
Up to now, we have established large and long-term impacts of early industrial pollution on the distribution of skills. However, it is still hard to determine if the results are mostly driven by the negative impacts of pollution on local productivity or consumer amenity. To disentangle these two channels, as well as to uncover how the initial differences in environmental amenities and the subsequent agglomeration forces each contribute to the differences in future employment outcomes would require a full structural model, which is presented in section 4.

8 Conclusion

The prolonged decline of former industrial cities in recent decades has gathered considerable attention and interest from both academia and the general public. In this paper, I evaluate the importance of environmental amenities in shaping the competitiveness of post-industrial cities. By estimating a structural spatial equilibrium model of within-city location choices of work and live for heterogeneous workers, I quantify the ways through which local environmental (dis)amenities differences lead to differences in skill distribution across cities. The estimates show that high-skilled workers respond more to a variety of local amenities, most notably pollution, and the re-sorting of workers further improves the local amenities in places with improving air quality. Further results also suggest that the misalignment of productivity and amenity of high-skilled sectors, driven by excessive central city industrial areas, contributes to the observed massive suburbanization trend and central city poverty of industrial cities. Moving polluted industries away from the central city could bring about significant welfare gains under strong enough production and residential agglomeration forces.

The analytical framework of this paper can be easily adapted to study the general equilibrium implications of improvement in other public amenities, such as public schools. Another extension is to incorporate zoning directly into my framework and evaluate the welfare implications of observed zoning policies in light of the new mechanisms illustrated in this paper.

Figure 1: Illustration of triple-difference specification:
Measure of industrial area pollution intensity and downwind status



Notes The up-left graph maps the location of TSP monitors around the Great lakes with at least one year of readings from 1970-1979. The up-right graph maps 1970 industrial areas (shaded areas) as well as 1970-1979 TSP monitors in Chicago. The lower graph illustrates my definition of whether of not a census tract is in the downwind direction of its closest industrial area. The solid arrowed line depicts the direction from the closest industrial area to the highlighted census tract. The shaded area in the left draws the range of summer wind direction around the highlighted tract. This range is defined by wind direction between the 10th and 90th percentiles of all the observations of April to September monthly wind direction from 2005 to 2010, after dropping months with too low average wind speed. The right shaded area draws the range of winter wind direction around the highlighted tract, defined by wind direction between the 10th and 90th percentiles of all the observations of October to March monthly wind direction from 2005 to 2010. The tract is only defined to be downwind to its closest industrial area if its direction (black arrowed line) to the area lies within BOTH wind ranges.

Table 1: Industrial Activities in the 1970s and 1970 Pollution

Variables	Monitor-level average TSP from 1971-1979					
Sample	Full Sample		Above-median polluted industrial area		Below-median polluted industrial area	
$1(disind \in 0-1km)$	23.71***	23.48***	22.36***	22.83***	11.11***	9.137***
	(1.510)	(1.683)	(2.526)	(2.923)	(0.808)	(0.749)
$1(disind \in 1-2km)$	12.07***	12.14***	8.897***	11.20***	7.130***	5.935***
	(1.455)	(1.663)	(2.377)	(2.786)	(0.825)	(0.795)
$1(disind \in 2-3km)$	6.456***	5.005***	3.598	4.623	5.154***	4.631***
	(1.500)	(1.687)	(2.729)	(3.072)	(0.756)	(0.804)
$1(disind \in 3-4km)$	7.329***	6.996***	4.606	4.842**	4.813***	4.132***
	(1.752)	(1.940)	(3.330)	(2.342)	(0.875)	(0.889)
$1(disind \in 0-1km)$*Downwind		8.997**		11.75**		
		(3.921)		(5.461)		(2.535)
$1(disind \in 1-2km)$*Downwind		4.403		9.872*		2.523
		(3.082)		(5.268)		(2.364)
$1(disind \in 2-3km)$*Downwind		11.98***		11.86***		-0.401
		(3.292)		(3.779)		(2.492)
$1(disind \in 3-4km)$*Downwind		5.224		3.300		1.226
		(5.674)		(9.281)		(3.978)
$1(disind > 4km)$*Downwind		1.112		-2.138		-2.624
		(2.930)		(6.520)		(3.040)
Observations	4,968	4,968	2,471	2,471	2,422	2,422
p-value (Sum of wind interacts=0)		0.0001		0.0028		0.5620

Notes Dependent variables are the average measure of TSP ambient concentration from 1970 to 1979 collected at each TSP monitor with positive reading during this period. $1(disind \in a-bkm)$ is an indicator of the distance of a TSP monitor from the closest 1970s industrial area is within a and b km. Downwind is an indicator of whether or not the TSP monitor is located downwind to the industrial area. Same elevation is a dummy that takes one if the TSP monitor is at the same elevation or less than 100m lower than its closest industrial area, and not obstructed by other areas in between. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

Table 2: Industrial Activities in the 1970s and 1970 Pollution

Variables	Monitor-level TSP: 1971-1979			Monitor-level PM10: 2000-2010		
Sample	Full Sample	Above-median polluted industrial area	Below-median polluted industrial area	Full Sample	Above-median polluted industrial area	Below-median polluted industrial area
$1(disind \in 0-1km)$	26.85***	22.36***	13.41***	7.159**	9.808**	2.899
	(2.528)	(1.876)	(1.588)	(2.980)	(4.125)	(3.520)
$1(disind \in 1-2km)$	14.79***	11.85***	8.491***	2.400	5.450**	0.154
	(2.922)	(4.352)	(1.760)	(2.385)	(2.230)	(3.463)
$1(disind \in 2-3km)$	6.910***	5.333	6.040***	2.679	0.158	-1.492
	(2.967)	(5.618)	(1.500)	(2.159)	(3.109)	(2.488)
$1(disind \in 3-4km)$	8.054***	1.323	8.837***	4.442**	4.917	3.523**
	(3.092)	(5.061)	(1.639)	(2.183)	(5.408)	(1.769)
$1(disind \in 0-1km)$*Same elevation	1.056	0.337	-0.575	-0.991	-3.664	2.097
	(2.468)	(3.660)	(1.408)	(2.858)	(3.881)	(2.452)
$1(disind \in 1-2km)$*Same elevation	1.637	0.869	0.622	2.724	0.103	1.319
	(2.793)	(3.949)	(1.422)	(2.536)	(2.255)	(3.598)
$1(disind \in 2-3km)$*Same elevation	4.732*	2.450	1.336	2.445	4.289	2.553
	(2.796)	(5.084)	(1.503)	(2.128)	(2.934)	(2.664)
$1(disind \in 3-4km)$*Same elevation	4.473	9.392**	-2.812	0.863	5.817	-4.458*
	(3.388)	(4.716)	(2.003)	(2.958)	(6.686)	(2.425)
Same elevation	5.629***	5.152	2.550**	5.206***	6.203**	3.045**
	(2.008)	(3.684)	(1.242)	(1.227)	(2.596)	(1.416)
Observations	4,968	2,471	2,422	1,893	821	842
R-squared				0.312	0.521	0.435
p-value (Sum of wind interacts=0)	0.0757	0.0213	0.5604	0.3421	0.8766	0.9539
p-value (Sum of elevation interacts=0)	0.0869	0.2029	0.5972	0.3069	0.4226	0.8452

Notes Dependent variables are the average measure of TSP ambient concentration from 1970 to 1979 collected at each TSP monitor with positive reading during this period. $1(disind \in a-bkm)$ is an indicator of the distance of a TSP monitor from the closest 1970s industrial area is within a and b km. Downwind is an indicator of whether or not the TSP monitor is located downwind to the industrial area. Same elevation is a dummy that takes one if the TSP monitor is at the same elevation or less than 100m lower than its closest industrial area, and not obstructed by other areas in between. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

Table 3: Industrial Activities in the 1970s and Current Pollution

Variables	Monitor-level average PM10 from 2000 to 2010					
Sample	Full Sample		Above-median polluted industrial area		Below-median polluted industrial area	
$1(disind \in 0-1km)$	3.233***	3.252***	1.845	1.912	3.369***	3.321***
	(0.849)	(0.892)	(1.726)	(1.853)	(0.863)	(0.925)
$1(disind \in 1-2km)$	1.877**	1.832**	1.163	0.854	2.219**	2.336**
	(0.820)	(0.861)	(1.746)	(1.822)	(1.098)	(1.168)
$1(disind \in 2-3km)$	1.921**	1.887*	0.282	0.272	2.349*	2.277
	(0.902)	(0.978)	(1.710)	(1.862)	(1.250)	(1.412)
$1(disind \in 3-4km)$	2.328	1.982	4.129	3.795	1.191	1.278
	(1.799)	(1.931)	(3.859)	(4.321)	(1.275)	(1.330)
$1(disind \in 0-1km)$*Downwind		-2.566*		-3.710**		-0.142
		(1.362)		(1.876)		(2.093)
$1(disind \in 1-2km)$*Downwind		-1.235		1.067		-1.363
		(1.544)		(3.922)		(2.082)
$1(disind \in 2-3km)$*Downwind		-2.393		-5.743		-0.254
		(2.183)		(3.965)		(3.307)
$1(disind \in 3-4km)$*Downwind		2.015		-0.750		-3.225
		(3.647)		(5.336)		(6.775)
$1(disind > 4km)$*Downwind		-2.897*		-3.819		-1.343
		(1.475)		(2.755)		(2.439)
Observations	1,893	1,893	951	951	942	942
R-squared	0.299	0.301	0.358	0.360	0.377	0.378
p-value (Sum of wind interacts=0)		0.3975		0.3089		0.5625

Notes Dependent variables are the average measure of PM10 ambient concentration from 2000 to 2010 collected at each PM10 monitor with positive reading during this period. $1(disind \in a-bkm)$ is an indicator of the distance of a PM10 monitor from the closest 1970 industrial area is within a and b km. Downwind is an indicator of whether or not the TSP monitor is located downwind to the industrial area. Same elevation is a dummy that takes one if the PM10 monitor is at the same elevation or less than 100m lower than its closest industrial area, and not obstructed by other areas in between. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

Table 4: MSA-level evidence

VARIABLES	Employment growth			Population growth		
Share of $1(disind \in 0-4km)$ tracts in total	-0.376***	-0.421***	-0.265***	-0.126	-0.244**	-0.0758
	(0.113)	(0.1000)	(0.101)	(0.119)	(0.114)	(0.123)
Share of $1(disind \in 0-4km)$*central tracts in total	-0.336		-0.458	-0.428		-0.606**
	(0.310)		(0.293)	(0.269)		(0.275)
Share of downwind tracts in total	-0.135	-0.117	-0.151	-0.400	-0.499	-0.542
	(0.387)	(0.454)	(0.419)	(0.433)	(0.489)	(0.467)
Share of $1(disind \in 0-4km)$*downwind tracts in total		-0.229	-1.079**		0.0868	-0.262
		(0.361)	(0.430)		(0.345)	(0.399)
Share of $1(disind \in 0-4km)$*central downwind tracts in total			6.407			10.33***
			(5.018)			(3.846)
Observations	198	198	198	198	198	198
R-squared	0.727	0.716	0.746	0.835	0.832	0.843

Table 5: Economic outcomes in 2000: Same elevation dummy

	Outcomes in 2000: Above-median pollution level							
	By place of work			By place of residence				
VARIABLES	Employ density	Highskill ratio	Median earning	Employ density	Highskill ratio	Median earning	Housing value	College ratio
$1(disind \in 0-1km)$*same elevation	0.401**	0.00783	-0.00608	0.278	0.00534	-0.0961*	-0.118*	-0.0345
	(0.174)	(0.0214)	(0.0240)	(0.218)	(0.0145)	(0.0555)	(0.0609)	(0.0237)
$1(disind \in 1-2km)$*same elevation	0.0357	-0.00709	0.0215	-0.0586	0.00604	-0.0370	-0.0911	-0.0294
	(0.157)	(0.0221)	(0.0236)	(0.217)	(0.0113)	(0.0780)	(0.0650)	(0.0250)
$1(disind \in 2-3km)$*same elevation	0.264	0.000794	-0.0158	0.200	0.0172	-0.0847	-0.0990*	-0.0424
	(0.178)	(0.0261)	(0.0280)	(0.224)	(0.0264)	(0.0986)	(0.0557)	(0.0463)
$1(disind \in 3-4km)$*same elevation	0.144	-0.0261	-0.0252	0.0818	-0.00868	-0.0916**	-0.145***	-0.0431*
	(0.178)	(0.0264)	(0.0309)	(0.184)	(0.0120)	(0.0400)	(0.0472)	(0.0259)
same elevation	0.266**	0.00235	0.0031	0.340**	-0.00762	0.0153	0.0329	0.00801
	(0.110)	(0.0126)	(0.0101)	(0.172)	(0.0176)	(0.0543)	(0.0410)	(0.0244)
$1(disind \in 0-1km)$	-0.133	-0.0478	0.00620	-0.145	-0.0492***	-0.104*	-0.121	-0.0732**
	(0.191)	(0.0357)	(0.0346)	(0.257)	(0.0148)	(0.0556)	(0.0754)	(0.0297)
$1(disind \in 1-2km)$	0.240	-0.00733	-0.0410	0.275	-0.0315***	-0.129*	-0.0880	-0.0521**
	(0.166)	(0.0315)	(0.0342)	(0.180)	(0.0117)	(0.0744)	(0.0718)	(0.0249)
$1(disind \in 2-3km)$	-0.125	-0.0145	-0.0128	-0.0420	-0.0388	-0.0597	-0.0320	-0.0272
	(0.180)	(0.0246)	(0.0334)	(0.205)	(0.0249)	(0.0925)	(0.0624)	(0.0424)
$1(disind \in 3-4km)$	-0.0903	0.0143	0.00933	-0.0382	0.00354	0.0291	0.0879*	0.0204
	(0.172)	(0.0305)	(0.0328)	(0.167)	(0.00941)	(0.0353)	(0.0519)	(0.0190)
Observations	8,255	8,255	8,111	8,282	8,282	8,107	7,997	8,258
R-squared	0.401	0.060	0.191	0.583	0.273	0.246	0.550	0.166
p-value (Sum of elevation interacts=0)	0.2265	0.7006	0.5512	0.4762	0.7133	0.1211	0.0113	0.0621

	Outcomes in 2000: Below-median pollution level							
	By place of work			By place of residence				
VARIABLES	Employ density	Highskill ratio	Median earning	Employ density	Highskill ratio	Median earning	Housing value	College ratio
$1(disind \in 0-1km)$*same elevation	-0.0974	-0.00862	-0.0113	-0.161	-0.00463	-0.0158	-0.102	-0.0187
	(0.190)	(0.0160)	(0.0301)	(0.199)	(0.0214)	(0.0635)	(0.0909)	(0.0442)
$1(disind \in 1-2km)$*same elevation	-0.143	-0.0435**	-0.0373	-0.252	-0.000998	-0.0302	-0.0747	-0.0273
	(0.191)	(0.0189)	(0.0316)	(0.155)	(0.0173)	(0.0512)	(0.0731)	(0.0331)
$1(disind \in 2-3km)$*same elevation	-0.234	-0.0262	-0.0245	-0.189	-0.00997	0.00329	-0.0269	-0.0155
	(0.199)	(0.0165)	(0.0419)	(0.149)	(0.0123)	(0.0619)	(0.0694)	(0.0249)
$1(disind \in 3-4km)$*same elevation	-0.293	-0.0320*	-0.0308	-0.239	-0.0122	-0.0368	-0.0995	-0.0117
	(0.202)	(0.0173)	(0.0341)	(0.193)	(0.0180)	(0.0768)	(0.0833)	(0.0324)
same elevation	0.942***	0.0310**	0.0265	0.898***	0.00551	-0.0498	0.0187	-0.00460
	(0.158)	(0.0128)	(0.0165)	(0.139)	(0.0155)	(0.0513)	(0.0629)	(0.0310)
$1(disind \in 0-1km)$	0.748***	0.000832	0.0201	0.543***	-0.0241	-0.115*	-0.0928	-0.0467
	(0.208)	(0.0201)	(0.0332)	(0.205)	(0.0233)	(0.0669)	(0.0984)	(0.0464)
$1(disind \in 1-2km)$	0.662***	0.0354*	0.0214	0.641***	-0.0192	-0.0785	-0.0800	-0.0204
	(0.199)	(0.0200)	(0.0312)	(0.160)	(0.0179)	(0.0520)	(0.0743)	(0.0328)
$1(disind \in 2-3km)$	0.564***	0.0252	0.0252	0.435***	-0.00150	-0.0685	-0.0592	-0.00979
	(0.175)	(0.0153)	(0.0379)	(0.139)	(0.0113)	(0.0621)	(0.0633)	(0.0233)
$1(disind \in 3-4km)$	0.534***	0.0317**	0.0226	0.442**	0.0114	0.0252	0.0768	0.00616
	(0.195)	(0.0152)	(0.0341)	(0.185)	(0.0163)	(0.0727)	(0.0749)	(0.0286)
Observations	7,870	7,870	7,371	7,869	7,869	7,367	7,803	7,870
R-squared	0.373	0.111	0.287	0.451	0.330	0.351	0.562	0.273
p-value (Sum of elevation interacts=0)	0.5421	0.0666	0.3677	0.8676	0.6487	0.2519	0.4629	0.3606

Notes Results from the upper panel are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. Dependent variables of the first three columns are employment density, the ratio of FIRE, IT, professional services, education and medical services in total employment, and median earning, counted at the place of work. The last five columns report results on employment density, the ratio of FIRE, IT, professional services, education and medical services in total employment, median earning, median housing value and ratio of college graduates among the population over 25 years old, counted at their place of residence. $1(disind \in x-ykm)$ is an indicator of whether or not the distance of a tract from the closest industrial area is within x to y km. Same elevation is a dummy that takes one if the PM10 monitor is at the same elevation or less than 100m lower than its closest industrial area, and not obstructed by other areas in between. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

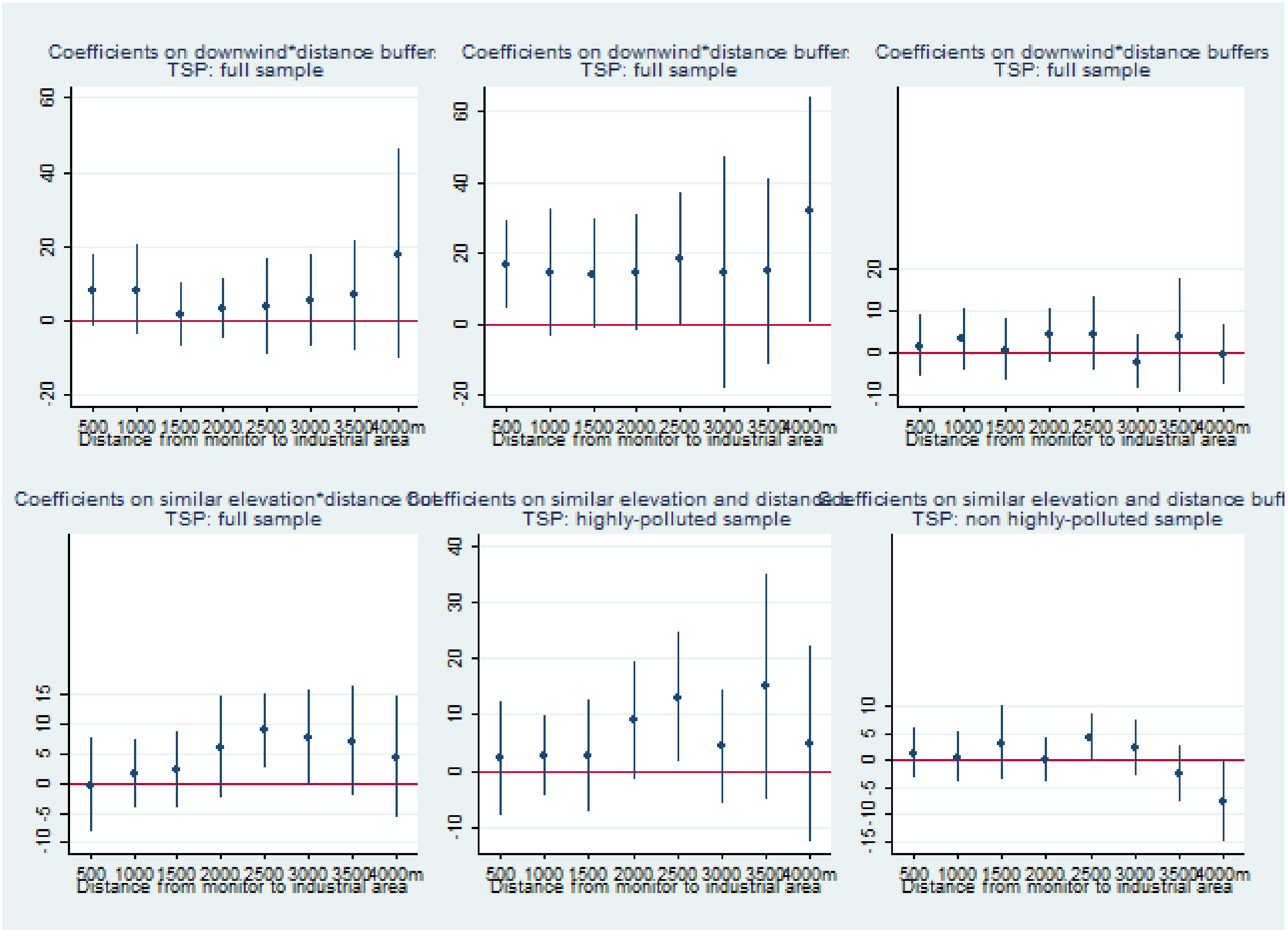
Table 6: Economic outcomes in 2000: Downwind dummy

	Outcomes in 2000: Above-median pollution level							
	By place of work			By place of residence				
VARIABLES	Employ density	Highskill ratio	Median earning	Employ density	Highskill ratio	Median earning	Housing value	College ratio
$1(disind \in 0-1km)$*Downwind	-0.0955	-0.0213*	-0.0346*	-0.0633	-0.0215***	-0.0124	-0.0957***	-0.0356***
	(0.102)	(0.0117)	(0.0194)	(0.0447)	(0.00709)	(0.0194)	(0.0291)	(0.0148)
$1(disind \in 1-2km)$*Downwind	-0.117	-0.0204***	-0.0280**	0.0114	-0.0320**	-0.0739***	-0.0814***	-0.0493***
	(0.0970)	(0.00629)	(0.0123)	(0.0389)	(0.0125)	(0.0260)	(0.0273)	(0.0155)
$1(disind \in 2-3km)$*Downwind	-0.115	-0.0100	-0.0190	-0.0954	-0.00510	-0.0192	-0.0124	-0.0190
	(0.116)	(0.00658)	(0.0176)	(0.0832)	(0.0125)	(0.0263)	(0.0308)	(0.0120)
$1(disind \in 3-4km)$*Downwind	-0.232	-0.00939	-0.0536**	-0.0196	-0.00364	-0.0236	0.0190	-0.0256
	(0.154)	(0.00985)	(0.0229)	(0.105)	(0.0166)	(0.0277)	(0.0537)	(0.0229)
$1(disind > 4km)$*Downwind	0.174	0.00614	0.0237	0.194	-0.00294	-0.0301	0.0225	-0.0206
	(0.185)	(0.0120)	(0.0217)	(0.135)	(0.0106)	(0.0407)	(0.0519)	(0.0193)
$1(disind \in 0-1km)$	0.0190	-0.0267	0.0428	-0.0136	-0.0344***	-0.163***	-0.188***	-0.0960***
	(0.238)	(0.0164)	(0.0362)	(0.252)	(0.00939)	(0.0460)	(0.0569)	(0.0219)
$1(disind \in 1-2km)$	0.0612	-0.0179	0.0299	0.0688	-0.00684	-0.0965**	-0.113**	-0.0580***
	(0.231)	(0.0140)	(0.0270)	(0.223)	(0.0107)	(0.0415)	(0.0470)	(0.0184)
$1(disind \in 2-3km)$	-0.0153	-0.0144	0.0131	0.113	-0.00966	-0.0788*	-0.0631	-0.0439**
	(0.145)	(0.0113)	(0.0300)	(0.172)	(0.00685)	(0.0466)	(0.0444)	(0.0213)
$1(disind \in 3-4km)$	0.0228	-0.00779	0.0279	0.0473	0.00579	-0.0251	-0.0108	-0.00287
	(0.106)	(0.00759)	(0.0215)	(0.0840)	(0.00660)	(0.0346)	(0.0452)	(0.0194)
Observations	8,173	8,173	8,023	8,203	8,203	8,020	7,933	8,176
R-squared	0.375	0.080	0.179	0.551	0.266	0.252	0.558	0.175
p-value (Sum of wind interacts=0)	0.1241	0.0159	0.0016	0.3498	0.2919	0.0870	0.0938	0.0027

	Outcomes in 2000: Below-median pollution level							
	By place of work			By place of residence				
VARIABLES	Employ density	Highskill ratio	Median earning	Employ density	Highskill ratio	Median earning	Housing value	College ratio
$1(disind \in 0-1km)$*Downwind	-0.153*	-0.00808	-0.0204	-0.0228	-0.00320	0.0225	-0.00648	-0.0133
	(0.0781)	(0.00637)	(0.0133)	(0.0653)	(0.00627)	(0.0198)	(0.0268)	(0.0106)
$1(disind \in 1-2km)$*Downwind	0.00521	0.00123	-0.0179	0.0237	2.47e-05	-0.0124	-0.0233	-0.00582
	(0.104)	(0.00538)	(0.0140)	(0.0794)	(0.00614)	(0.0301)	(0.0367)	(0.0123)
$1(disind \in 2-3km)$*Downwind	-0.122	-0.00629	0.0191	-0.0525	0.00331	0.0238	-0.0192	-0.00780
	(0.126)	(0.00876)	(0.0127)	(0.112)	(0.00615)	(0.0322)	(0.0316)	(0.0135)
$1(disind \in 3-4km)$*Downwind	-0.177	0.00707	-0.0400*	-0.0489	0.00241	0.00793	0.00539	0.0144
	(0.136)	(0.0106)	(0.0238)	(0.110)	(0.0102)	(0.0253)	(0.0443)	(0.0158)
$1(disind > 4km)$*Downwind	-0.391**	-0.0157	-0.00880	-0.186	-0.00779	-0.0233	-0.0239	-0.0269
	(0.112)	(0.00903)	(0.0132)	(0.107)	(0.0122)	(0.0328)	(0.0551)	(0.0233)
$1(disind \in 0-1km)$	0.442***	-0.0330***	-0.0172	0.338**	-0.0403***	-0.179***	-0.262***	-0.109***
	(0.158)	(0.0101)	(0.0208)	(0.157)	(0.00817)	(0.0290)	(0.0355)	(0.0187)
$1(disind \in 1-2km)$	0.403***	-0.0287***	-0.0388*	0.406***	-0.0309***	-0.155***	-0.209***	-0.0875***
	(0.140)	(0.00917)	(0.0209)	(0.151)	(0.00676)	(0.0290)	(0.0332)	(0.0183)
$1(disind \in 2-3km)$	0.267**	-0.0170*	-0.0391*	0.296**	-0.0204***	-0.130***	-0.147***	-0.0632***
	(0.119)	(0.00883)	(0.0204)	(0.134)	(0.00707)	(0.0315)	(0.0350)	(0.0183)
$1(disind \in 3-4km)$	0.178*	-0.0119*	-0.0196	0.214**	-0.0103*	-0.0431*	-0.0741**	-0.0392***
	(0.103)	(0.00677)	(0.0128)	(0.0986)	(0.00530)	(0.0220)	(0.0300)	(0.0135)
Observations	8,139	8,139	7,740	8,139	8,139	7,734	8,038	8,139
R-squared	0.327	0.105	0.267	0.424	0.330	0.310	0.540	0.254
p-value (Sum of wind interacts=0)	0.0629	0.7770	0.1600	0.7035	0.8898	0.5932	0.6523	0.7199

Notes Results from the upper panel are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. Dependent variables of the first three columns are employment density, the ratio of FIRE, IT, professional services, education and medical services in total employment, and median earning, counted at the place of work. The last five columns report results on employment density, the ratio of FIRE, IT, professional services, education and medical services in total employment, median earning, median housing value and ratio of college graduates among the population over 25 years old, counted at their place of residence. $1(disind \in x-ykm)$ is an indicator of whether or not the distance of a tract from the closest industrial area is within x to y km. Downwind is an indicator of whether or not the TSP monitor is located downwind to the industrial area. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

Figure 2: Estimated coefficients on 1970s pollution

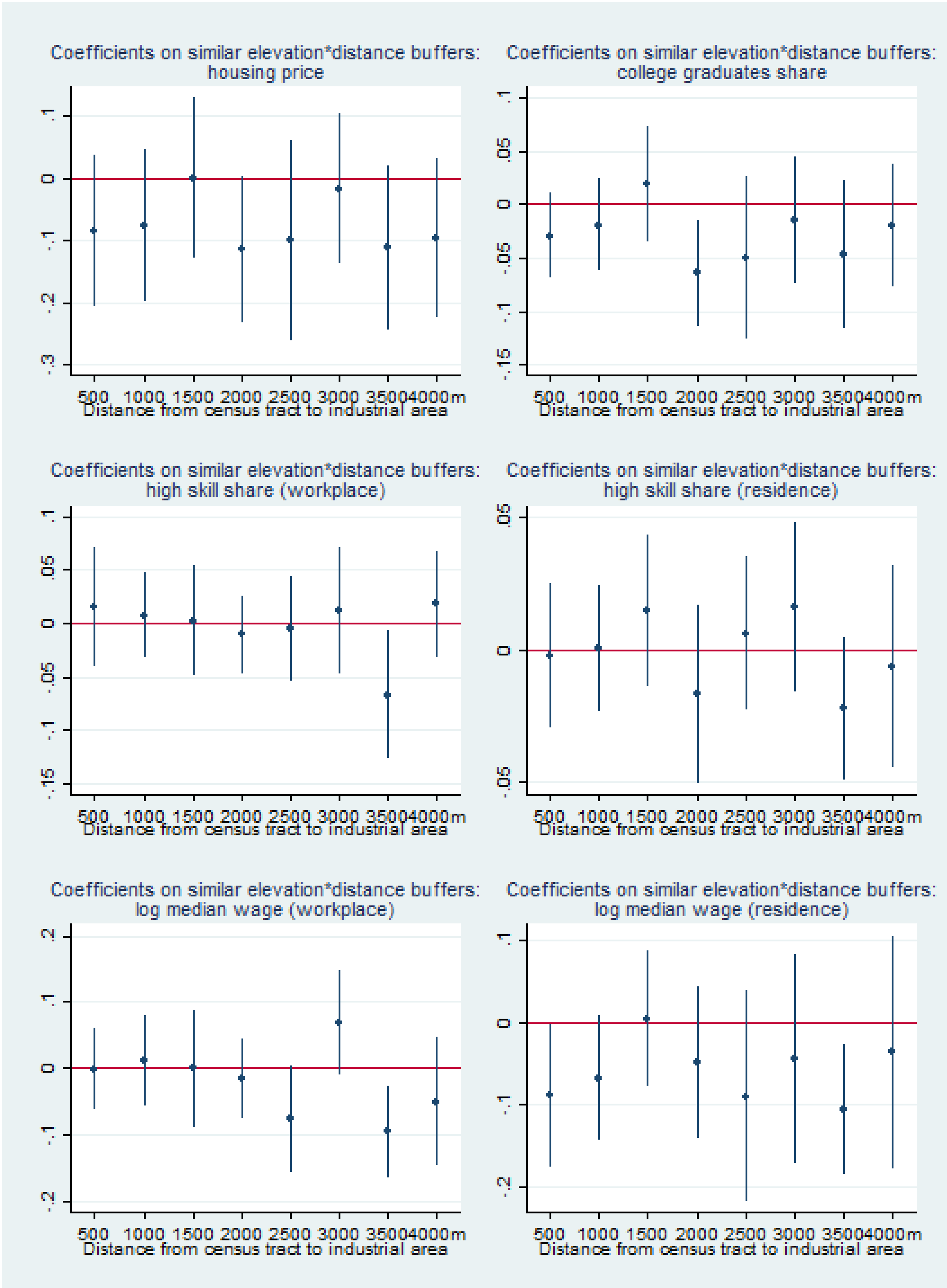


Notes The figures display the estimated coefficients and 95% confidence intervals in regressions where the dependent variable is average measure of TSPs ambient concentration at monitor level. The independent variables on the upper row are dummies of distance buffers of 500 meters are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. interval from each TSP monitor to the closest industrial area, interacted with a dummy of whether or not the TSP monitor is downwind to the industrial area. The independent variables on the lower row are dummies of distance buffers of 500 meters are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. interval from each TSP monitor to the closest industrial area, interacted with a dummy of whether or not the TSP monitor is at the same elevation or less than 100 meters lower than the industrial area, and not obstructed by anything between them. The graphs from the left to the right are coefficients obtained in the full sample,

Figure 3: Estimated coefficients on downwind*distance buffers: Economic outcomes

Notes The figures display the estimated coefficients and 95% confidence intervals in regressions where the dependent variables are housing price, college graduates share at residence, high skilled employment share at workplace and residence, median wage at workplace and residence. The independent variables are dummies of distance buffers of 500 meters are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. interval from each TSP monitor to the closest industrial area, interacted with a dummy of whether or not the TSP monitor is downwind to the industrial area. All the coefficients are obtained in regressions on a sample of census tracts that are closest to above-median polluted industrial areas.

Figure 4: Estimated coefficients on same elevation*distance buffers: Economic outcomes



Notes The figures display the estimated coefficients and 95% confidence intervals in regressions where the dependent variables are housing price, college graduates share at residence, high skilled employment share at workplace and residence, median wage at workplace and residence. The independent variables are dummies of distance buffers of 500 meters are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. interval from each TSP monitor to the closest industrial area, interacted with a dummy of whether or not the TSP monitor is at the same elevation or less than 100 meters lower than the industrial area, and not obstructed by anything between them.All the coefficients are obtained in regressions on a sample of census tracts that are closest to above-median polluted industrial areas.

Table 7: Growth from 1980-2000: Downwind dummy

	Growth from 1980 to 2000: Above-median pollution level					
VARIABLES	Employment	Manufacture employment	FIRE employment	Median income	Housing value	College graduates
$1(disind \in 0-1km)$*Downwind	-0.0561*	-0.0372	-0.119**	-0.0315***	-0.0578***	-0.0822**
	(0.0285)	(0.0382)	(0.0478)	(0.00962)	(0.0201)	(0.0374)
$1(disind \in 1-2km)$*Downwind	-0.0641*	-0.00678	-0.146**	-0.0629***	-0.0530*	-0.143***
	(0.0351)	(0.0463)	(0.0683)	(0.0228)	(0.0274)	(0.0473)
$1(disind \in 2-3km)$*Downwind	-0.0162	0.00772	-0.0597	-0.0226	-0.0126	-0.0577
	(0.0351)	(0.0476)	(0.0424)	(0.0178)	(0.0206)	(0.0524)
$1(disind \in 3-4km)$*Downwind	-0.0454	-0.0768	-0.0381	-0.0209	-0.000550	-0.0258
	(0.0412)	(0.0799)	(0.0453)	(0.0208)	(0.0299)	(0.0497)
$1(disind > 4km)$Downwind	0.101	0.157	0.141	0.00478	0.00788	0.147
	(0.0971)	(0.138)	(0.0952)	(0.0282)	(0.0336)	(0.0930)
$1(disind \in 0-1km)$	0.165	0.364**	0.223	0.0175	0.139**	0.341
	(0.153)	(0.176)	(0.197)	(0.0324)	(0.0546)	(0.253)
$1(disind \in 1-2km)$	0.145	0.267*	0.243	0.0369	0.126**	0.300
	(0.125)	(0.153)	(0.167)	(0.0272)	(0.0524)	(0.204)
$1(disind \in 2-3km)$	0.0955	0.194	0.113	0.0140	0.0830***	0.208
	(0.100)	(0.129)	(0.125)	(0.0256)	(0.0314)	(0.153)
$1(disind \in 3-4km)$	0.0751	0.170	0.0791	0.0302	0.0646***	0.128
	(0.0711)	(0.120)	(0.0926)	(0.0195)	(0.0214)	(0.105)
Observations	7,983	5,895	7,584	8,035	7,683	7,921
R-squared	0.326	0.337	0.247	0.229	0.545	0.204
p-value (Sum of wind interacts=0)	0.0557	0.3579	0.0120	0.0036	0.0085	0.0027

	Growth from 1980 to 2000: Below-median pollution level					
VARIABLES	Employment	Manufacture employment	FIRE employment	Median income	Housing value	College graduates
$1(disind \in 0-1km)$*Downwind	0.0223	0.0697	0.0504	0.0124	-0.00289	0.0499
	(0.0439)	(0.0531)	(0.0542)	(0.0155)	(0.0196)	(0.0523)
$1(disind \in 1-2km)$*Downwind	0.00732	-0.00384	0.00881	0.0129	-0.00151	0.0558
	(0.0286)	(0.0391)	(0.0438)	(0.0167)	(0.0206)	(0.0379)
$1(disind \in 2-3km)$*Downwind	-0.0637	-0.0910	-0.0891*	0.0130	0.00270	-0.0146
	(0.0424)	(0.0604)	(0.0512)	(0.0139)	(0.0175)	(0.0439)
$1(disind \in 3-4km)$*Downwind	0.213**	0.211**	0.134*	0.00647	-0.0247	0.188**
	(0.0518)	(0.0688)	(0.0592)	(0.0216)	(0.0331)	(0.0807)
$1(disind > 4km)$Downwind	0.0585	0.0669	0.00883	0.0288	0.00547	0.0721
	(0.0971)	(0.138)	(0.0952)	(0.0282)	(0.0336)	(0.0930)
$1(disind \in 0-1km)$	-0.0883	-0.0118	-0.204***	-0.0394*	-0.0149	-0.213**
	(0.0629)	(0.0617)	(0.0771)	(0.0235)	(0.0358)	(0.0931)
$1(disind \in 1-2km)$	-0.0957*	-0.0366	-0.182***	-0.0446**	-0.0128	-0.214***
	(0.0525)	(0.0546)	(0.0661)	(0.0192)	(0.0277)	(0.0760)
$1(disind \in 2-3km)$	-0.0799	-0.0352	-0.137**	-0.0533***	-0.0145	-0.176***
	(0.0492)	(0.0541)	(0.0686)	(0.0181)	(0.0267)	(0.0673)
$1(disind \in 3-4km)$	-0.0559	-0.0106	-0.0875*	-0.0308*	0.000763	-0.113**
	(0.0391)	(0.0460)	(0.0512)	(0.0157)	(0.0193)	(0.0568)
Observations	7,786	6,284	7,533	7,827	7,627	7,761
R-squared	0.381	0.334	0.334	0.244	0.523	0.250
p-value (Sum of wind interacts=0)	0.0733	0.1950	0.3408	0.2258	0.6812	0.0141

Notes Results from the upper panel are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level.Dependent variables are growth in total, manufacture, FIRE employment, median household income, median housing value and the number of college graduates from 1980 to 2000, all counted at the place of residence. $1(disind \in x-ykm)$ is an indicator of whether or not the distance of a tract from the closest industrial area is within x to y km. Downwind is an indicator of whether or not the TSP monitor is located downwind to the industrial area. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

Table 8: Growth from 1980-2000: Same elevation dummy

	Growth from 1980 to 2000: Above-median pollution level					
VARIABLES	Employment	Manufacture employment	FIRE employment	Median income	Housing value	College graduates
$1(disind \in 0-1km)$	0.114	0.250	0.108	0.0333	0.102	0.302
	(0.145)	(0.185)	(0.190)	(0.0354)	(0.0635)	(0.236)
$1(disind \in 1-2km)$	0.222	0.297	0.312*	0.0144	0.0942	0.297
	(0.153)	(0.197)	(0.180)	(0.0304)	(0.0598)	(0.223)
$1(disind \in 2-3km)$	0.262*	0.422**	0.248	0.0779**	0.0871**	0.404**
	(0.145)	(0.167)	(0.165)	(0.0325)	(0.0354)	(0.178)
$1(disind \in 3-4km)$	0.180*	0.390**	0.271**	0.0759**	0.0888***	0.289**
	(0.104)	(0.177)	(0.125)	(0.0318)	(0.0326)	(0.133)
$1(disind \in 0-1km)$*Same Elevation	0.0884**	0.0471	0.141**	0.00138	0.0209	0.0802
	(0.0381)	(0.0533)	(0.0665)	(0.0248)	(0.0359)	(0.0652)
$1(disind \in 1-2km)$*Same Elevation	-0.0605	-0.0594	-0.0890	0.0155	0.00365	-0.0109
	(0.0752)	(0.104)	(0.0673)	(0.0221)	(0.0342)	(0.0896)
$1(disind \in 2-3km)$*Same Elevation	-0.164	-0.285**	-0.162	-0.0677*	-0.00572	-0.218*
	(0.0997)	(0.119)	(0.115)	(0.0358)	(0.0293)	(0.126)
$1(disind \in 3-4km)$*Same Elevation	-0.0974	-0.311**	-0.204	-0.0512	-0.0367	-0.154
	(0.129)	(0.124)	(0.157)	(0.0378)	(0.0406)	(0.189)
Same Elevation	0.286*	0.340*	0.317*	0.0744		0.446**
	(0.169)	(0.198)	(0.175)	(0.0457)		(0.198)
Observations	6,947	5,063	6,590	6,990	6,677	6,888
R-squared	0.337	0.369	0.253	0.214	0.550	0.208
p-value (Sum of elevation interacts=0)	0.3063	0.0432	0.1674	0.1627	0.8459	0.3571

	Growth from 1980 to 2000: Below-median pollution level					
VARIABLES	Employment	Manufacture employment	FIRE employment	Median income	Housing value	College graduates
$1(disind \in 0-1km)$	0.0946	0.109	-0.0318	0.00174	-0.0167	-0.0507
	(0.0822)	(0.114)	(0.0917)	(0.0345)	(0.0397)	(0.0988)
$1(disind \in 1-2km)$	0.0477	0.0717	-0.0321	-0.00237	-0.0505	-0.0451
	(0.0871)	(0.109)	(0.121)	(0.0377)	(0.0458)	(0.110)
$1(disind \in 2-3km)$	0.00140	0.157	0.0289	-0.00280	-0.00229	-0.0273
	(0.0935)	(0.154)	(0.138)	(0.0316)	(0.0360)	(0.0996)
$1(disind \in 3-4km)$	-0.118**	-0.0878	0.00896	-0.0453	-0.000972	-0.135*
	(0.0478)	(0.0799)	(0.0768)	(0.0581)	(0.0461)	(0.0746)
$1(disind \in 0-1km)$*Same Elevation	-0.0809	-0.0419	-0.0742	-0.0278	0.0368	-0.0295
	(0.0758)	(0.0860)	(0.0734)	(0.0256)	(0.0329)	(0.0768)
$1(disind \in 1-2km)$*Same Elevation	-0.0649	-0.0693	-0.0935	-0.0251	0.0676*	-0.0678
	(0.0767)	(0.0859)	(0.105)	(0.0307)	(0.0398)	(0.0959)
$1(disind \in 2-3km)$*Same Elevation	-0.0103	-0.178	-0.124	-0.0417	0.00760	-0.0613
	(0.0866)	(0.147)	(0.143)	(0.0285)	(0.0323)	(0.0891)
$1(disind \in 3-4km)$*Same Elevation	0.145***	0.116	-0.0548	0.0229	0.00848	0.0923
	(0.0479)	(0.0739)	(0.0904)	(0.0577)	(0.0495)	(0.0693)
Same Elevation	0.0936	0.0999	-0.0446	0.00326		0.0543
	(0.114)	(0.131)	(0.110)	(0.0226)		(0.113)
Observations	6,563	5,154	6,329	6,598	6,423	6,532
R-squared	0.371	0.344	0.324	0.245	0.504	0.257
p-value (Sum of elevation interacts=0)	0.9307	0.3793	0.1403	0.4668	0.2417	0.7083

Notes Results from the upper panel are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level.Dependent variables are growth in total, manufacture, FIRE employment, median household income, median housing value and the number of college graduates from 1980 to 2000, all counted at the place of residence. $1(disind \in x-ykm)$ is an indicator of whether or not the distance of a tract from the closest industrial area is within x to y km. Same elevation is a dummy that takes one if the tract is at the same elevation or less than 100m lower than its closest industrial area, and not obstructed by other areas in between. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

Table 9: Amenities and housing quality

Above-median polluted industrial areas								
VARIABLES	2000 Violent crime rate	2000 Violent crime rate	2000 public school pc	2000 public school pc	1980 share no kitchen/plumbing	1980 share no kitchen/plumbing	2000 share no kitchen/plumbing	2000 share no kitchen/plumbing
$1(disind \in 0-4km)$	0.00076	0.000029	0.000603	0.000314	-0.000074	0.000506	-0.000173	-0.00111
	(0.000674)	(0.000526)	(0.000377)	(0.000418)	(0.00171)	(0.00244)	(0.000933)	(0.00106)
$1(disind \in 0-4km)$ Downwind	0.000346*		-0.000227*		0.000964		-0.000063	
	(0.000185)		(0.000144)		(0.00264)		(0.000541)	
Downwind	0.00003		0.000029		0.00322		-0.00151	
	(0.000299)		(0.000422)		(0.00452)		(0.00151)	
$1(disind \in 0-4km)$ Same Elevation		0.000868***		0.000329		-0.000609		0.00103
		(0.000276)		(0.000284)		(0.00273)		(0.000945)
Same Elevation		-0.000617**		-0.000183				
		(0.000271)		(0.000216)				
Observations	2,315	2,315	4,841	4,841	2,206	2,206	7,939	7,939
R-squared	0.343	0.342	0.005	0.005	0.2	0.2	0.088	0.088

Below-median polluted industrial areas								
VARIABLES	2000 Violent crime rate	2000 Violent crime rate	2000 public school pc	2000 public school pc	1980 share no kitchen/plumbing	1980 share no kitchen/plumbing	2000 share no kitchen/plumbing	2000 share no kitchen/plumbing
$1(disind \in 0-4km)$	0.000350***	-0.000018	0.000061***	0.000007	-0.000921	-0.00247	0.00144*	-0.00031
	(0.000115)	(0.000227)	0.000023)	(0.000035)	(0.0023)	(0.00276)	(0.000808)	(0.0014)
$1(disind \in 0-4km)$ Downwind	-0.000163		0.000016		-0.000531		-0.00187	
	(0.000198)		(0.000018)		(0.00161)		(0.00121)	
Downwind	0.00125***		-0.000027		0.00085		0.00152	
	(0.000307)		(0.000031)		(0.00374)		(0.00138)	
$1(disind \in 0-4km)$ Same Elevation		0.000318		0.000071*		0.00173		0.00181
		(0.00022)		(0.000036)		(0.00173)		(0.0011)
Same Elevation		0.000121		-0.000039				
		(0.000227)		(0.000032)				
Observations	1,209	1,209	3,822	3,822	2,224	2,224	5,925	5,925
R-squared	0.29	0.288	0.114	0.114	0.316	0.316	0.077	0.076

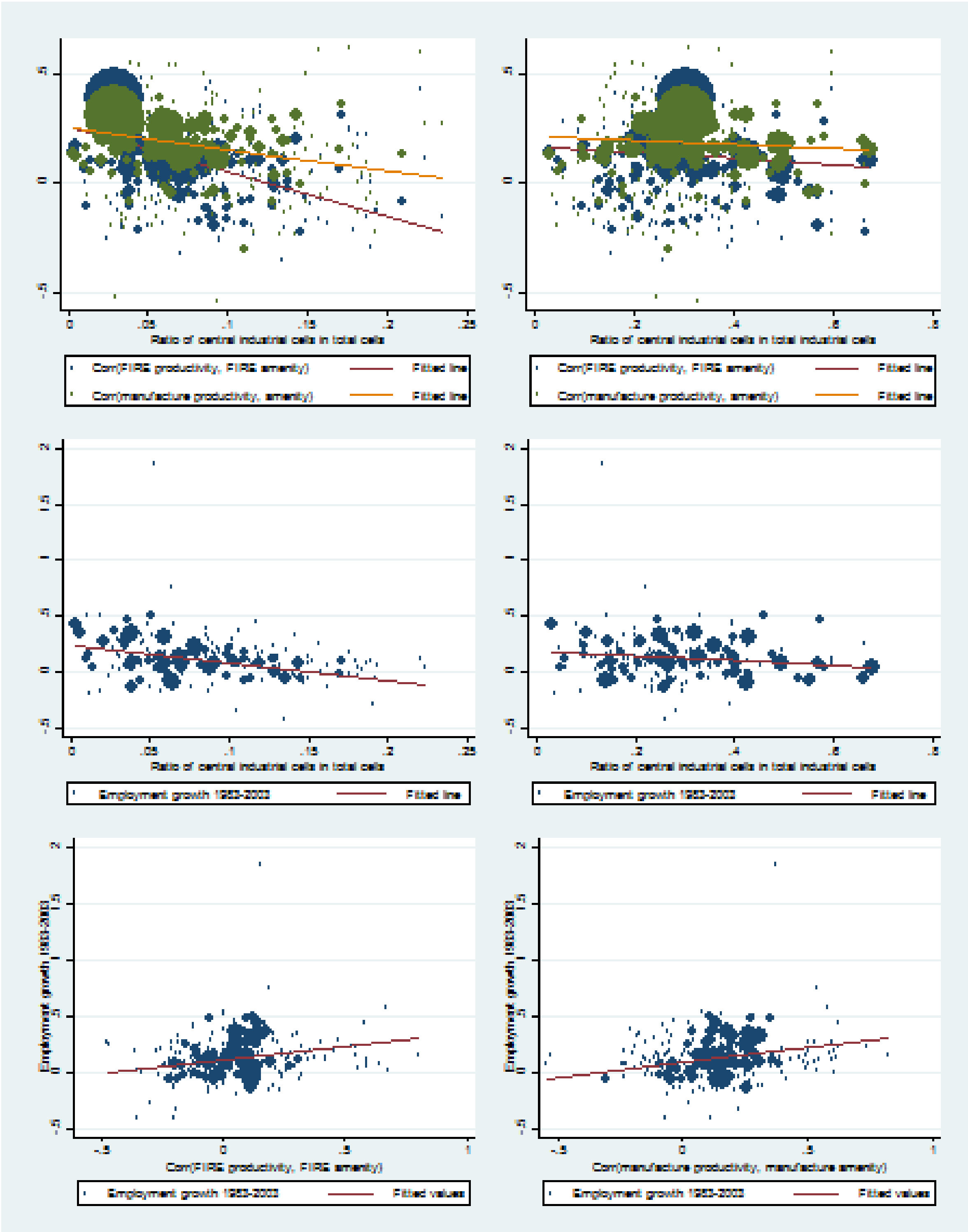
Notes Results from the upper panel are obtained from a sample of census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. Dependent variables are tract level violent crime rate in 2000, the number of public schools per capita in 2000, share of housing units without kitchen or plumbing devices in 1980 and 2000. $1(disind \in 0-4km)$ is an indicator of whether or not the distance of a tract from the closest industrial area is within 0 to 4 km. Same elevation is a dummy that takes one if the tract is at the same elevation or less than 100m lower than its closest industrial area, and not obstructed by other areas in between. Downwind is an indicator of whether or not the TSP monitor is located downwind to the industrial area. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

Table 10: MSA-level evidence

	Unweighted				Weighted			
VARIABLES	Employment growth		Population growth		Employment growth		Population growth	
$\frac{centralindustrialtracts}{totaltracts}$	-0.439*	-0.297	-0.506	0.0939	-0.700*	-0.437	-0.989**	-0.0394
	(0.213)	(0.199)	(0.369)	(0.128)	(0.341)	(0.339)	(0.374)	(0.162)
$\frac{non-centralindustrialtracts}{totaltracts}$	-0.152	-0.106	-0.229	-0.0851	-0.0444	0.0284	-0.114	-0.0234
	(0.171)	(0.152)	(0.195)	(0.101)	(0.148)	(0.134)	(0.138)	(0.0731)
$Manufactureratio_{77}$	-0.728**	-0.354	-0.810***	-0.0522	-1.039***	-0.590**	-1.121***	-0.109
	(0.250)	(0.222)	(0.171)	(0.110)	(0.261)	(0.214)	(0.194)	(0.0874)
$ln(Emp_{83})$	-0.0454	-0.0510			-0.0152	0.115		
	(0.0271)	(0.126)			(0.0182)	(0.0776)		
$ln(Pop_{83})$			-0.00884	0.776***			-0.00363	0.877***
			(0.0111)	(0.140)			(0.0205)	(0.170)
Observations	202	202	202	202	202	202	202	202
R-squared	0.223	0.556	0.290	0.787	0.339	0.699	0.401	0.853
Full control	N	Y	N	Y	N	Y	N	Y

Notes Dependent variables are MSA level employment growth from 1983 to 2003 or population growth from 1980 to 2000. $\frac{centralindustrialtracts}{totaltracts}$ is the ratio between the number of census tracts directly affected by industrial areas in central city, defined as the tracts that intersect an industrial area, and the number of total census tracts of the MSA. A tract is considered to be located in central city if its distance to the CBD is within the top quartile among all the tracts in this MSA. $\frac{non-centralindustrialtracts}{totaltracts}$ is the ratio between the number of non-central industrial affected tracts and that of total tracts of the MSA. $Manufactureratio_{77}$ is manufacture employment share in 1977. The first four columns report results on unweighted regressions and the last four report results on regressions weighted by the total number of census tracts of each MSA. Full control includes historical population level, census division dummies, physical geography and socioeconomic controls used in Duranton and Turner (2012). SE clustered at census division level.

Figure 5: Industrial zones, productivity amenity alignment and urban growth



Notes UL: Y axis: Correlation between the estimated productivity and amenity parameters for FIRE workers or manufacture workers, X axis: the share of central industrialized tracts in total tracts, with central defined as top quartile in distance to the CBD; UR: Y axis: Correlation between the estimated productivity and amenity parameters for FIRE workers or manufacture workers, X axis: the share of central industrialized tracts in total industrial tracts; ML: Y axis: growth in urban employment from 1983 to 2003, X axis: the share of central industrialized tracts in total tracts; MR: Y axis: growth in urban employment from 1983 to 2003, X axis: the share of central industrialized tracts in total industrial tracts; LL: Y axis: growth in urban employment from 1983 to 2003, X axis: Correlation between the estimated productivity and amenity parameters for FIRE workers; LR: Y axis: growth in urban employment from 1983 to 2003, X axis: Correlation between the estimated productivity and amenity parameters for manufacture workers.

Table 11: Assumed parameters of model

Parameter	Definition	Value
$1-\beta$	Consumer expenditure share in land	0.25
$1-\alpha$	Firm expenditure share in land	0.2
ϵ	Frechet Shape parameter	6.83
κ	Semi-elasticity of commuting cost on travel time	0.01
λ	Production externalities elasticity	0.07
δ	Production externalities spatial decay	0.36
η	Residential externalities elasticity	0.15
ρ	Residential externalities spatial decay	0.75

Notes From Ahlfeldt, Redding, Sturm, and Wolf (2015) [1]

Figure 6: Perceived quality-of-life by FIRE and manufacture workers around Manhattan, 2010

New York (Manhattan)
Amenities perceived by FIRE workers

New York (Manhattan)
Amenities perceived by manufacture workers

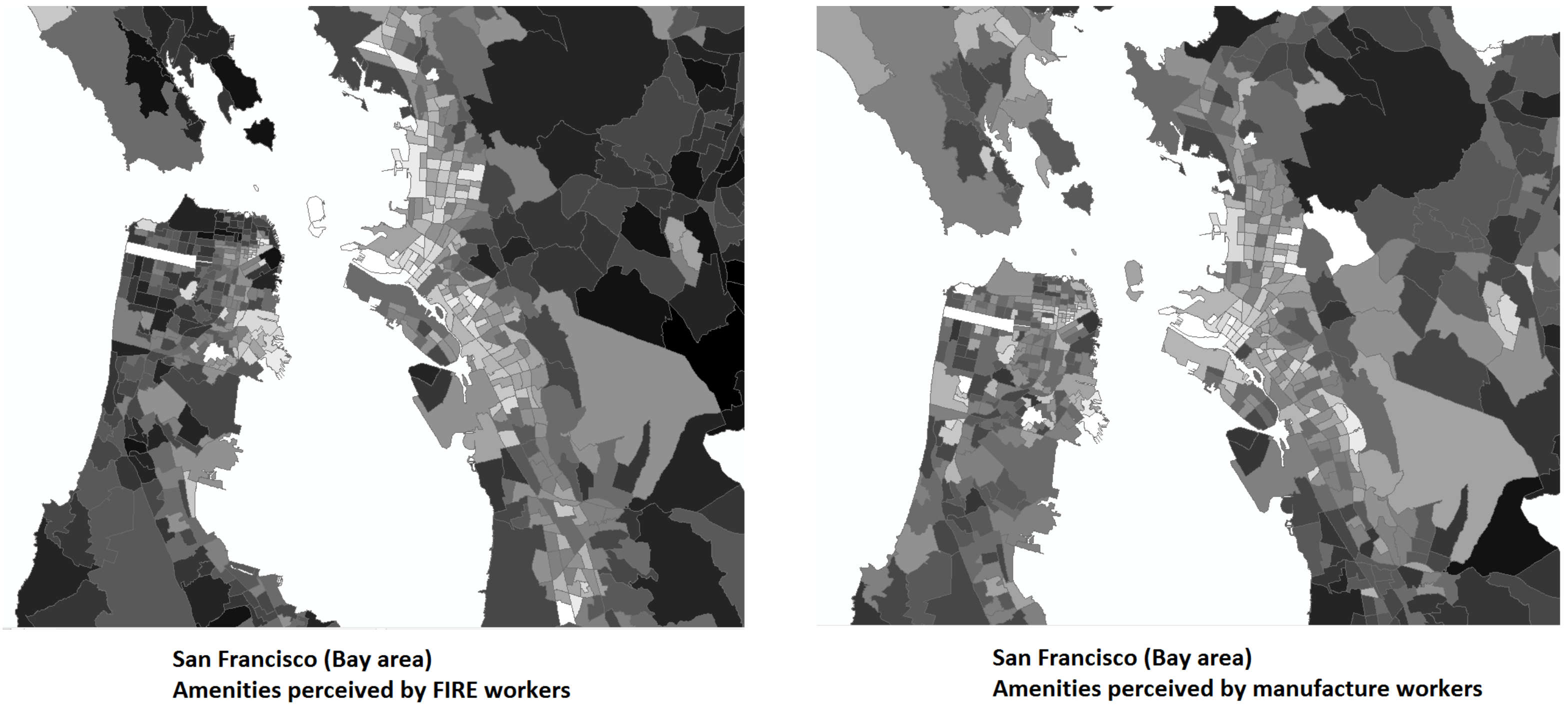
Notes Figure 1.(A) maps the perceived amenity by FIRE workers in 2000 around Manhattan, New York. Figure 1.(B) maps the perceived amenity by manufacture workers in 2000 in the same area. Perceived amenity is defined in equation (22), with H_{Ris} standing for the number of FIRE/Manufacture workers at residence and $\tilde{w_{ps}}$ standing for adjusted FIRE/Manufacture wages.

Figure 7: Perceived quality-of-life by FIRE and manufacture workers in Detroit, 2000

Detroit: Amenities perceived by FIRE workers **Detroit: Amenities perceived by manufacture workers**

Notes Figure 2.(A) maps the perceived amenity by FIRE workers in 2010 in Detroit. Figure 2.(B) maps the perceived amenity by manufacture workers in 2000 in Detroit. Perceived amenity is defined in equation (22), with H_{Ris} standing for the number of FIRE/Manufacture workers at residence and $\tilde{w_{ps}}$ standing for adjusted FIRE/Manufacture wages.

Figure 8: Perceived quality-of-life by FIRE and manufacture workers in the San Fransisco Bay Area, 2000

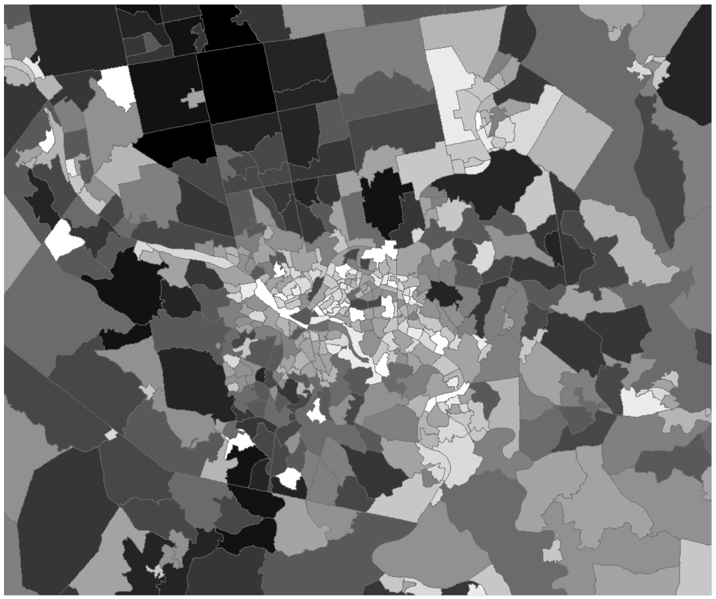


Notes Figure 3.(A) maps the perceived amenity by FIRE workers in 2010 in the San Fransisco Bay Area. Figure 3.(B) maps the perceived amenity by manufacture workers in 2010 in the San Fransisco Bay Area. Perceived amenity is defined in equation (22), with H_{Ris} standing for the number of FIRE/Manufacture workers at residence and $\tilde{w_{ps}}$ standing for adjusted FIRE/Manufacture wages.

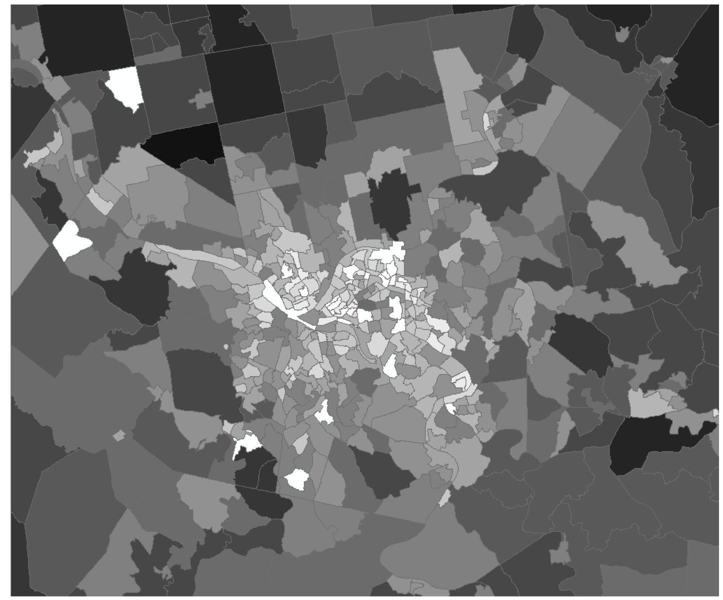
Figure 9: Perceived quality-of-life by FIRE and manufacture workers in Chicago, 2000

Notes Figure 4.(A) maps the perceived amenity by FIRE workers in 2010 in Chicago. Figure 4.(B) maps the perceived amenity by manufacture workers in 2010 in Chicago. Perceived amenity is defined in equation (22), with H_{Ris} standing for the number of FIRE/Manufacture workers at residence and $\tilde{w_{ps}}$ standing for adjusted FIRE/Manufacture wages.

Figure 10: Perceived quality-of-life by FIRE and manufacture workers in Pittsburgh, 2000



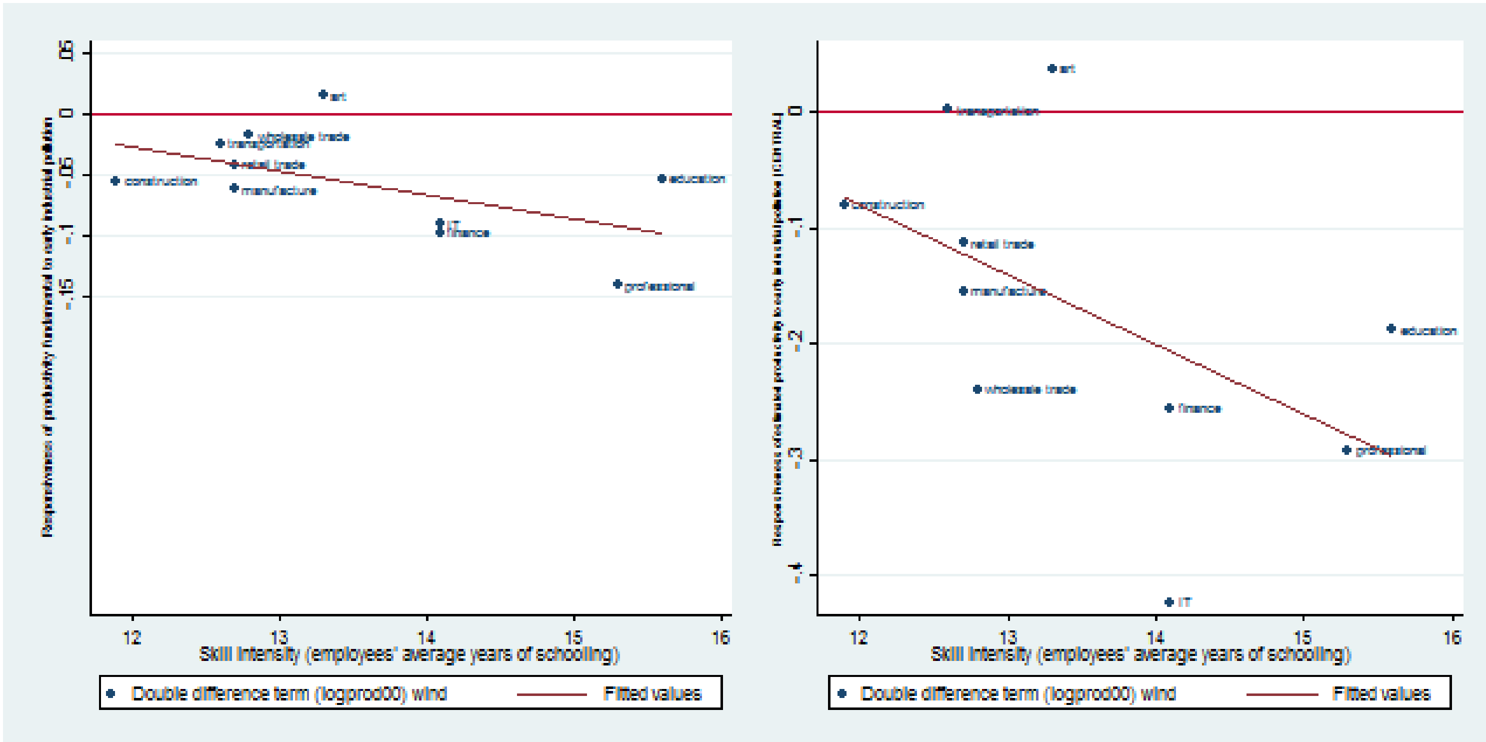
Pittsburgh: Amenities perceived by FIRE workers



Pittsburgh: Amenities perceived by manufacture workers

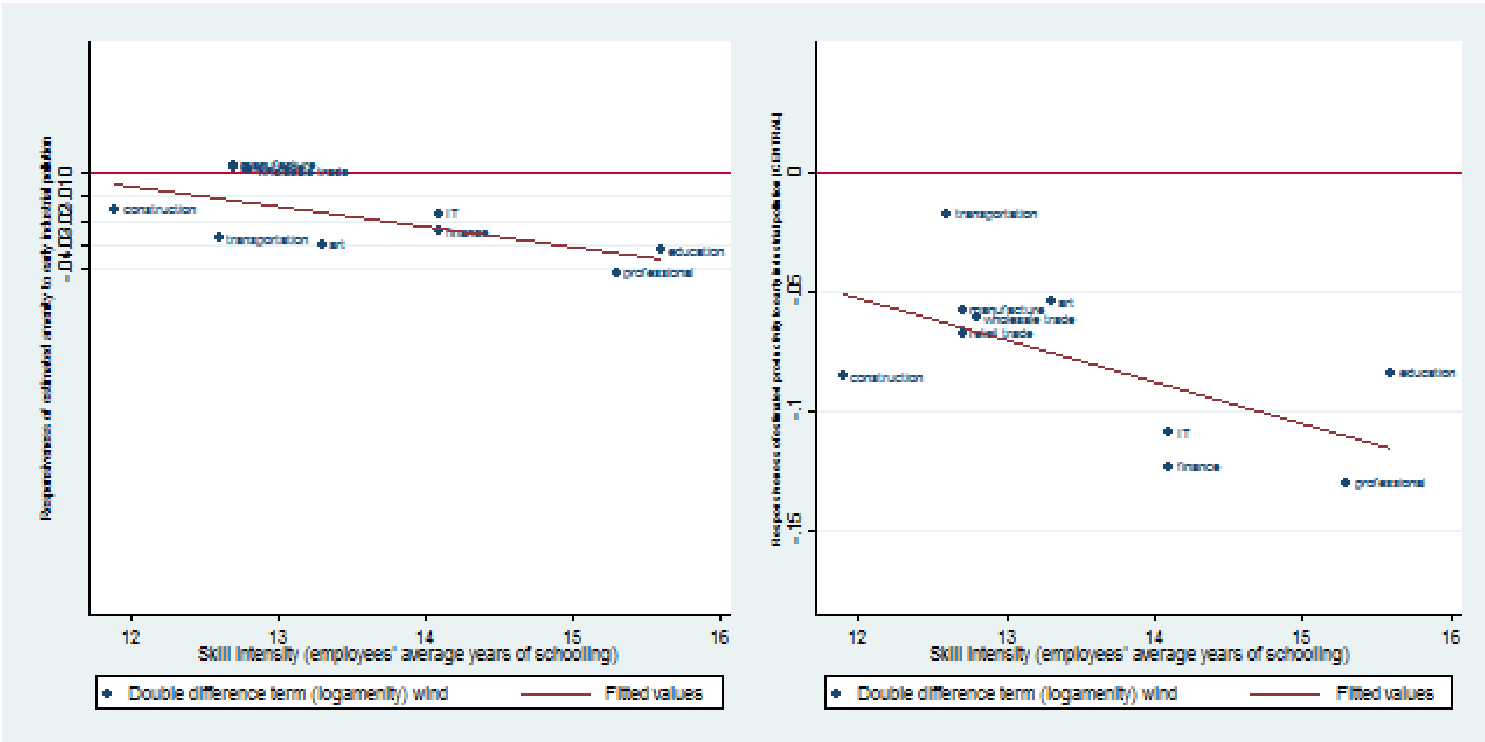
Notes Figure 5.(A) maps the perceived amenity by FIRE workers in 2010 in Pittsburgh. Figure 4.(B) maps the perceived amenity by manufacture workers in 2010 in Pittsburgh. Perceived amenity is defined in equation (22), with H_{Ris} standing for the number of FIRE/Manufacture workers at residence and $\tilde{w_{ps}}$ standing for adjusted FIRE/Manufacture wages.

Figure 11: Impacts of early pollution exposure on 2000 estimated sectoral productivity parameters



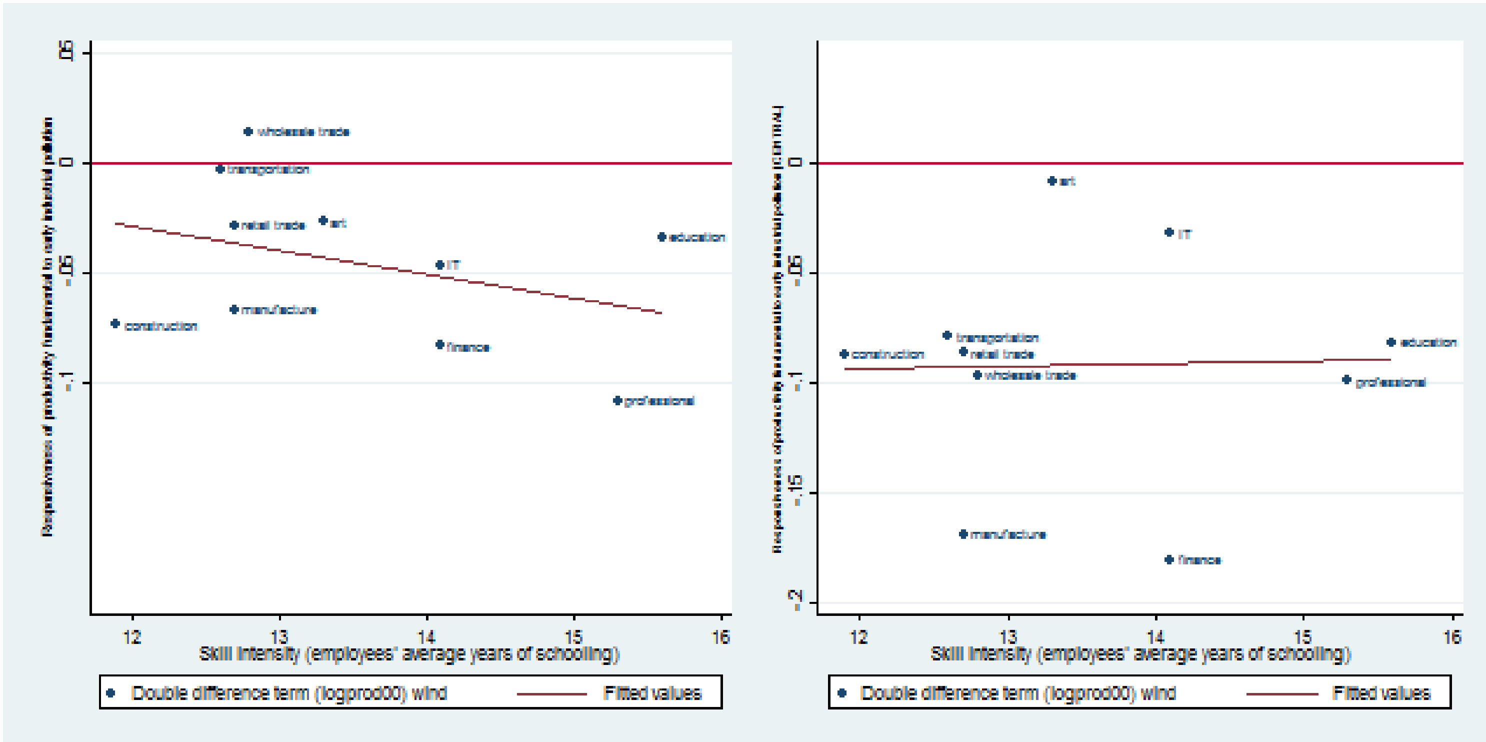
Notes Figure 11(A) maps the impacts of 1970 pollution exposure on industry-specific aggregate productivity in 2000 to the skill intensity of these industries. The y-axis shows the estimated coefficients of the interaction term of 0-4 km distance buffer to the 1970 industrial areas and a dummy of being downwind to them) where the LHS variables are industry-specific productivity parameters estimated from my structural model. The sample is limited to census tracts that are closest to industrial areas with pollution intensity above the median. The x-axis plots the skill intensity of each industry proxied by the average years of schooling of their employees. Figure 11(B) is the same except that the triple difference estimates are obtained in a sample of tracts within the central city.

Figure 12: Impacts of early pollution exposure on 2000 estimated sectoral amenity parameters



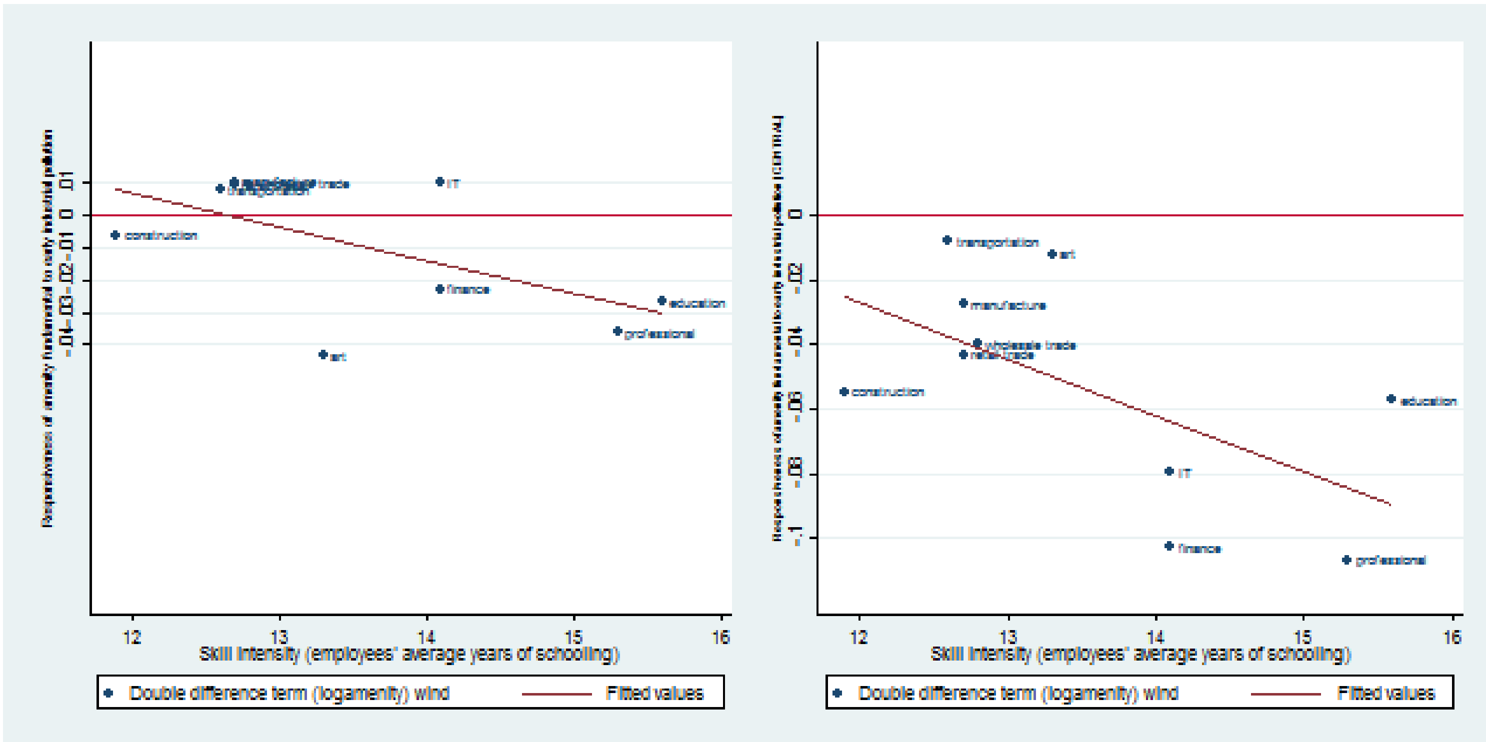
Notes Figure 13(A) maps the impacts of 1970 pollution exposure on industry-specific aggregate productivity in 2000 to the skill intensity of these industries. The y-axis shows the estimated coefficients of the interaction term of 0-4 km distance buffer to the 1970 industrial areas and a dummy of being downwind to them where the LHS variables are industry-specific amenity parameters estimated from my structural model.The sample is limited to census tracts that are closest to industrial areas with pollution intensity above the median. And the x-axis plots the skill intensity of each industry proxied by the average years of schooling of their employees. Figure 13(B) is the same except that the triple difference estimates are obtained in a sample of tracts within the central city.

Figure 13: Impacts of early pollution exposure on 2000 estimated sectoral production fundamental parameters



Notes Figure 13(A) maps the impacts of 1970 pollution exposure on industry-specific aggregate productivity in 2000 to the skill intensity of these industries. The y-axis shows the estimated coefficients of the interaction term of 0-4 km distance buffer to the 1970 industrial areas and a dummy of being downwind to them where the LHS variables are industry-specific production fundamental parameters estimated from my structural model. Production fundamentals are defined as aggregate productivity divided by a workplace agglomeration intensity function. The sample is limited to census tracts that are closest to industrial areas with pollution intensity above the median. The x-axis plots the skill intensity of each industry proxied by the average years of schooling of their employees. Figure 13(B) is the same except that the triple difference estimates are obtained in a sample of tracts within the central city.

Figure 14: Impacts of early pollution exposure on 2000 estimated sectoral residential fundamental parameters



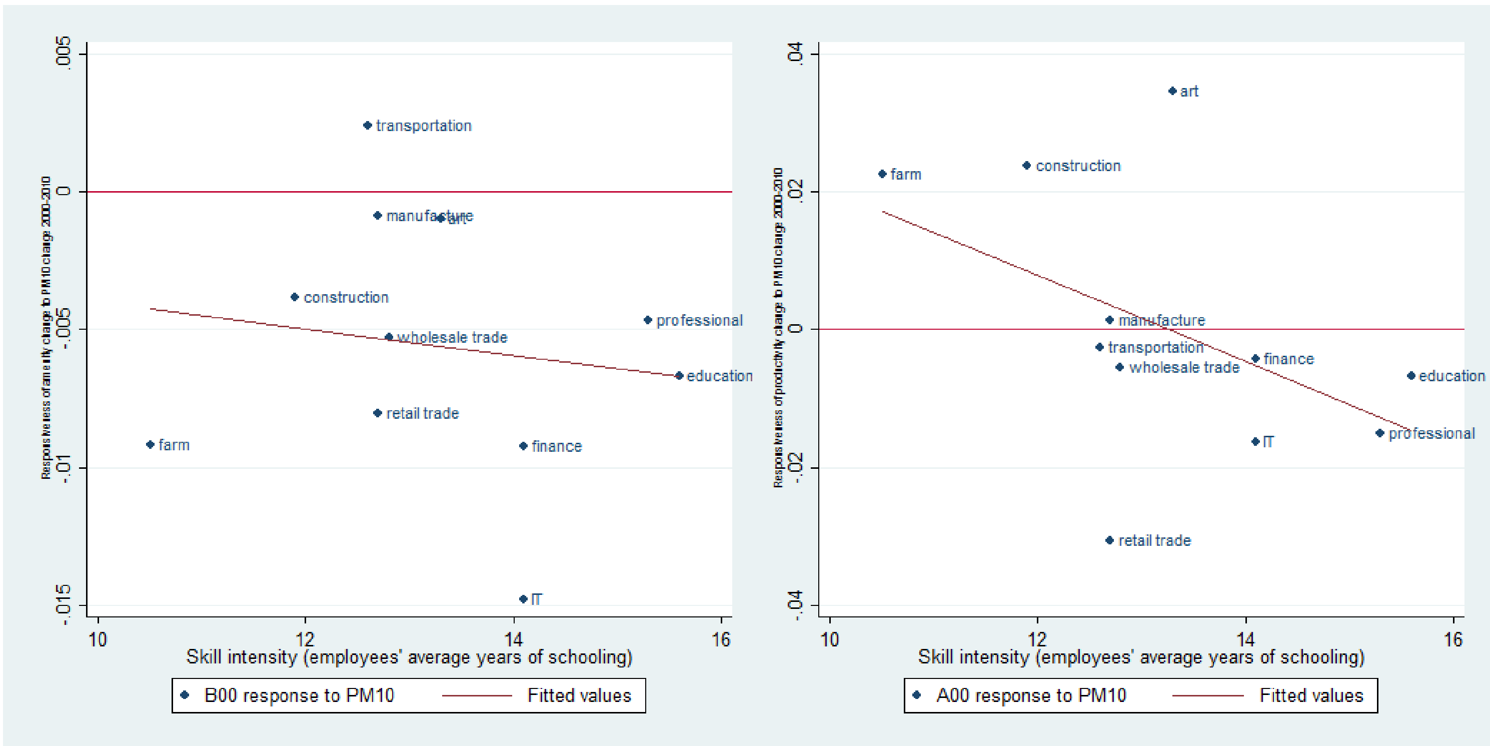
Notes Figure 14(A) maps the impacts of 1970 pollution exposure on industry-specific aggregate productivity in 2000 to the skill intensity of these industries. The y-axis shows the estimated coefficients of the interaction term of 0-4 km distance buffer to the 1970 industrial areas and a dummy of being downwind to them where the LHS variables are industry-specific residential fundamental parameters estimated from my structural model. Residential fundamentals are defined as aggregate productivity divided by a residence agglomeration intensity function. The sample is limited to census tracts that are closest to industrial areas with pollution intensity above the median. The x-axis plots the skill intensity of each industry proxied by the average years of schooling of their employees. Figure 14(B) is the same except that the triple difference estimates are obtained in a sample of tracts within the central city.

Table 12: Change in amenity and productivity from 2000 to 2010

Industries	FIRE	IT	Edu Med	Professional	Public admin	Art Entertain	Manufacture	Wholesale	Retail	Utility
				Change in log aggregate amenity from 2000 to 2010						
$\Delta PM10$	-0.00923*	-0.0148*	-0.00667**	-0.00466*	-0.00488*	-0.00099	-0.0008	-0.0053	-0.0081	-0.00241
	(0.00556)	(0.00769)	(0.0029)	(0.00245)	(0.00289)	(0.00478)	(0.00653)	(0.0043)	(0.00619)	(0.00444)
Public Schools	0.0195***	0.00496	0.0140**	0.0146**	0.00983**	0.00719	0.0116**	0.0117*	0.00553	0.00762
	(0.00514)	(0.00580)	(0.00632)	(0.00651)	(0.00492)	(0.00490)	(0.00491)	(0.00618)	(0.00394)	(0.00525)
Observations	2,294	1,882	2,653	2,630	2,204	2,400	2,368	2,067	2,396	2,274
0.792	0.844	0.734	0.730	0.826	0.936	0.817	0.744	0.923	0.811	
				Change in log aggregate productivity from 2000 to 2010						
$\Delta PM10$	-0.00427	-0.0692	-0.0068	-0.0150	0.0170	0.0346	0.00139	-0.00544	-0.0307	-0.00206
	(0.0200)	(0.0844)	(0.0083)	(0.0189)	(0.0198)	(0.0269)	(0.0120)	(0.0268)	(0.0264)	(0.00191)
Public Schools	0.00657	0.0200	0.0537	0.000358	0.0164	0.0232	0.00370	-0.0185	-0.0104	-0.00402
	(0.0130)	(0.0219)	(0.0631)	(0.0231)	(0.0170)	(0.0258)	(0.0221)	(0.0244)	(0.0174)	(0.0203)
Observations	1,982	1,127	2,298	2,170	1,572	1,632	2,072	1,873	2,049	1,718
R-squared	0.088	0.085	0.154	0.171	0.114	0.119	0.151	0.109	0.078	0.104

Notes Dependent variables in the upper panel are the log changes in aggregate amenity perceived by workers from different sectors from 2000 to 2010, defined by equation (22). Dependent variables in the upper panel are the log changes in aggregate productivity of different sectors from 2000 to 2010, defined by equation (18). Only tracts within 2 km to a PM10 monitor station are kept in the sample. MSA fixed effects are controlled for. SE clustered at MSA level.

Figure 15: Responses of changes in productivity and amenity to PM10 changes (2000-2010)



Notes Figure 15(A) maps the impacts of pollution reduction on industry-specific aggregate productivity changes from 2000 to 2010 to the skill intensity of these industries. The y-axis shows the estimated coefficients of the regression specified in equation (25), where the LHS variables are industry-specific productivity parameters changes and RHS variable is the instrumented PM10 change from 2000-2010. And the x-axis plots the skill intensity of each industry proxied by the average years of schooling of their employees. Figure 15(B) is the same except that the triple difference estimates are obtained in a sample of tracts within the central city.

A Evidence from the Clean Air Act of 1970

The empirical part of the main text has presented evidence of the importance of environmental amenities in shaping urban skill composition and growth. In this section, I complement the previous cross-sectional evidence with time-series evidence of the effects of pollution reduction on short to mid long distribution of skills.

In particular, I examine how the sharp reductions in TSPs induced by the 1970 Clean Air Act Amendments (CAAA) contribute to subsequent employment growth in different sectors. I find larger CAAA-induced improvement in air quality to be associated with higher employment growth, especially in skilled sectors in the following two decades. These findings are again consistent with both adverse impacts of pollution on development of high-skilled sectors in cities and reinforcing agglomeration forces as an important mechanism behind these impacts.

The 1970 passage of the Clean Air Act Amendments (CAAA) has been extensively studied by Greenstone (2002) [32] and Chay and Greenstone (2003) [16] as a natural experiment that leads to plausibly exogenous variation in TSPs reductions across counties with different "attainment" status in the mid-1970s. The legislation imposed strict regulations on industrial polluters in "nonattainment" counties with TSPs concentrations exceeding the federal ceiling. I follow the literature and use nonattainment status as an instrumental variable for TSPs reductions to estimate their impacts on future employment growth. More specifically, to evaluate the benefits of pollution reduction at smaller geographical units, I exploit local regulators' incentives to target the areas around monitors that are most likely to keep the county out of attainment. The National Ambient Air Quality Standard (NAAQS) for TSP not only stipulated the maximum level of the TSP annual average but also required the daily reading of TSP concentration not to exceed a particular level more than once per year. Under normal circumstances, a county is designated to be out of attainment if at least one of the monitors within the county had daily TSP concentration exceeding both standards [16]. Therefore, two bad days in a year would be enough to bring a monitor/county out of attainment, which creates some randomness in regulatory stringency conditional on the initial level of pollution.

I capture the differential enforcement of CAAA within nonattainment county by assigning nonattainment status to each monitor within a county. To carefully examine the potential effects of nonattainment status on further pollution cut, I run the following specification on

[16] The level of the standard was to be compared to measurements made at sites that represent "community-wide air quality" recording the highest level, or, if specific requirements were satisfied, to average measurements from multiple community-wide air quality monitoring sites ("spatial averaging"); 36 FR 8186 Apr 30, 1971

an annual panel of TSP readings from around 5000 TSP monitors across the US with TSP readings during the 1970s.

$$\Delta TSP_{i,t}^{j} = \alpha_1 CountyNonAtt_{j,t} + \alpha_2 MonitorNonAtt1_{i,t}^{j} + \alpha_3 MonitorNonAtt2_{i,t}^{j} + \theta_t + \Delta\epsilon_{i,t} \quad (26)$$

where $\Delta TSP_{i,t}^{j}$ is the change in TSP readings from year $t-1$ to year t, at monitor i in county j, $MonitorNonAtt1_{i,t}^{j}$ is a dummy that takes one if the average annual TSP reading of monitor i in year $t-1$ in county j exceeds $75\mu g/m^3$, effectively breaking the first NAAQS standard. $MonitorNonAtt2_{i,t}^{j}$ is a dummy that takes one if the second highest TSP reading in year $t-1$ at monitor i from county j exceeds $260\mu g/m^3$, effectively breaking the second NAAQS standard. $CountyNonAtt_{j,t}$ is the county level nonattainment status in year t for county j.[17]

It is evident from Table A11 that county level nonattainment status plays little role in the changes of TSP conditional on monitor level nonattainment status. The first four columns, consistent with the findings of Chay and Greenstone (2003), suggest that both counties in and out of attainment exert similar efforts in pollution reduction before 1974, and the differential enforcement of CAA only occurs after 1974. The last column also indicates that after controlling for a polynomial of previous year average TSP reading, both monitor level nonattainment statuses (exceeding the annual average threshold and exceeding the second highest reading threshold) have significant impacts on further TSP reduction, although the effect is much larger for nonattainment based on the second highest reading throughout the year. As a result, to minimize the concerns of mean reversion in pollution, I focus only on the nonattainment status that relies on the second highest reading. In another word, I am capturing the variation in pollution reduction induced by differential regulatory efforts as a result of two bad days in the past year, which is pretty random in nature.

As the outcomes are only observed in decades, I need to aggregate my specification (3) to the whole period spanning from 1974 to 1979 by adding up both sides of equation (3). The adjusted first stage of my instrumental variable specification is accordingly:

$$\Delta TSP_{ic}^{1979-1974} = \delta \bar{TSP}_{ic,1973-1976} + \beta N_i + X'_{ic,1970}\phi + \alpha_c + \epsilon_{ic}$$

where $\Delta TSP_{ic}^{1979-1974}$ is the change in TSP level from 1974 to 1979 at tract i, $\bar{TSP}_{ic,1973-1976}$ is the average TSP level from 1973 to 1976, and N_i is the share of nonattainment years from 1974 to 1977.

[17]The actual county level attainment status is not available before 1978, therefore I generate a predicted attainment status according to the rules, which assigns nonattainment status to a county once any monitors within the county breaks the rule.

The second stage examines the relationship between employment growth in different sectors and TSP reductions driven purely by CAAA regulation:

$$\Delta ln(y_{ic}^{1980-1970}) = \theta \Delta TSP_{ic}^{1979-1971} + X'_{ic,1970}\gamma + \alpha_c + \nu_{ic} \tag{27}$$

where $\Delta ln(y_{ic}^{1980-1970})$ is the log changes in outcome from 1970 to 1980. Only tracts within 2 kilometers to the closest TSP monitors with TSP concentration readings in the year 1980, 1970, 1974, 1975 and 1976 are kept in the sample. The measure of TSP concentration at a tract is the reading collected from its closest TSP monitor. To examine the long-run implications of improving air quality as a result of agglomeration forces, I also estimate an alternative specification of (4) where the left-hand side variable becomes $\Delta ln(y_{ic}^{1990-1980})$.

As shown in Table A12, the OLS estimation suggests that TSP changes from 1974 to 1979 has little correlation with the changes in employment during this period, which is likely to be biased upwards due to the fact that positive economic shocks can induce both employment growth and additional emission; and a negative pollution effect. The IV estimation, reported in Table A13, reveals a different pattern. It is indicated that the variation in TSP reduction driven purely by differential local regulation efforts, result in significant growth in employment during the same period, especially in finance, education, medical services, retail and communications. The lower panel of Table A13 reports the impacts of 1974 to 1979 TSP reduction on sectoral employment growth in the next decade. It is shown that smaller and marginally statistical significant effects are found in employment growth in similar high-skilled sectors from 1980 to 1990 as a result of 1974 to 1979 CAAA-induced TSP changes, which is again consistent with the idea that initial sorting of employment around environmental amenities remain persistent as a result of further agglomeration forces.

B Triple difference approach

B.1 Reduced form evidence

In the main text, I explore the variation in historical pollution driven by wind and topography patterns by interacting both wind and topography features with distance indicators. I also exploit the variation in the pollution intensity of historical industrial sites by splitting the sample into two according to the pollution intensity of industrial areas that each census tract is closest to, and find wind and topography conditions only matter for industrial areas with above-median pollution intensity. Another way to exploit both the variation in pollution intensity and wind/topography conditions is a triple difference design, by interacting the distance-to-industrial-areas indicators with the level of historical pollution of these areas and a dummy of downwind/same elevation, which takes the form of:

$$y_{ic} = \sum \mathrm{I_{ikm}} * TSP_m * Downwind_{im}\beta_{k_1} + \sum \mathrm{I_{ikm}} * Downwind_{im}\beta_{k_2} + \sum \mathrm{I_{ikm}} * \beta_{k3}$$
$$+ \sum \mathrm{I_{ikm}} * TSP_m\beta_{k_4} + \theta TSP_m + \gamma Downwind_{im} + \delta TSP_m * Downwind_{im} + X_i'\eta + \alpha_c + \epsilon_{ic} \tag{28}$$

where TSP_m is the average measure of total suspended particle reported by EPA from 1971-1979 around industrial area m, $Downwind_{im}$ is a dummy variable that takes value one if tract i is located in the downwind of industrial area m. Similarly, I assign average TSP reading from 1970-1979 of the closest monitor to industrial area m to be the pollution intensity of it (TSP_m) I drop industrial areas that are not within 2 kilometers to the closest monitor, which takes up about 30% in my sample. I standardize the TSP measures to be of mean zero and standard deviation one for ease of interpretation.

We can repeat the exercise with the same elevation dummy variable:

$$y_{ic} = \sum \mathrm{I_{ikm}} * TSP_m * Sameelevation_{im}\beta_{k_1} + \sum \mathrm{I_{ikm}} * Sameelevation_{im}\beta_{k_2} + \sum \mathrm{I_{ikm}} * \beta_{k3}$$
$$+ \sum \mathrm{I_{ikm}} * TSP_m\beta_{k_4} + \theta TSP_m + \gamma Sameelevation_{im} + \delta TSP_m * Sameelevation_{im} + X_i'\eta + \alpha_c + \epsilon_{ic} \tag{29}$$

Table A7 reports the estimated results. It is clear that being more exposed to 1970 industrial pollution due to downwind position translates into higher pollution level measured by average TSP reading from 1970-1979. The triple difference terms are negative over the board for most of my outcomes, apart from residential density. The patterns are quite comparable across variables counted at place of work and place of residence: early industrial pollution not only negatively affects the share of high-skilled workers who live in more exposed areas and their earnings, but also the share of skilled employees who work in more affected tracts. Median earnings of both workers who work and residents who live in dirtier tracts are lower. Housing prices and the share of college graduates are also lower in these tracts. It suggests that historically dirtier places are low in both productivity and amenity now. The coefficients on double difference terms of distance buffers to the closest industrial area and its historical pollution are negative and significant for most of the outcomes. But the signs and significance are mixed for coefficients on double difference terms of distance buffers and downwind dummy, which suggests that whatever the wind conditions are, being closer to an industrial area hurts, but being downwind to an industrial area only matters if this area is polluted enough.

Table A9 report results on growth from 1980 to 2000, following the same specifications. It is clear that tracts closer to 1970 industrial areas experience slower growth in total, manufacture, FIRE employment, median income, housing value and the number of college graduates in the subsequent two decades, and these negative growth effects are stronger if the relevant industrial areas are more polluted prior to 1980, and the tracts are more exposed due to downwind location to them. Since from 1980 onward the air quality around the US is improving greatly, and the improvement is greater in areas that are more heavily polluted initially[18], the negative growth impact is not caused by worsening air pollution, but more of a result of self-reinforcing agglomeration forces. Tracts that have been able to attract more educated workforce and residents due to better environmental amenities are able to attract more if educated people would like to live and work near other educated people.

To further analyze the dynamics of the agglomeration patterns, I look at the responses of outcomes from 1940 to 2010 to industrial pollution exposure around the 1970s[19].

The results are shown in Table **??**. Each cell reports the coefficient of a separate regression with the dependent variables being census outcomes from different years and the independent variable being the triple interaction term of distances to the closest industrial area, its correspondent pollution level and whether or not the tract locates downwind to it. For ease of interpretation, I condense four distance buffers into a single indicator of whether or not a tract is within 4 kilometers to the closest industrial area.

This coefficient is intended to capture the variation in historical industrial pollution independent of the initial industrial composition and socioeconomic characteristics of each tract. It is observed that the estimated coefficients are not only negative and significant for almost all of the outcomes after 1970, but they are getting larger in absolute value, indicating increasingly negative impacts of early industrial pollution over time on housing price, college share and log median household income. The biggest jump in outcomes between two consecutive censuses in adverse impacts of industrial pollution exposure occurs from 1980 to 1990, which is the accelerating period in the structural transformation process, with an astonishing 60% growth in service jobs over the decade [41]. A plausible interpretation is that with massive secular growth in the service sector, small differences in initial conditions could be significantly magnified because it is the period where service-based agglomerates were

[18] It is shown in the second column of Table A4 that tracts that are closer to more polluted industrial areas experience larger cut in pollution level from 1980 to 2000.

[19] Census outcomes from 1970 onwards are matched to 2010 tracts according to the Longitudinal Tract Database (LTDB) (Logan, Xu, and Stults, 2014) [37]. So all the distance measures are calculated based on 2010 tracts. Earlier tracts are not easily matched to 2010 tracts, so I calculate their distances to industrial areas/CBD/transportation lines/TSP monitors based on the geography of 1940/1950 tracts.

quickly forming, and the location choices of newly-added service jobs were highly dependent on earlier clustering of skills.

B.2 Impacts on structural estimates

C Placebo checks

One concern over specification (4) is that the location choice of early industrial sites might take into consideration of its pollution diffusion to nearby neighborhoods driven by wind patterns. More specifically, a potentially heavily polluted plant might avoid wealthy neighborhoods downwind if the latter can exert enough influence. However, before 1970, the public awareness of environmental issues is still in its incipience and probably not strong enough to alter the location decisions of industrial sites, especially because of their indirect environmental implication through wind patterns.

To confirm that the placement of early industrial sites does not weigh in the socioeconomic characteristics of downwind and upwind neighborhoods with much difference, I run a set of falsification tests, using the outcomes in 1940 and 1950. A problem with running the falsification tests using 1970s industrial areas directly is that some of these industrial sites might have been set up before 1970, or maybe even before 1940, and as a result we might capture partial early treatment effects in this specification. Table A15 present the results. I find tracts that are close to 1970 industrial areas tend to be denser but less educated regarding college graduates share, which could be driven by both selection bias or early partial treatment effects. However, the triple interaction terms of distance buffers with 1970 industrial area pollution level and downwind position are quite small and largely positive for 1950 median income and college share.

Table A1: Determinants of local amenity perceived by different sectors

VARIABLES	FIRE	IT	Edu Med	Professional	Public admin
violent crime rate	-0.0145***	-0.00725***	-0.00736***	-0.00707***	-0.00762***
	(0.00177)	(0.000876)	(0.000706)	(0.000744)	(0.000837)
$1(industrialarea)$	-0.238***	-0.155***	-0.127***	-0.137***	-0.0891***
	(0.0451)	(0.0265)	(0.0181)	(0.0252)	(0.0203)
disind<1km	-0.198***	-0.122***	-0.0984***	-0.112***	-0.0794***
	(0.0471)	(0.0277)	(0.0178)	(0.0247)	(0.0204)
disind$\in 1-2km$	-0.182***	-0.111***	-0.0982***	-0.109***	-0.0767***
	(0.0447)	(0.0278)	(0.0190)	(0.0235)	(0.0211)
disind$\in 2-3km$	-0.118***	-0.0921***	-0.0564***	-0.0823***	-0.0483**
	(0.0393)	(0.0273)	(0.0162)	(0.0230)	(0.0202)
disind$\in 3-4km$	-0.0883**	-0.0758***	-0.0417**	-0.0542***	-0.0358**
	(0.0374)	(0.0197)	(0.0171)	(0.0177)	(0.0163)
Public school	0.0146*	0.00584	0.0108**	0.00192	0.0144**
	(0.00761)	(0.00540)	(0.00454)	(0.00474)	(0.00552)
Distance to highway	9.18e-06	3.26e-06	6.77e-06**	2.46e-06	8.83e-06**
	(5.71e-06)	(3.53e-06)	(2.72e-06)	(2.77e-06)	(4.09e-06)
Distance to the CBD	0.00523***	0.00358**	0.00341**	0.00275*	0.00444**
	(0.00157)	(0.00161)	(0.00169)	(0.00155)	(0.00170)
Dostance to railway	0.0269***	0.0195***	0.00901***	0.0124***	0.0124***
	(0.00739)	(0.00528)	(0.00294)	(0.00309)	(0.00409)
Distance to water	1.64e-07	-7.88e-07	8.80e-07	-8.85e-07	-4.45e-07
	(1.10e-06)	(6.83e-07)	(8.20e-07)	(6.50e-07)	(9.31e-07)
Beach	0.128***	0.266***	0.111**	0.130**	0.181***
	(0.0369)	(0.0222)	(0.0486)	(0.0567)	(0.0283)
Observations	3,450	3,373	3,469	3,468	3,428
	0.852	0.942	0.967	0.956	0.941

VARIABLES	Art Entertain	Manufacture	Wholesale	Retail	Utility
violate crime rate	-0.00464***	-0.04643***	-0.00851***	-0.00744***	-0.00306***
	(0.000430)	(0.000691)	(0.000809)	(0.000769)	(0.00105)
$1(industrialarea)$	-0.0329*	0.0136	-0.00951	-0.0588***	-0.0113
	(0.0186)	(0.0162)	(0.0204)	(0.0196)	(0.0265)
disind<1km	-0.0335*	-0.0134	-0.0252	-0.0641***	-0.0374
	(0.0171)	(0.0144)	(0.0191)	(0.0175)	(0.0278)
disind$\in 1-2km$	-0.0394**	-0.0324**	-0.0362**	-0.0643***	-0.0382
	(0.0189)	(0.0160)	(0.0176)	(0.0181)	(0.0339)
disind$\in 2-3km$	-0.0187	-0.0199	-0.0332*	-0.0387**	-0.0238
	(0.0161)	(0.0131)	(0.0187)	(0.0147)	(0.0271)
disind$\in 3-4km$	-0.00763	-0.000762	-0.0217	-0.0205	-0.0262
	(0.0155)	(0.0132)	(0.0161)	(0.0137)	(0.0288)
numpubsch00	0.00863***	0.00631	0.00841*	0.00571	0.00519
	(0.00301)	(0.00539)	(0.00455)	(0.00405)	(0.00471)
near_dist_hw	-1.07e-06	1.78e-06	-7.94e-07	3.29e-06	1.12e-05***
	(2.77e-06)	(2.97e-06)	(2.85e-06)	(2.61e-06)	(3.77e-06)
near_dist_cbd	0.00356**	0.00588***	0.00280	0.00285	0.00329
	(0.00142)	(0.00125)	(0.00244)	(0.00200)	(0.00216)
near_dist_rail12	0.00635**	0.00716*	0.00938***	0.00869***	0.0120**
	(0.00314)	(0.00360)	(0.00329)	(0.00259)	(0.00567)
near_dist_waterbody	1.14e-06**	-1.62e-07	-1.31e-06	-4.06e-07	-8.75e-07
	(5.37e-07)	(9.50e-07)	(9.05e-07)	(6.36e-07)	(1.45e-06)
beach	0.0997***	0.0313	0.0493	0.0428***	0.535***
	(0.0200)	(0.0633)	(0.0561)	(0.0149)	(0.0510)
Observations	3,465	3,457	3,379	3,467	1,610
	0.971	0.959	0.946	0.967	0.953

Notes Dependent variable is estimated amenity level in 2000 perceived by different sectors, defined in equation (22). Only tracts with 2000 crime rate data are kept. MSA fixed effects are controlled for. SE clustered at MSA level.

Table A2: Determinants of local amenity perceived by different sectors

VARIABLES	FIRE	IT	Edu Med	Professional	Public admin
PM10 2000	-0.0145***	-0.00574***	-0.00815***	-0.00545***	-0.0106***
	(0.00424)	(0.00187)	(0.00145)	(0.00186)	(0.00177)
$1(industrialarea)$	-0.226***	-0.112***	-0.123***	-0.130***	-0.0970***
	(0.0611)	(0.0312)	(0.0266)	(0.0309)	(0.0318)
disind<1km	-0.217***	-0.0933***	-0.120***	-0.128***	-0.100***
	(0.0612)	(0.0327)	(0.0279)	(0.0327)	(0.0326)
disind$\in 1-2km$	-0.162***	-0.0647**	-0.0920***	-0.116***	-0.0968***
	(0.0586)	(0.0307)	(0.0252)	(0.0287)	(0.0303)
disind$\in 2-3km$	-0.155**	-0.0476	-0.0603**	-0.111***	-0.0760**
	(0.0682)	(0.0368)	(0.0272)	(0.0330)	(0.0344)
disind$\in 3-4km$	-0.00872	0.00505	-0.00790	-0.0183	0.00770
	(0.0540)	(0.0258)	(0.0230)	(0.0237)	(0.0261)
Public school	0.0400***	0.0106**	0.0188***	0.0146***	0.0196***
	(0.00855)	(0.00458)	(0.00397)	(0.00397)	(0.00460)
Distance to highway	8.34e-06**	4.51e-06**	3.42e-06*	2.99e-06*	4.98e-06**
	(3.67e-06)	(2.26e-06)	(1.82e-06)	(1.77e-06)	(2.23e-06)
Distance to the CBD	-0.000128	-0.000338	-0.000228	-0.000279	-0.000557
	(0.000426)	(0.000513)	(0.000447)	(0.000461)	(0.000603)
Distance to railway	0.0117	0.00447	0.00360	0.00472	0.00170
	(0.00856)	(0.00701)	(0.00339)	(0.00390)	(0.00394)
Distance to water	-2.54e-06*	-9.05e-07	-6.07e-07	-1.02e-06*	-9.55e-07
	(1.44e-06)	(7.47e-07)	(6.20e-07)	(5.99e-07)	(7.86e-07)
Observations	5,236	5,027	5,264	5,260	5,194
R-squared	0.921	0.977	0.984	0.981	0.976

VARIABLES	Art Entertain	Manufacture	Wholesale	Retail	Utility
PM10 2000	-0.00465**	-0.00571**	-0.00590**	-0.00767***	-0.00536**
	(0.00217)	(0.00258)	(0.00243)	(0.00185)	(0.00222)
$1(industrialarea)$	-0.0660***	-0.0161	-0.0534*	-0.0769***	-0.0189
	(0.0236)	(0.0244)	(0.0285)	(0.0283)	(0.0377)
disind<1km	-0.0780***	-0.0573**	-0.0813***	-0.101***	-0.0675*
	(0.0250)	(0.0248)	(0.0286)	(0.0282)	(0.0353)
disind$\in 1-2km$	-0.0779***	-0.0875***	-0.0837***	-0.101***	-0.0522
	(0.0204)	(0.0238)	(0.0272)	(0.0265)	(0.0342)
disind$\in 2-3km$	-0.0715***	-0.0528**	-0.0470*	-0.0755***	-0.0607*
	(0.0239)	(0.0221)	(0.0247)	(0.0248)	(0.0346)
disind$\in 3-4km$	-0.0250	-0.0173	-0.0187	-0.0133	-0.0206
	(0.0194)	(0.0256)	(0.0254)	(0.0229)	(0.0339)
Public school	0.0173***	0.0140***	0.0170***	0.0156***	0.0277***
	(0.00357)	(0.00402)	(0.00445)	(0.00359)	(0.00616)
Distance to highway	4.51e-06**	3.24e-06	3.36e-06	3.28e-06	6.19e-06***
	(2.09e-06)	(2.24e-06)	(2.39e-06)	(2.00e-06)	(2.17e-06)
Distance to the CBD	-0.000128	-0.000338	-0.000228	-0.000279	-0.000557
	(0.000426)	(0.000513)	(0.000447)	(0.000461)	(0.000603)
Distance to railway	0.00463	-0.00278	0.00162	0.00427	-0.00276
	(0.00357)	(0.00366)	(0.00597)	(0.00326)	(0.00314)
Distance to water	-6.90e-07	-4.53e-07	-6.14e-07	-1.07e-06*	-8.00e-07
	(7.03e-07)	(7.02e-07)	(7.51e-07)	(6.41e-07)	(8.72e-07)
Observations	5,258	5,233	5,114	5,260	5,247
R-squared	0.988	0.979	0.976	0.984	0.952

Notes Dependent variable is estimated amenity level in 2000 perceived by different sectors, defined in equation (22). Only tracts within 2 km to a PM10 monitor station are kept in the sample. MSA fixed effects are controlled for. SE clustered at MSA level.

Table A3: Correlation between industrial area proximity and other outcomes

VARIABLES	PM102000	PM growth 80-00	Brownfields	Toxic release inventories	Age of house in 1970	Share house no kitchen	Predicted change jobs 70-00
1($industrialarea$)	0.0628**	-0.0178	0.226***	0.720***	0.514	0.00407***	-0.0997***
	(0.0275)	(0.0454)	(0.0357)	(0.104)	(0.524)	(0.00141)	(0.0101)
disind<1km	0.0578**	-0.0302	0.0322	-0.0751	0.0186	0.00238*	-0.0529***
	(0.0284)	(0.0436)	(0.0339)	(0.106)	(0.438)	(0.00126)	(0.00985)
disind$\in 1-2km$	0.0487*	-0.00914	0.0193	-0.202*	-0.124	0.000464	-0.0246***
	(0.0273)	(0.0397)	(0.0287)	(0.113)	(0.398)	(0.00115)	(0.00848)
disind$\in 2-3km$	0.0371	0.0186	0.0152	-0.0572	-0.107	-0.000912	-0.0168***
	(0.0247)	(0.0342)	(0.0216)	(0.126)	(0.348)	(0.000878)	(0.00611)
disind$\in 3-4km$	0.00931	0.0105	-0.00586	-0.115	-0.344	-0.000721	0.00263
	(0.0189)	(0.0276)	(0.0165)	(0.111)	(0.321)	(0.000942)	(0.00538)
Observations	10,266	9,145	38,574	5,560	9,262	9,234	35,189
R-squared	0.632	0.350	0.041	0.128	0.330	0.172	0.360

Notes PM102000 is the level of PM10 reading recorded in 2000. PM growth 80-00 is defined as log(PM10,2000)-log(TSP,1980), where PM10 and TSP are normalized. Brownfields are the number of brownfield sites that require cleanup reported by Cleanups in My Community (CIMC) currently. Toxic release inventories are the number of Toxic release inventories (TRI) in 2000 published by the EPA. Predicted change jobs 70-00 is a Bartik-style predicted change in the number of jobs at each tract based on their industrial composition in 1970 and national trend in industrial employment growth from 1970 to 2000 in 41 sectors.

Table A4: Correlation between industrial area proximity and other outcomes

VARIABLES	PM102000	PM growth 80-00	Brownfields	Toxic release inventories	Age of house in 1970	Share house no kitchen	Predicted change jobs 70-00
1($industrialarea$)	0.0279	-0.00469	0.336***	0.876***	0.526	0.00491**	-0.107***
	(0.0340)	(0.0449)	(0.0528)	(0.143)	(0.567)	(0.00243)	(0.0145)
disind<1km	0.0338	-0.0256	0.100*	0.0131	0.336	0.00392*	-0.0534***
	(0.0363)	(0.0443)	(0.0522)	(0.152)	(0.511)	(0.00218)	(0.0135)
disind$\in 1-2km$	0.0282	-0.0133	0.0846**	0.0364	0.306	0.00306*	-0.0178
	(0.0360)	(0.0428)	(0.0410)	(0.183)	(0.546)	(0.00180)	(0.0133)
disind$\in 2-3km$	0.0243	0.0153	0.0534	0.204	0.125	0.000499	-0.0117
	(0.0288)	(0.0355)	(0.0368)	(0.207)	(0.478)	(0.00159)	(0.00970)
disind$\in 3-4km$	0.0137	0.00186	0.0125	-0.0729	-0.0361	-0.000810	0.00830
	(0.0259)	(0.0341)	(0.0266)	(0.152)	(0.346)	(0.00136)	(0.00832)
TSP7179*1($industrialarea$)	0.0254**	-0.140***	0.116**	0.115**	0.353*	9.40e-05	-0.0193***
	(0.0100)	(0.00882)	(0.0453)	(0.0456)	(0.205)	(0.000454)	(0.00571)
TSP7179*disind<1km	0.00878	-0.117***	0.0422	0.109	0.467	0.000119	-0.00899**
	(0.00779)	(0.00560)	(0.0345)	(0.0686)	(0.313)	(0.000478)	(0.00449)
TSP7179*disind$\in 1-2km$	0.0134*	-0.116***	0.0958	-0.0945	0.303	0.000621	-0.00512
	(0.00803)	(0.0120)	(0.0619)	(0.129)	(0.231)	(0.000581)	(0.00361)
TSP7179*disind$\in 2-3km$	0.0133	-0.112***	0.0498*	0.0878	1.924***	0.00141*	-0.00908
	(0.00811)	(0.0178)	(0.0283)	(0.162)	(0.286)	(0.000769)	(0.00669)
TSP7179*disind$\in 3-4km$	0.00340	-0.112***	0.0137	-0.144	0.741*	0.000108	-0.00331
	(0.00953)	(0.0186)	(0.0209)	(0.121)	(0.410)	(0.00116)	(0.00462)
Observations	7,271	6,998	19,971	3,087	4,430	4,409	18,787
R-squared	0.635	0.516	0.049	0.161	0.387	0.211	0.397

Table A5: Determinants of local amenity perceived by workers from different sectors

VARIABLES	FIRE	IT	Edu Med	Professional	Public admin	Art entertain
$1(industrialarea)$	-0.186***	-0.100***	-0.0924***	-0.0972***	-0.0824***	-0.0410***
	(0.0208)	(0.0118)	(0.0101)	(0.0106)	(0.0102)	(0.00865)
disind<1km	-0.219***	-0.107***	-0.1062***	-0.110***	-0.105***	-0.0646***
	(0.0224)	(0.0131)	(0.0101)	(0.0118)	(0.0129)	(0.00942)
disind$\in 1-2km$	-0.153***	-0.0731***	-0.0765***	-0.0811***	-0.0822***	-0.0509***
	(0.0223)	(0.0125)	(0.0116)	(0.0132)	(0.0123)	(0.00977)
disind$\in 2-3km$	-0.104***	-0.0530***	-0.0504***	-0.0582***	-0.0562***	-0.0402***
	(0.0218)	(0.0144)	(0.0108)	(0.0133)	(0.0129)	(0.00985)
disind$\in 3-4km$	-0.0370**	-0.0216***	-0.0239***	-0.0222***	-0.0305***	-0.0269***
	(0.0147)	(0.00818)	(0.00635)	(0.00764)	(0.00767)	(0.00540)
Public school	0.0503***	0.0290***	0.0278***	0.0206***	0.0287***	0.0236***
	(0.00406)	(0.00277)	(0.00200)	(0.00247)	(0.00176)	(0.00161)
Distance to highway	4.37e-07	3.87e-08	4.41e-07	-5.96e-07	9.72e-07	4.88e-07
	(1.18e-06)	(7.02e-07)	(6.09e-07)	(6.55e-07)	(6.75e-07)	(6.36e-07)
Distance to the CBD	0.00728***	0.00488***	0.00591***	0.00451***	0.00592***	0.00541***
	(0.000829)	(0.000436)	(0.000479)	(0.000533)	(0.000446)	(0.000450)
Beach	0.212***	0.0797**	0.0866***	0.0803***	0.0947***	0.0885***
	(0.0566)	(0.0316)	(0.0270)	(0.0284)	(0.0300)	(0.0259)
Distance to railway	0.00978***	0.00452*	0.00459**	0.00564***	0.00292	0.00316**
	(0.00366)	(0.00267)	(0.00190)	(0.00169)	(0.00216)	(0.00138)
Distance to water	-5.15e-07	-2.88e-07	5.20e-08	-9.28e-08	-3.14e-07	-1.26e-07
	(7.14e-07)	(4.20e-07)	(4.89e-07)	(4.25e-07)	(4.37e-07)	(3.64e-07)
Observations	32,790	31,605	32,962	32,900	32,683	32,770
R-squared	0.930	0.981	0.985	0.983	0.980	0.989

VARIABLES	Manufacture	Wholesale	Retail	Farming	Construction	Utility
$1(industrialarea)$	-0.0289***	-0.0735***	-0.0665***	-0.0591***	-0.0631***	-0.0498***
	(0.00873)	(0.00944)	(0.00899)	(0.0121)	(0.0101)	(0.00876)
disind<1km	-0.0816***	-0.111***	-0.0986***	-0.139***	-0.085***	-0.0732***
	(0.00880)	(0.00980)	(0.0103)	(0.0115)	(0.0117)	(0.00959)
disind$\in 1-2km$	-0.0739***	-0.0846***	-0.0780***	-0.121***	-0.082***	-0.0600***
	(0.00923)	(0.0114)	(0.0118)	(0.0118)	(0.0143)	(0.00983)
disind$\in 2-3km$	-0.0488***	-0.0604***	-0.0535***	-0.0791***	-0.0509***	-0.0506***
	(0.00917)	(0.0104)	(0.0114)	(0.0121)	(0.0117)	(0.00828)
disind$\in 3-4km$	-0.0310***	-0.0325***	-0.0272***	-0.0427***	-0.0347***	-0.0262***
	(0.00729)	(0.00736)	(0.00665)	(0.0105)	(0.00667)	(0.00751)
Public school	0.0278***	0.0264***	0.0252***	0.0388***	0.0301***	0.0293***
	(0.00204)	(0.00212)	(0.00187)	(0.00259)	(0.00182)	(0.00172)
Distance to highway	6.53e-07	9.19e-08	-4.05e-08	3.29e-06***	9.86e-07	8.31e-07
	(6.99e-07)	(6.57e-07)	(6.53e-07)	(7.41e-07)	(7.15e-07)	(6.52e-07)
Distance to the CBD	0.00765***	0.00591***	0.00643***	0.00642***	0.00711***	0.00580***
	(0.000545)	(0.000427)	(0.000541)	(0.000626)	(0.000574)	(0.000387)
Beach	0.0422	0.0772**	0.0797***	0.131***	0.0853***	0.0908***
	(0.0331)	(0.0316)	(0.0262)	(0.0454)	(0.0308)	(0.0334)
Distance to railway	-9.45e-05	0.00155	0.00316**	0.00108	0.00237	0.00179
	(0.00193)	(0.00285)	(0.00145)	(0.00158)	(0.00166)	(0.00194)
Distance to water	-6.49e-08	-2.38e-07	-1.03e-07	-8.95e-07	-2.87e-07	-7.56e-07*
	(4.22e-07)	(4.56e-07)	(4.52e-07)	(5.61e-07)	(5.52e-07)	(4.06e-07)
Observations	32,839	32,254	32,931	21,632	32,764	32,775
R-squared	0.982	0.980	0.985	0.932	0.981	0.980

Notes Dependent variable is estimated amenity level in 2000 perceived by workers from different sectors, defined in equation (22), with H_{Ris} standing for the number of workers from sector s at place of residence and $\tilde{w_{ps}}$ standing for adjusted wages of sector s at place of work. MSA fixed effects are controlled for. SE clustered at MSA level.

Table A6: Determinants of local productivity by different sectors

VARIABLES	FIRE	IT	Edu Med	Professional	Public admin	Art entertain
$1(industrialarea)$	0.0111	0.0126	0.0399***	0.0202***	0.0615***	0.00212
	(0.00794)	(0.0114)	(0.00709)	(0.00776)	(0.00914)	(0.00948)
disind<1km	-0.00252	0.0168	0.0342***	-0.0124	0.0549***	-0.0100
	(0.00825)	(0.0111)	(0.00786)	(0.00781)	(0.00863)	(0.0110)
disind$\in 1-2km$	0.000521	-0.0113	0.0175*	-0.0218**	0.0356***	-0.00304
	(0.00875)	(0.0114)	(0.00929)	(0.00895)	(0.00925)	(0.0115)
disind$\in 2-3km$	-0.0161*	-0.0155	0.0155*	0.00548	0.0317***	0.00943
	(0.00952)	(0.0152)	(0.00793)	(0.00909)	(0.0106)	(0.0118)
disind$\in 3-4km$	0.00715	0.0110	0.00633	0.00553	0.0268**	0.00794
	(0.0112)	(0.0140)	(0.00736)	(0.0121)	(0.0127)	(0.0136)
Public School	-0.00536***	-0.00681**	0.0284***	-0.00455**	-0.00718***	-0.0177***
	(0.00197)	(0.00295)	(0.00154)	(0.00195)	(0.00204)	(0.00206)
Distance to highway	-8.53e-07**	-1.57e-06**	-5.02e-07*	-7.46e-07*	-8.11e-07**	2.48e-07
	(3.86e-07)	(6.10e-07)	(3.04e-07)	(4.00e-07)	(3.95e-07)	(4.44e-07)
Distance to CBD	-0.00146***	-0.00199***	-0.00158***	-0.00103***	-0.00132***	-0.00226***
	(0.000285)	(0.000320)	(0.000280)	(0.000175)	(0.000231)	(0.000317)
Beach	-0.0168	0.0270	-0.0481	0.00835	0.0608	0.00724
	(0.0431)	(0.0544)	(0.0341)	(0.0395)	(0.0436)	(0.0424)
Distance to railway	0.00198**	0.00333***	-3.05e-05	0.00195**	4.55e-05	0.00205**
	(0.000897)	(0.00121)	(0.000883)	(0.000869)	(0.000875)	(0.000881)
Distance to water	-4.44e-08	-2.26e-07	-8.67e-08	-5.71e-08	-8.36e-08	1.33e-07
	(1.48e-07)	(1.66e-07)	(1.11e-07)	(1.65e-07)	(2.35e-07)	(1.77e-07)
Observations	29,106	20,723	32,681	30,397	23,498	27,201
R-squared	0.207	0.193	0.289	0.188	0.223	0.212

VARIABLES	Manufacture	Wholesale	Retail	Farming	Construction	Utility
$1(industrialarea)$	0.0279***	-0.000651	0.0358***	0.0239*	-0.0060*	0.0219**
	(0.00908)	(0.0119)	(0.00872)	(0.0136)	(0.0067)	(0.00855)
disind<1km	-0.0303***	-0.00916	0.00985	0.0361**	-0.0156*	0.00628
	(0.00976)	(0.0117)	(0.0108)	(0.0163)	(0.0076)	(0.00915)
disind$\in 1-2km$	-0.0202*	-0.00318	-0.00263	-0.00124	-0.0185**	-0.00363
	(0.0107)	(0.0125)	(0.0105)	(0.0192)	(0.0082)	(0.0117)
disind$\in 2-3km$	-0.0146	-0.00265	-0.00878	0.0387**	-0.0046	-0.00335
	(0.0109)	(0.0136)	(0.0123)	(0.0191)	(0.0085)	(0.0117)
disind$\in 3-4km$	-0.00487	0.0124	-0.00669	0.0306	0.0148	0.00184
	(0.0130)	(0.0165)	(0.0154)	(0.0222)	(0.0095)	(0.0135)
Publich School	-0.00605***	0.000406	-0.0123***	-0.0124***	-0.0068***	-0.00549**
	(0.00222)	(0.00257)	(0.00230)	(0.00350)	(0.00198)	(0.00218)
Distance to highway	-1.47e-06***	-7.66e-07	-1.17e-06***	-3.97e-07	-1.88e-06	-1.48e-06***
	(4.83e-07)	(5.13e-07)	(4.29e-07)	(5.10e-07)	(4.05e-07)	(4.24e-07)
Distance to CBD	0.000139	-0.000536*	-0.000893***	-0.000907***	-0.000424	-0.000753***
	(0.000359)	(0.000293)	(0.000241)	(0.000335)	(0.000265)	(0.000225)
Beach	0.0413	0.103*	-0.0446	0.0135	-0.00169	0.0539
	(0.0558)	(0.0529)	(0.0443)	(0.0462)	(0.0271)	(0.0409)
Distance to railway	0.00311**	0.00250*	0.00100	0.00263*	0.00147	0.00228**
	(0.00129)	(0.00133)	(0.00112)	(0.00160)	(0.00098)	(0.00103)
Distance to water	9.09e-08	-2.24e-07	-2.29e-09	-2.68e-07	-1.42e-07	5.16e-08
	(1.80e-07)	(2.59e-07)	(2.10e-07)	(2.57e-07)	(2.05e-07)	(1.44e-07)
Observations	26,870	23,170	26,365	13,214	13,214	24,394
R-squared	0.151	0.131	0.174	0.160	0.160	0.143

Notes Dependent variable is estimated productivity of different sectors in 2000, defined in equation (18). MSA fixed effects are controlled for. SE clustered at MSA level.

Table A7: The role of 1970 pollution: 2000 outcomes

	By place of work				By place of residence				
VARIABLES	1971-79 log TSP	Employ density	Highskill ratio	Median earning	Employ density	Highskill ratio	Median earning	Housing value	College ratio
IND1*TSP7179*Upwind	0.00904	-0.0890	-0.0158	-0.0183	0.0297	-0.0186**	-0.0712**	-0.108**	-0.0370**
	(0.0316)	(0.101)	(0.0162)	(0.0226)	(0.0594)	(0.00836)	(0.0286)	(0.0495)	(0.0163)
IND2*TSP7179*Upwind	0.0355	-0.114	-0.0179	-0.0172	-0.0645	-0.0200*	-0.0620***	-0.146***	-0.0423**
	(0.0359)	(0.162)	(0.0226)	(0.0198)	(0.0707)	(0.0109)	(0.0238)	(0.0460)	(0.0193)
IND3*TSP7179*Upwind	0.0303	-0.133	-0.0334*	-0.0319*	0.0240	-0.0180	-0.0165	-0.0750*	-0.0231
	(0.0325)	(0.114)	(0.0171)	(0.0193)	(0.0824)	(0.0111)	(0.0268)	(0.0445)	(0.0153)
IND4*TSP7179*Upwind	0.115**	-0.0250	0.0448	-0.103**	-0.00473	-0.0283	-0.0996	-0.0778	-0.0457
	(0.0561)	(0.370)	(0.0335)	(0.0430)	(0.274)	(0.0211)	(0.108)	(0.0957)	(0.0384)
IND1*TSP7179	0.136***	-0.101**	-0.00708	0.00169	-0.124***	-0.00846**	0.00612	0.0151	0.00470
	(0.0108)	(0.0454)	(0.00514)	(0.00673)	(0.0357)	(0.00396)	(0.0156)	(0.0239)	(0.0105)
IND2*TSP7179	0.104***	-0.0627	0.00211	-0.00322	-0.0855**	-0.00424	0.00767	0.0250	0.00691
	(0.0236)	(0.0572)	(0.00459)	(0.00753)	(0.0395)	(0.00288)	(0.0170)	(0.0252)	(0.0111)
IND3*TSP7179	0.101***	0.0153	0.00255	-0.00322	-0.00939	-0.00982*	-0.0191	-0.0113	-0.00933
	(0.0175)	(0.0489)	(0.00608)	(0.00665)	(0.0442)	(0.00547)	(0.0194)	(0.0255)	(0.00996)
IND4*TSP7179	0.0439*	-0.0998	-0.000489	0.00727	-0.104*	-0.000947	0.0207	0.0410	0.0171
	(0.0263)	(0.0676)	(0.00461)	(0.00797)	(0.0542)	(0.00197)	(0.0184)	(0.0253)	(0.0107)
IND1*Upwind	0.0186	-0.00178	0.0235	-0.00679	0.167	0.00714	0.0945**	-0.0150	0.0135
	(0.204)	(0.204)	(0.0241)	(0.0293)	(0.151)	(0.0143)	(0.0475)	(0.0689)	(0.0267)
IND2*Upwind	-0.102	-0.115	0.0230	-0.0453	0.155	0.00363	0.0844*	0.0106	0.0165
	(0.221)	(0.220)	(0.0251)	(0.0313)	(0.154)	(0.0167)	(0.0455)	(0.0747)	(0.0290)
IND3*Upwind	-0.0248	0.00929	0.0242	0.00107	-0.0207	0.000126	0.0132	-0.0663	-0.00561
	(0.257)	(0.255)	(0.0296)	(0.0364)	(0.187)	(0.0183)	(0.0544)	(0.0784)	(0.0309)
IND4*Upwind	0.525*	0.642**	0.0332	-0.0566	0.391**	0.000686	-0.0516	0.0193	0.0368
	(0.278)	(0.301)	(0.0276)	(0.0356)	(0.172)	(0.0160)	(0.0674)	(0.0716)	(0.0295)
IND1	0.0584**	0.516**	-0.0186	0.0168	0.239	-0.0412***	-0.205***	-0.255***	-0.105***
	(0.0292)	(0.220)	(0.0168)	(0.0240)	(0.193)	(0.00942)	(0.0329)	(0.0529)	(0.0198)
IND2	0.0435*	0.455**	-0.00562	-0.00315	0.287	-0.0259***	-0.165***	-0.201***	-0.0820***
	(0.0257)	(0.195)	(0.0144)	(0.0179)	(0.184)	(0.00871)	(0.0311)	(0.0432)	(0.0172)
IND3	0.00560	0.217	-0.000269	-0.00773	0.181	-0.0137*	-0.122***	-0.115**	-0.0539***
	(0.0194)	(0.135)	(0.0118)	(0.0183)	(0.132)	(0.00736)	(0.0324)	(0.0480)	(0.0196)
IND4	0.00913	0.107	-0.00136	-0.0138	0.0890	-0.00464	-0.0519**	-0.0487	-0.0249*
	(0.0157)	(0.0953)	(0.0111)	(0.0149)	(0.0897)	(0.00556)	(0.0224)	(0.0417)	(0.0143)
Observations	10,565	10,508	10,508	10,176	10,532	10,532	10,170	10,251	10,510
R-squared	0.635	0.369	0.072	0.228	0.521	0.296	0.291	0.552	0.225

Table A8: The role of 1970 pollution: 2000 outcomes CENTRAL

	By place of work				By place of residence				
VARIABLES	1971-79 log TSP	Employ density	Highskill ratio	Median earning	Employ density	Highskill ratio	Median earning	Housing value	College ratio
IND1*Upwind *TSP7179	-0.244	-1.727***	-0.131**	-0.0301	-1.603***	-0.148***	-0.160	-0.556***	-0.227***
	(0.214)	(0.482)	(0.0600)	(0.136)	(0.446)	(0.0357)	(0.160)	(0.177)	(0.0563)
IND2*Upwind *TSP7179	-0.198	-2.043***	-0.154**	-0.00867	-1.703***	-0.185***	-0.191	-0.726***	-0.291***
	(0.216)	(0.482)	(0.0637)	(0.142)	(0.458)	(0.0415)	(0.166)	(0.217)	(0.0744)
IND3*Upwind *TSP7179	-0.224	-1.968***	-0.162***	-0.0501	-1.761***	-0.171***	-0.137	-0.569***	-0.243***
	(0.222)	(0.482)	(0.0580)	(0.136)	(0.439)	(0.0389)	(0.163)	(0.194)	(0.0661)
IND4*Upwind *TSP7179	-0.0250	-0.931	0.0281	-0.358**	-0.865*	-0.158***	-0.578**	-0.255	-0.0899
	(0.179)	(0.684)	(0.112)	(0.158)	(0.468)	(0.0496)	(0.276)	(0.219)	(0.0930)
IND1*TSP7179	0.159*	-0.209	-0.0366*	0.0197	-0.172	-0.0167**	0.0821	0.195*	0.0578*
	(0.0809)	(0.236)	(0.0192)	(0.0435)	(0.134)	(0.00808)	(0.0765)	(0.102)	(0.0349)
IND2*TSP7179	0.104	-0.0664	-0.00825	0.0233	-0.126	-0.00544	0.0845	0.209**	0.0666*
	(0.0850)	(0.247)	(0.0200)	(0.0464)	(0.132)	(0.00689)	(0.0746)	(0.101)	(0.0345)
IND3*TSP7179	0.0920	-0.162	-0.0247	0.0225	-0.116	-0.0184*	0.0734	0.166	0.0441
	(0.0894)	(0.258)	(0.0223)	(0.0461)	(0.121)	(0.0109)	(0.0767)	(0.103)	(0.0378)
IND4*TSP7179	0.0704	-0.258	-0.0273	0.00336	-0.115	-0.00189	0.109*	0.210**	0.0639*
	(0.0705)	(0.265)	(0.0197)	(0.0417)	(0.149)	(0.0145)	(0.0598)	(0.0910)	(0.0371)
IND1*Upwind	-0.0215	0.745***	-0.0109	0.0633	0.614***	-0.0200	0.0450	-0.0895	0.0566
	(0.0892)	(0.272)	(0.0473)	(0.0705)	(0.233)	(0.0289)	(0.0971)	(0.136)	(0.0482)
IND2*Upwind	-0.0619	0.790**	0.0588	0.0181	0.610**	0.00367	0.00853	0.0133	0.0844
	(0.101)	(0.359)	(0.0472)	(0.0649)	(0.244)	(0.0414)	(0.104)	(0.190)	(0.0708)
IND3*Upwind	-0.122	1.056**	0.0231	0.131*	0.626**	-0.00114	-0.162	-0.280	0.0283
	(0.0977)	(0.407)	(0.0510)	(0.0753)	(0.295)	(0.0492)	(0.112)	(0.182)	(0.0801)
IND4*Upwind	0.0182	1.051**	0.0122	0.0877	0.775***	-0.0113	-0.315	-0.100	0.103*
	(0.104)	(0.453)	(0.0829)	(0.0666)	(0.262)	(0.0309)	(0.204)	(0.148)	(0.0614)
IND1	0.0998	0.530	0.114**	0.0255	0.175	-0.0209	-0.202**	-0.179	-0.0942*
	(0.0753)	(0.644)	(0.0562)	(0.0567)	(0.290)	(0.0310)	(0.0811)	(0.170)	(0.0509)
IND2	0.108*	0.463	0.0902**	0.0208	0.235	-0.00784	-0.173**	-0.171	-0.0829
	(0.0616)	(0.566)	(0.0454)	(0.0516)	(0.268)	(0.0281)	(0.0747)	(0.163)	(0.0501)
IND3	0.0587	0.182	0.0914**	-0.0181	0.238	-0.00883	-0.184***	-0.130	-0.0863**
	(0.0502)	(0.351)	(0.0375)	(0.0430)	(0.194)	(0.0229)	(0.0688)	(0.138)	(0.0372)
IND4	0.0297	0.237	0.0549**	-0.0194	0.300**	0.00140	-0.0920*	-0.0579	-0.0467*
	(0.0295)	(0.195)	(0.0254)	(0.0323)	(0.123)	(0.0150)	(0.0493)	(0.101)	(0.0265)
Observations	2,872	2,837	2,837	2,800	2,854	2,854	2,799	2,710	2,837
R-squared	0.647	0.457	0.136	0.304	0.547	0.394	0.382	0.603	0.368

Table A9: The role of 1970 pollution: Growth from 1980 to 2000

	Growth from 1980 to 2000					
VARIABLES	Employment	Manufacture employment	FIRE employment	Median income	Housing value	College graduates
IND1*Upwind *TSP7179	-0.0161	-0.00800	-0.0363	-0.0214**	0.0128	-0.0131
	(0.0233)	(0.0297)	(0.0332)	(0.0101)	(0.0159)	(0.0302)
IND2*Upwind *TSP7179	-0.0503*	-0.0547	-0.0645*	0.00935	0.00900	-0.0446
	(0.0277)	(0.0523)	(0.0332)	(0.0135)	(0.0146)	(0.0329)
IND3*Upwind *TSP7179	-0.0441	-0.0686	0.000227	-0.00646	0.00956	-0.0639
	(0.0327)	(0.0439)	(0.0466)	(0.0110)	(0.0179)	(0.0500)
IND4*Upwind *TSP7179	-0.0481	-0.0177	-0.0659	-0.0399*	-0.0167	-0.0922
	(0.0548)	(0.0696)	(0.0550)	(0.0241)	(0.0189)	(0.0694)
IND1*TSP7179	-0.0157	-0.00949	-0.0197	0.000921	-0.00178	-0.0100
	(0.0127)	(0.0184)	(0.0182)	(0.00438)	(0.00545)	(0.0144)
IND2*TSP7179	-0.000302	-0.00225	0.00494	-0.00663	0.00356	-0.00855
	(0.0110)	(0.0139)	(0.0138)	(0.00546)	(0.00745)	(0.0144)
IND3*TSP7179	0.00303	0.0328	-0.0556	-0.0171*	-0.00678	-0.0175
	(0.0299)	(0.0377)	(0.0361)	(0.00998)	(0.0113)	(0.0365)
IND4*TSP7179	-0.0224	-0.0290*	-0.0387	0.00320	-0.000243	-0.0176
	(0.0138)	(0.0166)	(0.0248)	(0.00400)	(0.00339)	(0.0190)
IND1*Upwind	-0.00143	-0.0430	-0.0169	-0.0122	0.0221	-0.00299
	(0.0547)	(0.0532)	(0.0705)	(0.0142)	(0.0356)	(0.0541)
IND2*Upwind	0.0355	0.0203	0.0584	-0.0312***	-0.0233	0.0181
	(0.0390)	(0.0560)	(0.0451)	(0.0114)	(0.0231)	(0.0396)
IND3*Upwind	0.00124	0.00544	-0.0193	-0.0135	-0.0143	0.00977
	(0.0480)	(0.0588)	(0.0536)	(0.0193)	(0.0234)	(0.0581)
IND4*Upwind	-0.0342	-0.0200	-0.104*	-0.0222	-0.0378	-0.0206
	(0.0557)	(0.0726)	(0.0618)	(0.0226)	(0.0248)	(0.0696)
IND1	-0.0196	-0.0737***	-0.0208	0.0224***	0.0207**	-0.0678**
	(0.0223)	(0.0279)	(0.0295)	(0.00818)	(0.00925)	(0.0291)
IND2	-0.0443**	-0.0973***	-0.0576*	0.0133	0.0127	-0.0927***
	(0.0215)	(0.0265)	(0.0300)	(0.00873)	(0.0117)	(0.0251)
IND3	-0.0355	-0.115***	-0.0687*	-0.00702	0.00616	-0.0867**
	(0.0320)	(0.0332)	(0.0404)	(0.0126)	(0.0178)	(0.0407)
IND4	-0.0170	-0.0719**	-0.0117	0.0126	0.0238	-0.0566
	(0.0268)	(0.0312)	(0.0365)	(0.0123)	(0.0229)	(0.0416)
Observations	12,499	9,602	11,889	12,607	12,200	12,420
R-squared	0.306	0.305	0.244	0.233	0.502	0.184

Table A10: The role of 1970 pollution: Growth from 1980 to 2000 (CENTRAL)

	Growth from 1980 to 2000					
VARIABLES	Employment	Manufacture employment	FIRE employment	Median income	Housing value	College graduates
IND1*Upwind *TSP7179	-0.198	0.214	-0.414**	-0.259***	-0.358**	-0.241
	(0.124)	(0.224)	(0.196)	(0.0853)	(0.148)	(0.199)
IND2*Upwind *TSP7179	-0.206	0.407	-0.390*	-0.285***	-0.439***	-0.111
	(0.145)	(0.293)	(0.208)	(0.0952)	(0.145)	(0.190)
IND3*Upwind *TSP7179	-0.0944	0.467**	-0.349*	-0.127	-0.240	-0.411
	(0.105)	(0.205)	(0.181)	(0.101)	(0.173)	(0.279)
IND4*Upwind *TSP7179	0.0556	0.451**	-0.358*	-0.320*	-0.339**	-0.366*
	(0.0874)	(0.214)	(0.214)	(0.181)	(0.145)	(0.221)
IND1*TSP7179	-0.0649	-0.0173	0.120	-0.00411	0.0143	0.0702
	(0.0860)	(0.101)	(0.102)	(0.0477)	(0.0618)	(0.0654)
IND2*TSP7179	-0.0740	-0.0143	-0.117	-0.00156	0.0244	-0.0392
	(0.0890)	(0.106)	(0.105)	(0.0469)	(0.0611)	(0.0682)
IND3*TSP7179	0.0532	-0.0292	-0.112	-0.0108	-0.0121	0.0454
	(0.0839)	(0.103)	(0.109)	(0.0493)	(0.0621)	(0.0700)
IND4*TSP7179	-0.0535	-0.152	-0.00571	-0.0210	-0.0433	-0.0330
	(0.0923)	(0.106)	(0.114)	(0.0465)	(0.0573)	(0.0614)
IND1*Upwind	-0.0298	-0.0397	-0.0751	-0.0459	-0.113	-0.0106
	(0.0879)	(0.125)	(0.164)	(0.0775)	(0.0834)	(0.154)
IND2*Upwind	-0.0752	-0.0280	-0.0507	- 0.0704	-0.169	-0.0234
	(0.109)	(0.174)	(0.190)	(0.0914)	(0.105)	(0.166)
IND3*Upwind	-0.0468	-0.00334	-0.0190	0.0732	-0.0803	-0.239
	(0.114)	(0.145)	(0.204)	(0.0859)	(0.134)	(0.275)
IND4*Upwind	-0.00567	-0.00630	-0.208	-0.0493	0.123	0.101
	(0.0557)	(0.145)	(0.148)	(0.146)	(0.134)	(0.161)
IND1	-0.0956	0.127	-0.218	-0.0675	-0.168	0.0119
	(0.0964)	(0.154)	(0.140)	(0.0838)	(0.121)	(0.131)
IND2	-0.126	0.0425	-0.205	-0.0668	-0.165*	-0.0543
	(0.0770)	(0.132)	(0.140)	(0.0729)	(0.0990)	(0.105)
IND3	-0.0903	0.0185	-0.228**	-0.0980**	-0.132*	-0.0307
	(0.0591)	(0.105)	(0.0987)	(0.0460)	(0.0739)	(0.0743)
IND4	-0.0628	-0.0243	-0.0712	-0.0355	-0.0604	-0.0107
	(0.0496)	(0.0948)	(0.0911)	(0.0353)	(0.0522)	(0.0886)
Observations	3,530	2,435	3,289	3,569	3,388	3,488
R-squared	0.346	0.405	0.257	0.299	0.484	0.222

Table A11: Evidence from 1970 Clean Air Act: First stage

	Yearly change in average TSP reading							
CountyAtt	-1.456	1.797*	4.289***	4.251***	-0.999**	1.156**	2.957***	2.916***
	(1.035)	(1.022)	(1.080)	(1.071)	(0.655)	(0.620)	(0.657)	(0.646)
*MonitorAtt*1		-1.167*		-0.833		-2.252***		-0.817**
		(0.605)		(0.677)		(0.400)		(0.409)
*MonitorAtt*2		-0.592		-0.364		-3.042***		-3.334***
		(0.901)		(0.958)		(0.618)		(0.650)
Observations	7,985	7,970	7,985	7,970	21,311	21,279	21,311	21,279
Year Range	1971-1974	1971-1974	1971-1974	1971-1974	1974-1979	1974-1979	1974-1979	1974-1979
Last year TSP cubic function	N	N	Y	Y	N	N	Y	Y
Number of siteid	3,745	3,735	3,745	3,735	5,522	5,518	5,522	5,518

Notes Data is a panel of TSP monitoring sites with observations from 1971 to 1979. Dependent variable is the change in average TSP level from the previous year. The first four columns report results from 1971 to 1974, and the last four report results from 1974 to 1979. A cubic function of last year average TSP reading is controlled for in some specifications. $MonitorNonAtt1$ is a dummy that takes one if the average annual TSP reading of monitor exceeds $75\mu g/m^3$, effectively breaking the first NAAQS standard. $MonitorNonAtt2$ is a dummy that takes one if the second highest TSP reading from year $t-1$ exceeds $260\mu g/m^3$, effectively breaking the second NAAQS standard. $CountyNonAtt$ is the county level nonattainment status.

Table A12: Evidence from 1970 Clean Air Act: OLS Estimation

OLS estimation results

	Growth from 1970 to 1980					
	FIRE employment	Manufacture employment	FIRE employment	Retail employment	Wholesale employment	College graduates
ΔTSP	-0.0002	0.0012	0.00058	-0.00067	0.00067	0.00042
	(0.0011)	(0.00074)	(0.0012)	(0.00084)	(0.0008)	(0.0015)
Observations	7075	6,355	7,075	7,058	6,382	7,338
R-squared	0.370	0.295	0.164	0.368	0.337	0.161
	Farm employment	Construction employment	Pubadmin employment	Medical employment	Business service employment	Communication transportation employment
ΔTSP	-0.00203	0.00115	0.00048	-0.00062	0.00065	-0.00031
	(0.0016)	(0.00077)	(0.001)	(0.0009)	(0.0013)	(0.00090)
Observations	4,032	6,205	6,636	7,302	7,013	6,957
R-squared	0.156	0.367	0.298	0.303	0.304	0.320

Notes Dependent variables are growth in employment in different sectors and college graduates from 1970 to 1980. Independent variable is the change in TSP level from 1974 to 1979. Only tracts within 2 kilometers to the closest TSP monitors with TSP concentration readings from 1980, 1970, 1974, 1975 and 1976 are kept in the sample.

Table A13: Evidence from 1970 Clean Air Act: IV estimation

	IV estimation results					
	Growth from 1970 to 1980					
	FIRE employment	Manufacture employment	Edu Med employment	Retail employment	Wholesale employment	College graduates
ΔTSP	-0.0150**	-0.00597	-0.0187*	-0.0175**	-0.0156**	-0.0124*
	(0.00679)	(0.00461)	(0.00998)	(0.00715)	(0.00764)	(0.00708)
Observations	6,935	6,355	7,075	7,058	6,382	7,338
R-squared	0.218	0.269	0.042	0.246	0.273	0.110
	Farm employment	Construction employment	Pubadmin employment	Medical employment	Business service employment	Communication transportation employment
ΔTSP	-0.00621	-0.0103*	-0.0118*	-0.00786	-0.0237**	-0.0256***
	(0.00883)	(0.00585)	(0.00715)	(0.00554)	(0.00967)	(0.00894)
Observations	4,032	6,205	6,636	7,302	7,013	6,957
R-squared	0.153	0.325	0.255	0.288	0.167	0.121
	Growth from 1980 to 1990					
	FIRE employment	Manufacture employment	FIRE employment	Retail employment	Wholesale employment	College graduates
ΔTSP	-0.00948*	-0.0111	0.00357	-0.00567	-0.0148**	-0.00473
	(0.00516)	(0.00993)	(0.00703)	(0.00574)	(0.00669)	(0.00723)
Observations	7,097	6,622	7,060	7,417	6,565	7,394
R-squared	0.160	0.173	0.173	0.186	0.202	0.147
	Farm employment	Construction employment	Pubadmin employment	Medical employment	Business service employment	Communication transportation employment
ΔTSP	-0.00104	-0.00621	-0.00567	-0.0196***	-0.00715	-0.00996*
	(0.00986)	(0.00788)	(0.00579)	(0.00674)	(0.00762)	(0.00556)
Observations	3,916	6,853	6,414	7,287	7,333	6,982
R-squared	0.166	0.250	0.190	0.101	0.405	0.183

Notes Dependent variables are growth in employment in different sectors and college graduates from 1970 to 1980 or from 1980 to 1990. IV estimation have changes in TSPs from 1974 to 1979 instrumented by the ratio of years when the second highest TSP reading exceeds the federal standard from 1974 to 1977. Only tracts within 2 kilometers to the closest TSP monitors with TSP concentration readings from 1980, 1970, 1974, 1975 and 1976 are kept in the sample.

Table A14: New industrial zones from 1950-70 and outcomes in 1950 – placebo check

VARIABLES	%College graduates50	log income 1950	Manager share50	Professional share50	%College graduates50	log income 1950	Manager share50	Professional share50	%College graduates50	log income 1950	Manager share50	Professio share50
IND(0-4km)	-0.00899	-0.0699	-0.0134*	-0.00220	-0.00955	-0.0676	-0.0135*	-0.00215	-0.00901	-0.0745**	-0.0135*	-0.00192
	(0.0168)	(0.0422)	(0.00868)	(0.0170)	(0.0175)	(0.0436)	(0.00794)	(0.00899)	(0.0162)	(0.0350)	(0.00780)	(0.00884
Downwind					-0.00366	0.0237	-0.000974	-0.000361	-0.0136	0.0307	-0.00608	-0.00295
					(0.00929)	(0.0539)	(0.00684)	(0.00877)	(0.00878)	(0.0654)	(0.00529)	(0.00835
IND(0-4km) *Downwind					0.0199	-0.0558	0.00403	-0.00317	0.0718*	-0.0246	0.0152	0.0148
					(0.0332)	(0.184)	(0.0149)	(0.0137)	(0.0369)	(0.126)	(0.0164)	(0.0165)
TSP7179									-0.0174***	-0.0439***	-0.0129***	-0.00658
									(0.00661)	(0.0165)	(0.00323)	(0.00427
TSP7179*Downwind *IND(0-4km)									0.0789	0.182	0.00607	0.0307
									(0.0514)	(0.206)	(0.0314)	(0.0248)
TSP7179*Downwind									0.0184*	-0.0152	0.00926**	0.00479
									(0.0102)	(0.0296)	(0.00373)	(0.00549
TSP7179*IND(0-4km)									0.0102	-0.0974***	0.000798	0.00377
									(0.0142)	(0.0266)	(0.00604)	(0.00756
Observations	8,388	7,132	8,261	8,261	8,388	7,132	8,261	8,261	8,388	7,132	8,261	8,261
R-squared	0.203	0.259	0.159	0.112	0.203	0.224	0.159	0.112	0.205	0.261	0.160	0.112

Notes IND(0-4km): A dummy=1 if the tract is within 4 km to the nearest industrial area added during 1950-1970

Table A15: 1970 industrial pollution and outcomes in 1950 – placebo check

VARIABLES	Population density	Log median income	College graduates share	Population density	Log median income	College graduates share	Population density	Log median income	College graduates share
IND1	0.417*	-0.0454	-0.0462**	0.388*	-0.0488	-0.0426**	2.234**	0.180	0.0568
	(0.231)	(0.0483)	(0.0190)	(0.229)	(0.0493)	(0.0197)	(0.869)	(0.301)	(0.0935)
IND2	0.496**	-0.0248	-0.0303	0.478**	-0.0260	-0.0315*	2.208***	0.274	0.0224
	(0.192)	(0.0422)	(0.0183)	(0.191)	(0.0439)	(0.0187)	(0.812)	(0.295)	(0.0904)
IND3	0.400***	0.00400	-0.0176	0.359**	0.00819	-0.0185	1.808**	0.270	0.0737
	(0.147)	(0.0350)	(0.0156)	(0.146)	(0.0355)	(0.0154)	(0.758)	(0.301)	(0.0851)
IND4	0.334***	0.0320	-0.00617	0.268**	0.0421	-0.00747	2.065**	0.414	0.0898
	(0.111)	(0.0276)	(0.0144)	(0.108)	(0.0290)	(0.0124)	(0.869)	(0.285)	(0.0809)
IND1*Downwind				1.127	0.0345	-0.0625	-0.471	-0.0901	-0.167***
				(0.764)	(0.128)	(0.104)	(0.448)	(0.156)	(0.0343)
IND2*Downwind				1.063	0.0179	-0.0171	-0.510	-0.0832	0.0152
				(0.777)	(0.135)	(0.106)	(0.508)	(0.176)	(0.0868)
IND3*Downwind				1.437*	-0.0637	-0.0143	0.151	-0.474	-0.111
				(0.775)	(0.134)	(0.106)	(0.551)	(0.339)	(0.0944)
IND4*Downwind				1.930**	-0.161	-0.00825	-0.00643	-0.890*	-0.105
				(0.796)	(0.130)	(0.106)	(0.153)	(0.487)	(0.264)
IND1*Downwind *TSP7179							-0.00365	0.000371	0.000903***
							(0.00640)	(0.00144)	(0.000244)
IND2*Downwind *TSP7179							-0.00359	0.000318	-0.000426
							(0.00726)	(0.00193)	(0.000797)
IND3*Downwind*TSP7179							-0.00810	0.00333	0.000561
							(0.00707)	(0.00368)	(0.000986)
IND4*Downwind*TSP7179							-0.00603	0.00758	0.000409
							(0.00615)	(0.00550)	(0.00322)
IND1 *TSP7179							-0.0161	-0.00519	-0.00166
							(0.0117)	(0.00470)	(0.00121)
IND2*TSP7179							-0.0152	-0.00598	-0.00114
							(0.0113)	(0.00462)	(0.00121)
IND3*TSP7179							-0.0113	-0.00552	-0.00175
							(0.0105)	(0.00463)	(0.00117)
IND4*TSP7179							-0.0161	-0.00629	-0.00179
							(0.0121)	(0.00436)	(0.00127)
Observations	7,095	7,097	7,069	7,095	7,097	7,069	3,680	3,680	3,679
R-squared	0.450	0.261	0.215	0.453	0.262	0.218	0.524	0.356	0.240

Table A16: Placebo Checks: Split sample

VARIABLES	%College graduates40	%College graduates50	log income 1950	Manager share50	Professional share50
$1(disind \in 0-1km)$*Downwind	-0.00943	-0.0103	0.0851**	-0.000378	-0.00769
	(0.00645)	(0.00880)	(0.0409)	(0.00462)	(0.00701)
$1(disind \in 1-2km)$*Downwind	0.0250*	0.0219**	0.0731	0.0163*	0.00924
	(0.0122)	(0.00995)	(0.0454)	(0.00854)	(0.00734)
$1(disind \in 2-3km)$*Downwind	0.00584	0.0408	0.107	-0.0303	0.0350**
	(0.0592)	(0.0417)	(0.0973)	(0.0296)	(0.0171)
$1(disind \in 3-4km)$*Downwind	-0.0224	0.0253	0.159	-0.0377	0.203***
	(0.0675)	(0.0436)	(0.126)	(0.0438)	(0.0545)
Downwind	0.00854	-0.0383	-0.114	0.0134	-0.0188
	(0.0613)	(0.0402)	(0.0938)	(0.0307)	(0.0174)
$1(disind \in 0-1km)$	-0.0575	-0.0502	-0.178	-0.0111	-0.00714
	(0.0596)	(0.0443)	(0.124)	(0.0226)	(0.0290)
$1(disind \in 1-2km)$	-0.0485	-0.0454	-0.152	-0.0114	-0.00645
	(0.0564)	(0.0401)	(0.110)	(0.0212)	(0.0243)
$1(disind \in 2-3km)$	-0.0286	-0.0513	-0.110	-0.00355	-0.0182
	(0.0491)	(0.0352)	(0.0932)	(0.0203)	(0.0212)
$1(disind \in 3-4km)$	-0.00909	-0.0328	-0.0598	-0.00271	-0.0159
	(0.0645)	(0.0384)	(0.106)	(0.0207)	(0.0175)
Observations	1,012	2,241	1,987	2,244	2,244
R-squared	0.167	0.189	0.273	0.236	0.121

VARIABLES	%College graduates40	%College graduates50	log income 1950	Manager share50	Professional share50
$1(disind \in 0-1km)$*Downwind	-0.0287**	-0.0332**	0.0330	-0.0222***	-0.0147**
	(0.0140)	(0.0157)	(0.0462)	(0.00671)	(0.00658)
$1(disind \in 1-2km)$*Downwind	-0.00382	0.0702	0.0278	0.00287	0.0454
	(0.0315)	(0.0644)	(0.0664)	(0.0181)	(0.0395)
$1(disind \in 2-3km)$*Downwind	-0.00574	-0.0108	-0.158	-0.0336**	0.0209
	(0.0262)	(0.0540)	(0.165)	(0.0154)	(0.0225)
$1(disind \in 3-4km)$*Downwind	0.142*	-0.0143	-0.0660	-0.0469**	-0.00900
	(0.0701)	(0.104)	(0.350)	(0.0230)	(0.0508)
Downwind	-0.0534	-0.0694	0.0681	0.000358	-0.000425
	(0.148)	(0.106)	(0.101)	(0.0173)	(0.0720)
$1(disind \in 0-1km)$	-0.0593	0.0202	-0.187*	-0.0190	0.0139
	(0.0424)	(0.0377)	(0.103)	(0.0192)	(0.0196)
$1(disind \in 1-2km)$	-0.0605*	0.00327	-0.110	-0.0154	0.00331
	(0.0347)	(0.0288)	(0.0821)	(0.0156)	(0.0149)
$1(disind \in 2-3km)$	-0.0332	0.00154	-0.104*	-0.0140	0.00721
	(0.0242)	(0.0211)	(0.0541)	(0.0114)	(0.0102)
$1(disind \in 3-4km)$	-0.0200	0.00533	0.00339	-0.000348	-0.00247
	(0.0193)	(0.0129)	(0.0374)	(0.00967)	(0.0102)
Observations	1,023	2,071	1,713	2,076	2,076
R-squared	0.358	0.281	0.413	0.230	0.172

Notes Results from the upper panel are obtained from a sample of 1950 census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. Dependent variables are the share of college graduates in 1940 and 1950, log median income in 1950, the share of managers and professional/technical occuptions in total employment, $1(disind \in x-ykm)$ is an indicator of whether or not the distance of a tract from the closest industrial area is within x to y km. Downwind is an indicator of whether or not the TSP monitor is located downwind to the industrial area. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

Table A17: Placebo Checks: Split sample

	Above-median polluted industrial areas				
VARIABLES	%College graduates50	%College graduates40	log income 1950	Manager share50	Professional share50
$1(disind \in 0-4km)$	-0.0402*	-0.0340***	-0.123***	-0.0185***	-0.00587
	(0.0232)	(0.0115)	(0.0401)	(0.00656)	(0.00848)
$1(disind \in 0-4km)$ Downwind	0.0332	0.0196	0.0503	0.0174	0.00771
	(0.0274)	(0.0262)	(0.127)	(0.0136)	(0.0175)
Downwind	-0.0134	-0.0195**	0.00746	-0.00935	-0.00788
	(0.0100)	(0.00851)	(0.0547)	(0.00597)	(0.00842)
Observations	2,418	4,084	3,563	3,984	3,984
R-squared	0.248	0.218	0.321	0.219	0.132

	Below-median polluted industrial areas				
$1(disind \in 0-4km)$	0.00399	-0.0250**	-0.0985**	-0.0220***	-0.0109***
	(0.0139)	(0.0101)	(0.0466)	(0.00792)	(0.00403)
$1(disind \in 0-4km)$ Downwind	-0.0114	-0.00426	0.00858	0.00750	-0.00484
	(0.0152)	(0.0120)	(0.0704)	(0.0120)	(0.00829)
Downwind	0.0105	0.0278*	0.0586*	0.0217***	0.0153
	(0.0174)	(0.0149)	(0.0328)	(0.00549)	(0.00969)
Observations	1,886	4,236	3,504	4,202	4,202
R-squared	0.261	0.231	0.251	0.151	0.131

Notes Results from the upper panel are obtained from a sample of 1950 census tracts that are closest to industrial areas with above-median pollution level in the 1970s, and those from the lower panel from those closest to industrial areas with below-median pollution level. Dependent variables are the share of college graduates in 1940 and 1950, log median income in 1950, the share of managers and professional/technical occuptions in total employment, $1(disind \in x-ykm)$ is an indicator of whether or not the distance of a tract from the closest industrial area is within x to y km. Downwind is an indicator of whether or not the TSP monitor is located downwind to the industrial area. Controls include CBSA fixed effects, the distance from each monitor to transportation lines, natural amenities and the CBD. Robust standard errors are clustered at CBSA level.

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