Local Environmental Quality and Inter-Jurisdictional Spillovers

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Abstract

We investigate the classic question of how the provision of a local publicly-provided good—air quality—varies with the degree of decentralization of policymaking. Exploiting exogenous variation in the natural topography of the United States to instrument for the number of local government jurisdictions in a metropolitan area, we show that areas with more jurisdictions have significantly lower air quality, and significantly higher concentrations of the toxic air pollutants most closely associated with cancer and non-cancer health risks. By contrast, local drinking water quality—a publicly-provided good not subject to spillovers—does not vary with the number of jurisdictions. Differences in industrial activity explain much of the difference in air quality; areas with more jurisdictions have significantly higher employment in power generation and distribution, and this difference explains the majority of variation in sulfur dioxide emissions—a major component of air quality. Further, areas with more jurisdictions have higher employment in chemical manufacturing, and this explains the majority of variation in concentrations of toxic air pollutants used heavily in this industry. Finally, we provide evidence that these environmental impacts may have real economic effects: we estimate the increase in pollution from doubling the number of jurisdictions lowers housing values by at least 3%.

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1 Introduction

Since the seminal work of Oates (1972), it has been argued that local publicly-provided goods with significant spillovers will be under-provided by local governments, as each government bears the entire cost of provision but obtains only a portion of the benefits for its citizens.[1] However, Ostrom (1990), Lubell et al. (2002), and Feiock (2007) have argued that in metropolitan areas with many jurisdictions, these jurisdictions will negotiate provision levels jointly and hence have outcomes similar to those under centralized decision-making. That is, spillovers will not result in under-provision. We consider this question empirically in the context of local air quality in the United States: if spillovers are important, then metropolitan areas comprised of many competing jurisdictions should have lower average air quality than do metropolitan areas with few local governments. By contrast, if spillovers are not important, air quality should not vary systematically with the number of jurisdictions.

We find that U.S. metropolitan areas with more jurisdictions do, in fact, have lower air quality. Using the U.S. Environmental Protection Agency's (EPA) measure of air pollution, the Air Quality Index (AQI), we find that doubling the number of jurisdictions (e.g., increasing from one to two, or from two to four, the number of county governments in a metropolitan area) results in a 7.4 point increase in the AQI, which is about a half standard deviation increase in the pollution level. It also leads to an additional two weeks per year with air quality levels that the EPA considers unhealthy (i.e., air quality levels for which the EPA recommends that children and those with respiratory problems limit their outdoor activities). This is a large increase over the metropolitan area average of three weeks per year with unhealthy air. We also examine the effects of having more jurisdictions on the concentrations of toxic air pollutants that the EPA considers to be the main airborne drivers of long-term health impacts including cancer. We find that increasing the number of jurisdictions significantly increases the concentration of most measured cancer drivers and

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[1] Such an effect has also been demonstrated in second generation models of fiscal federalism (i.e., models of local governments that explicitly consider local policymaker incentives). See Besley and Coate (2003).

non-cancer health hazards. Our results imply that areas with more local governments are subject to more polluted air and, moreover, that air quality might improve with greater centralization of regulatory authority on decisions affecting air pollution.

As a placebo analysis, we examine the effects of having more jurisdictions on public drinking water quality. This is a local, environmental, publicly-provided good with*out* significant spillovers. In contrast to our findings on air quality, we find no systematic differences in drinking water quality (defined in terms of total violations of EPA Safe Drinking Water Act regulations) as a function of the number of jurisdictions. The difference between this result and our results for air quality suggest that the presence of spillovers is a defining characteristic explaining why air quality is lower in areas with more jurisdictions.

Local governments play a key role in determining local environmental outcomes. First, the ability to determine zoning restrictions typically gives counties the ability to allow or prevent the siting of polluting facilities such as utilities, power plants, and chemical manufacturing plants (Bernstein, 1993). Second, county governments have significant control over policies affecting traffic congestion, infrastructure, and public transit (Gore and Robinson, 2009), all of which can affect ambient concentrations of various environmental pollutants. For example, counties can develop building standards and codes which improve energy and water efficiency, build reliable public transportation systems, create bicycling lanes and pedestrian-friendly neighborhoods, and procure and install energy-efficient infrastructure (such as street lights, parking meters, pumping equipment, and municipal vehicles). Finally, county governments can establish Local Implementation Plans (LIPs) and can influence State Implementation Plans (SIPs), both of which are plans for complying with the EPA's Clean Air Act. Many county governments establish Air Pollution Control Boards to make and enforce local rules and regulations.

Local government commitment to combating pollution varies widely. For example, despite vocal protests of environmental groups, state and local authorities in Wisconsin permitted Wisconsin Energy Corporation to construct two new units of a coal-fired power plant in Oak Creek (near Milwaukee) in 2005 . The Sierra Club condemned this decision, saying "This will be the seventh-largest power plant in the country in an area that already violates federal air quality standards. They will be burning the dirtiest type of fuel and using the dirtiest type of combustion technology. The EPA sat on their hands and did nothing" (Slevin, 2005). By contrast, the city of Portland, Oregon has undertaken multiple actions to accomplish a 13 percent per capita reduction in greenhouse gas emissions over the period from 1990 to 2009 (Bailey, 2007). These have included obtaining 10 percent of electricity from renewable sources, planting 750,000 trees, and retrofitting thousands of residences to be more energy efficient (Gore and Robinson, 2009).

Empirical studies of the environmental policies of local governments have concentrated on whether there is evidence of a "race to the bottom" or a "race to the top" between competing jurisdictions over environmental protection. That is, does the presence of many jurisdictions tend to reduce or improve environmental quality? It has focused on a variety of environmental goods and has yielded mixed results. List and Co (2000), for example, find evidence of a "race to the bottom" in foreign direct investment (FDI), where states compete more strongly for FDI by adopting relatively loose environmental requirements. Gray and Shadbegian (2002) use data for U.S. paper and pulp mills to show that regulators, whose behavior is consistent with maximizing political support, count benefits received by people outside their jurisdiction as only half as important as benefits received by those within their jurisdiction. Whitford and Helland (2003) find that local industrial facilities' emissions into the air and water are systematically higher in counties that border other states. And Sigman (2007) uses international data and finds that decentralization leads to increased variability in water quality (though there are not robust effects on average water quality).

By contrast, Levinson (1999) shows that "Not in My Back Yard" taxes can lead to inefficiently high environmental protection (where the magnitude of the inefficiencies depends on tax elasticities). List and Gerking (2000) provide evidence that environmental quality in the U.S. did not decline following Reagan's devolution of responsibility for environmental regulation to states. Millimet (2003), using a modified approach, shows that environmental protection actually improved following this devolution of power. And Lipscomb and Mobarak (2007) exploit evolving county boundaries in Brazil to show a zero net effect of the number of municipalities on water quality.

Empirical work in this area has been significantly challenged by the fact that the number of jurisdictions is likely endogenous to any measure of environmental quality. For example, older MSAs might have more jurisdictions since travel was more difficult hundreds of years ago when their boundaries were drawn. However, older MSAs may also be more likely to have a legacy of industrial activity that is politically-protected and heavily polluting. Also, highly-educated MSAs may have more politically-active residents that demand more jurisdictions. However, educated individuals may also be less likely to pollute, more likely to recycle, and more willing to support green policy initiatives, leading to cleaner air and water. As these two examples suggest, the direction of the omitted variable bias is uncertain.

One of the primary contributions of our paper is a solution to this identification problem; we exploit natural variation in the topography of the U.S. to generate exogenous variation in the number of local government jurisdictions. Specifically, we use the total miles of small streams in a given metropolitan statistical area (MSA) (an urbanized entity defined by the U.S. Census) to instrument for its number of county government jurisdictions. The presence of more small streams increased the number of "natural break-points" between jurisdictions at the time of an MSA's founding, thus increasing the number of jurisdictions created. Boundaries are likely to carry over to the modern era given the costs and complications of changing them. Thus, we expect an MSA with more miles of small streams to have more jurisdictions today. However, the number of miles of small streams should not directly affect environmental quality in the modern era.[2] Hence, we interpret our estimates as causal effects of the number of jurisdictions on environmental quality.

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[2] This instrument was first suggested by Hoxby (2000); see Section 2.1 for a discussion. We exclude major rivers from consideration since these could conceivably have a direct impact on productivity and growth, thereby affecting environmental quality.

Another important contribution of our paper is that it specifically assesses the mechanisms through which a larger number of jurisdictions affects environmental quality. First, our analysis of water quality indicates that spillovers are a defining characteristic explaining why the provision of a publicly-provided environmental good is or is not affected by having more jurisdictions.[3] Second, we investigate the hypothesis that the decrease in local air quality can be explained by the presence of more industrial activity in metropolitan areas with more jurisdictions. We show that differences in emissions of sulfur dioxide—a major component of the AQI—can largely be explained by differences in the size of the power generation industry (as measured by employment in the industry per land area). Moreover, for the case of toxic air pollutants, which are used heavily in chemical manufacturing, we show that a large share of the increased concentration of these pollutants due to more jurisdictions seems to come from higher employment in this narrow industry.

The remainder of the paper is organized as follows. Section 2 describes our empirical approach. Section 3 presents our main empirical results, while Section 4 explores possible causal channels. Finally, Section 5 concludes.

2 Empirical Strategy

We investigate the effect of the number of jurisdictions on local environmental quality in U.S. metropolitan areas. Specifically, we use data on Metropolitan Statistical Areas (MSAs) and Consolidated Metropolitan Statistical Areas (CMSAs), which we collectively refer to as MSAs. MSAs are comprised of an urbanized nucleus with a population of at least 50,000 and the collection of adjacent communities that have a high degree of integration with the nucleus (as evidenced by commuter patterns).[4] Geographically, MSAs are defined by the set

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[3] Note that drinking water contamination is due to inadequate maintenance of the public water distribution system; contaminants are introduced from the soil surrounding pipes and corrosion turbercles into the water distribution network directly, as well as indirectly through uncovered storage facilities and water main breaks. See Environmental Protection Agency (2006) for a through discussion of the causes of contamination events in local water supplies.

[4] MSAs and CMSAs are two mutually exclusive geographic units. CMSAs are larger than MSAs as they contain *multiple* urbanized nuclei that are integrated with one another, rather than one nucleus.

of counties of which they are comprised.[5,6]

Assume, briefly, that we have accurate measures of local environmental quality and the number of jurisdictions, and that all variation in the number of jurisdictions is exogenous. In that case we can recover causal estimates of the effect of the number of jurisdictions on environmental quality by estimating the following empirical specification:

$$q_i = \beta_0 + \beta_N \log(N_i) + \gamma \mathbf{X}_i + \alpha_j + \epsilon_i \tag{1}$$

where i indexes MSAs. We denote by q_i local environmental quality, by N_i the number of jurisdictions in MSA i, and by α_j state group fixed effects.[7] We denote by $\mathbf{X}_i$ a vector of control variables for MSA i, described in Section 2.3.

2.1 Identification

There are several possible sources of omitted variable bias likely to bias ordinary least squares (OLS) estimates of β_N. First, heavily populated areas are likely to have more cars and trucks on the road simply because they have more residents overall. This may lead to lower air quality. However, heavily populated areas may also be more difficult to run with just one or a small number of local governments—especially if residents are ethnically, racially, or politically diverse and tend to live in internally-homogenous communities that demand separate jurisdictions. Second, older MSAs might have more jurisdictions since travel was more difficult hundreds of years ago when their boundaries were drawn. However, older MSAs may also be those where manufacturing and other polluting industries are disproportionately situated, since such polluting industries became integral parts of these MSAs long before

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[5] New England is an exception, as MSAs there are primarily defined as collections of cities and townships that frequently cross county lines. As data on many of our covariates are not available at more disaggregated levels than the county, we exclude New England MSAs from our analysis.

[6] See Hatfield and Kosec (2012) for more information on MSAs.

[7] Because some MSAs cross state lines, we created state dummies for each state and for each "state group" (collection of two or more states) created by multi-state MSAs. There are 37 states or state groups containing more than one MSA, and it is variation among MSAs within each of these that we exploit.

concerns with air quality arose, and there is a great deal of path dependency. Finally, areas with a larger number of jurisdictions may attract wealthier and more-educated citizens,[8] and these citizens may demand a higher level of environmental quality. As these different potential sources of omitted variable bias may skew OLS estimates in different directions, it is not possible to sign the direction of bias. The magnitude of the bias would tend to shrink as we added controls for population, MSA founding year, and average income to Eq. (1), but it would be impossible to say when all bias had been eliminated.[9]

To address these threats to identification, we exploit exogenous variation in the natural topography of the United States. Specifically, we instrument for the number of jurisdictions in an MSA with the number of miles of small streams in the MSA, computed using Geographic Information System (GIS) data from the Environmental Systems Research Institute's (ESRI) Data and Maps software (2008). We focus on only *small* streams, and ignore major rivers.[10] We do so by counting up total miles of streams, intermittent streams[11], braided streams, falls, and intracoastal waterways[12], but ignoring canals, intermittent canals, dams, and aqueducts (which are all man made) and also omitting rivers (which are large and may have a direct effect on environmental quality).[13] We argue that more small streams should lead to more jurisdictions in a given area, but should not affect local environmental quality through any other channel than the number of jurisdictions.

Our instrumental variables strategy is motivated by the history of U.S. county formation. The median county founding year is 1848, a time when geographic obstacles like streams were focal "break-points" between jurisdictions because they were easy to describe and communicate. This was especially important before the advent of GPS, GIS, and advanced mapping

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[8] See Hatfield and Kosec (2012) for some evidence that this is the case.

[9] Further, such control variables themselves are likely to be endogenous to environmental quality.

[10] For more details on ESRI streams data, see Hatfield and Kosec (2012).

[11] According to the USGS, an intermittent stream is a stream that "contains water for only part of the year, but more than just after rainstorms and snow melt."

[12] An intracoastal waterway is one of the series of natural inlets, saltwater rivers, bays, and sounds along the U.S. coastline that are so designated by the U.S. Army Corps of Engineers. We only consider those portions of intracoastal waterways contained within MSA boundaries, which is a fraction of total U.S. intracoastal waterways.

[13] Exact definitions of each come from the USGS in the National Atlas of the United States.

techniques. Having more small streams made it relatively less costly to divide metropolitan areas into more jurisdictions. Conversely, having few small streams encouraged fewer jurisdictions.

Figure 1 provides an example of how small streams have contributed to the demarcation of county boundaries in the greater Houston area today. County boundaries frequently coincide with streams. An example of the opposite effect is the Phoenix, AZ MSA, where few streams—and only two county governments—can be found.

Our first stage equation states that the number of jurisdictions, measured as $\log N_i$, is a function of the number of miles of small streams, s_i:

$$\log(N_i) = \delta_0 + \delta_s s_i + \theta \mathbf{X}_i + \pi_j + \eta_i \tag{2}$$

where π_j denotes state group fixed effects. In the results section, we demonstrate that this instrument satisfies the inclusion restriction: it is positively correlated with the number of jurisdictions in MSA i. We argue that the exclusion restriction holds since small streams are very easy to get around, and unlikely to affect modern day air quality or water quality. A possible concern is that miles of small streams, even if it does not have a direct impact on air quality, is correlated with other natural geographic features that do. We alleviate such concerns by including a variety of topographic and climatic controls for each MSA i, captured above by $\mathbf{X}_i$. These are described in more detail in Section 2.3.

Hoxby (2000) uses a similar approach to obtain identification; she instruments for the degree of Tiebout choice over schools in a metropolitan area using a count of small streams. She argues that a larger number of streams implies a larger number of *natural* school district boundaries, especially since these boundaries were drawn up long ago, when streams increased travel time to school. However—in the spirit of our argument—she maintains that streams are exogenous to modern-day school productivity.[14] While there has been some

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[14] Since Hoxby (2000), Baqir (2001), Cutler and Glaeser (1997), and Hatfield and Kosec (2012) have used streams as an instrumental variable for a variety of features of the institutional environment in U.S. metropolitan areas.

controversy regarding whether a hand count and classification of what is a “small” stream is appropriate and objective (see Rothstein (2007)), our use of GIS data to measure miles of small streams circumvents this criticism.

2.2 Variable Measurement

2.2.1 The Number of Jurisdictions

We capture the number of jurisdictions using the number of county governments in an MSA. Counties are the primary legal divisions of most states, and are therefore one of the most important and powerful components of sub-national governance.[15] Moreover, their powers are relatively uniformly-defined across MSAs. By contrast, other sub-national governments—such as municipalities and townships—are less uniformly defined, and some states lack one or the other of these government forms.[16] Data on the number of counties in each MSA come from the Census Bureau (1999).

2.2.2 Environmental quality

We measure air quality using the Environmental Protection Agency’s (EPA) Air Quality Index (AQI). The AQI describes how clean or polluted air is in different areas with respect to five major air pollutants regulated by the Clean Air Act (1970): ground-level ozone, particle pollution (also known as particulate matter), carbon monoxide, sulfur dioxide, and nitrogen dioxide. For each of these pollutants, the EPA has established a maximum concentration level beyond which the pollutant is thought to harm public health after a few hours or days of breathing the air. The AQI ranges from 0 to 500. AQI values below 100 are considered healthy, while AQI values above 100 indicate unhealthy air—meaning that the EPA recommends that children and those with respiratory problems limit their outdoor

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[15] Since they have county-like control over their territory, we include independent cities (e.g., St. Louis, MO) and consolidated city-counties (e.g., San Francisco, CA)—also known as functional county governments—in our total.

[16] For example, only about half of states have townships.

activities. The EPA reports the AQI of each metropolitan area (MSA) in the U.S. each day.[17] We take the average AQI of each MSA over the period 1999-2002. While MSA boundaries are periodically redefined, this is a period during which MSA boundaries were continuously defined in the same way,[18] permitting us to meaningfully summarize an MSA's average AQI over the period. By using more than a single year of data, we ensure that our results are not driven by outliers, and convey in a more meaningful sense the average air quality of an MSA. Our first measure of air quality is the AQI itself; the mean AQI for an MSA is 44, with a standard deviation of 14. Our second measure is the percent of days for which the AQI exceeds 100 (indicating unhealthy air); the mean is 3.1 weeks (6% of days), with a standard deviation of 4.2 weeks (8% of days).

We also considered alternative measures of air quality by considering the ambient concentrations of ten air pollutants associated with more non-cancer health problems and eight air pollutants associated with higher rates of cancer.[19] Specifically, we chose the universe of pollutants which the EPA classifies as either: national non-cancer hazard drivers (acrolein); regional non-cancer hazard drivers (2,4-toluene diisocyanate, chlorine, chromium compounds, diesel engine emissions, formaldehyde, hexamethylene diisocyanate, hydrochloric acid, manganese compounds, and nickel compounds); national cancer risk drivers (benzene); or regional cancer risk drivers (1,3-butadiene, arsenic compounds, chromium compounds, coke oven emissions, hydrazine, tetrachloroethylene, and naphthalene). The classification as national or regional refers to whether the pollutant is thought to have significant adverse effects[20] on over 25 million people (making it a "national" pollutant) or on between 1 and 24 million people (making it a "regional" pollutant). The concentrations of each of these

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[17] The EPA calculates the AQI using data on the concentrations of the five major air pollutants listed above. These pollutant data are generally collected by the state government at pre-determined air monitoring sites. Because the AQI is computed in the same way for all areas of the U.S., AQI values can be compared across geographic areas.

[18] Specifically, 1999-2002 is the period during which MSAs were as defined for the 2000 Census.

[19] Exposure to pollution poses neurological, respiratory, reproductive, and developmental health risks. Specific risks include anemia, asthma, bronchitis, cancer, cardiovascular diseases, emphysema, heart attack, high blood pressure, and damage to the brain, lungs and kidneys (Environmental Protection Agency, 2010).

[20] Adverse effects are defined as an estimated upper-bound lifetime cancer risk exceeding 10 in a million.

pollutants are their average ambient concentrations (in micrograms per cubic meter) over the period 1999-2002, as measured by the EPA.[21]

We measure water quality using information from the EPA's Safe Drinking Water Information System (SDWIS) database. The database records each public drinking water utility's total number of violations of the Safe Drinking Water Act (SDWA) regulations in each year. Violations (and the associated penalties) are handed out to ensure that water systems provide safe water. There are several types of violations; we focus on two broad types. First, SDWA regulations establish maximum contaminant levels (i.e., maximum permissible concentrations in the water) for pollutants thought to harm public health. Second, they stipulate specific requirements (related to frequency and technique) for monitoring and reporting pollutant levels. The EPA has established, and enforces, maximum contaminant levels for a number of pollutants: coliform bacteria, disinfectant byproducts, total trihalomethanes, volatile organic contaminants, synthetic organic contaminants, nitrates, arsenic, other inorganic contaminants, and radionuclides. Water utilities exceeding the permitted level of any one of these pollutants are given a violation, as are water utilities failing to follow EPA-stipulated monitoring and reporting protocols. Monitoring (and thus the award of violations) are typically done each quarter.

Local authorities have discretion in what they require of utilities in terms of water quality. For example, recent studies have identified chemicals regulated by the SDWA which pose risks at smaller concentrations than previously known. However, many of the SDWA's maximum contaminant levels for those chemicals have not been updated since the 1970s or 1980s. Some officials overseeing local water systems have tried to go above and beyond what is legally required; others simply seek to meet minimal state and federal requirements, and still others frequently violate state and federal requirements (incurring fines) (Duhigg, 2009).

We used utility-level data to create MSA-level data by taking a weighted average of the number of violations for each utility in the MSA, where the weight of given utility is the

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[21] EPA (1999-2002) uses measurements where available, and the outcome from emissions estimates inserted into air dispersion models otherwise.

the share of population that the utility serves. If a utility serves many people, its violations accordingly matter more than do violations by a utility that serves only a few people. This measure gives us the number of violations we expect a randomly-drawn person in the MSA to face from his utility. Specifically, we create two measures of water quality for an MSA: total maximum contaminant level violations during 1999-2002 faced by the average resident, and total monitoring and reporting violations during 1999-2002 faced by the average resident.

More formally, we denote the number of water quality violations by water utility k as v_k. To calculate the average number of water quality violations that an average resident is subject to, we calculate a weighted average of violations, where the weights are given by the number of residents served by that utility, denoted p_k. Hence, our measure of water quality in MSA i is given by

$$\bar{v}_i = \frac{\sum_{k \in K_i} v_k p_k}{\sum_{k \in K_i} p_k} \tag{3}$$

where K_i is the set of water utilities in MSA i. Hence, $\bar{v}_i$ is the average number of violations (either maximum contaminant level or monitoring and reporting) incurred by a water utility serving a randomly-selected resident of MSA i during the four years of 1999-2002. During this time, the average utility experienced 0.2 maximum contaminant level violations (one every 20 years) and 2.9 monitoring and reporting violations (one every 1.4 years).

It is important to note that certain states may be more or less stringent in their monitoring and enforcement activities related to drinking water quality. This may make it relatively more or relatively less likely for a utility to be cited for violating the SDWA in one state as opposed to another. This underscores the importance of estimating Equation 1 with state fixed effects.

2.3 Additional Controls and Data Sources

A possible concern is the potential correlation of miles of small streams with other topographic and climatic features of an MSA that predispose it to lower air quality. For example, one may be concerned that there are more small streams where there is access to a major river, which creates industrial opportunities and pollution. Alternately, one may be concerned that there are more small streams where there is more rainfall, which can transport pollutants through runoff. In Eqs. (1) and (2), we thus account for a vector of control variables, $\mathbf{X}_i$, for each MSA i.

We first add indicators for bordering the Pacific Ocean, the Atlantic Ocean, one of the Great Lakes, or a major river using data and definitions from the Environmental Systems Research Institute's (ESRI) Data and Maps software (2008).[22] Next, we include the logged land area of the MSA in thousands of square miles, and the standard deviation of elevation in the MSA (divided by 100), also using data from ESRI (2008).[23] The standard deviation of elevation accounts for the fact that certain areas may be more or less prone to pollution because they are situated in valleys or on rough terrain that traps pollutants. Finally, we include various weather controls: average hours of sunshine in January during 1940-1970 (in 100s), average monthly precipitation during 1970-2000 (in inches), and average heating degree days and cooling degree days per month during 1970-2000 (in 100s). Heating and cooling degree days are used to estimate amounts of energy required to maintain a comfortable indoor temperature. Each day, heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, and cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$. Data on hours of sunshine come from the GIS data in the 2002 Climate Atlas of the U.S., while all other weather data are from the National Climatic Data Center (NCDC) (2008).

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[22] Specifically, we use ESRI's (2008) 30-meter resolution, GTOP030 data series, for the USA. ESRI identifies 55 major rivers in the US. Of them, 34 branch off from one of seven major river systems—the Mississippi (12950 miles), St. Lawrence (7152 miles), Colorado (2703 miles), Columbia (2343 miles), Rio Grande (2144 miles), Yukon (1866 miles), and Nelson Saskatchewan (569 miles)—and 21 are not a part of a system.

[23] Since MSA land area is likely to be endogenous to environmental outcomes, we use an MSA's 1970 land area rather than its modern-day land area, as in Hatfield and Kosec (2012).

The inclusion of these controls explicitly allows them to have a direct impact on environmental quality, and ensures that our IV results are not driven by their correlation with our instrument. We find that their inclusion has little effect on the sign, magnitude, or significance of β_N in Eq. (1), and does not compromise the strength of our first stage in Eq. (2). Table 1 summarizes the dataset (compiled from the various sources detailed above), where an observation is an MSA.

2.4 Analysis of Mechanisms

As our empirical analysis suggests that having more jurisdictions leads to lower air quality, we then consider what mechanisms may help explain the results. First, we investigate how the number of jurisdictions affects employment per square mile in electric power generation, transmission, and distribution (NAICS code 2211) and chemical manufacturing (NAICS code 325); we use data from the Census Bureau's 2002 Economic Census to capture total employment in each MSA in these two key industries. We selected these two industries because they are among the industries that most clearly and directly contribute to the types of environmental pollution we examine. Specifically, data from the EPA (2008) show that 75% of sulfur dioxide pollution—one of the major components of the AQI—is the direct result of electric power generation. Additionally, nearly all of the 17 toxic air pollutants described earlier are used in or are products or byproducts of chemical manufacturing.[24] We normalize each of these measures by the land area of an MSA. Total land area captures in some sense the total amount of air that might be polluted by manufacturing activity. Since air pollution is typically measured as a concentration of the pollutant present in the air, this makes land area an important denominator in the measurement of industrial activity. We then log each of these normalized variables.

Next, we examine what share of the reduction in air quality due to more jurisdictions seems to come from more jurisdictions attracting more manufacturing activity of these two

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[24] Two exceptions are diesel engine emissions and coke oven emissions.

types. Specifically, we see whether and to what extent the effects of total jurisdictions on air quality are attenuated by controlling for these employment measures in our baseline air quality regressions. Controlling for employment per square mile allows us to recover that part of the effect of more jurisdictions that is *not* due to more activity in these industries.[25]

3 Results

3.1 OLS Results: Effects on Air Quality

Table 2 presents the results from OLS regressions of average air quality during 1999-2002 on the logged number of county governments. We use two measures of air quality: the Air Quality Index (AQI, where a higher score indicates more air pollution), and the percent of days that the AQI exceeds 100 (indicating unhealthy air). We find evidence of a robust, positive correlation between the number of county governments and each of these variables. Furthermore, the coefficient on the logged number of county governments varies little according to which topographic and climate controls are included. Having more counties in a metropolitan area is associated with more air pollution and with more days per year of dangerous air.

For the AQI measure of air quality, our baseline specification (which includes our full set of controls) appears in Column (4). We find that a 1 unit increase in the log of the number of county governments results in an 8.2 point increase in the AQI. Doubling the number of county governments—e.g., going from one to two, or from two to four—implies increasing the logged number of county governments by ln(2); hence, doubling the number of county governments is associated with a $\ln(2) \times 8.2 = 5.7$ point increase in the AQI. This is a sizeable, 40% of a standard deviation increase in the AQI, and is statistically significant

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[25] We had hoped to additionally analyze the mechanism of public transit. It may be the case that places with fewer governments coordinate better on public transit, lowering pollution. However, we were unable to obtain public transit data at the MSA-level. Data from the National Transit Database were at the Urbanized Area (UZA)-level, and UZAs are not mappable into MSAs. Data from the Nationwide Personal Transportation Survey covered only 114 urban areas, or less than half of our MSAs.

at the 1% level in this and all other specifications.

Importantly, however, not all increases in the AQI are considered dangerous to human health since an AQI under 100 is considered to be safe. Hence, we consider a second measure of air quality: the percent of days with an AQI over 100. Using this measure similarly suggests that more county governments are associated with greater air pollution; the baseline specification (with the full set of controls) appears in Column (8). We find that a 1 unit increase in the log of the number of county governments results in an additional 4.2 percent of days having an AQI above 100. With 365 days in a year, this means an additional 15 days per year with unhealthy air. This implies that doubling the number of county governments is associated with an additional $\ln(2) \times 4.2 = 2.9$ percent of days having an AQI above 100, which is equal to an additional 11 days per year with unhealthy air. The result is statistically significant at the 1% level in this and all other specifications.

3.2 IV First Stage Results

Table 3 presents estimates of the first stage instrumental variable regressions. The logged number of county governments is robustly positively correlated with the number of miles of small streams. Both the strength of the first stage and the size and magnitude of the coefficient on miles of small streams vary little according to which topographic and climate controls are included. Our baseline specification, in column (4), indicates that an additional 100 miles of small streams in an MSA is associated with an approximate 22% increase in the number of county governments. The t-statistic on total miles of small streams is 12.8 (implying an F-Statistic of 162.8), revealing a strong excluded instrument.

3.3 IV Results: Effects on Air Quality

Table 4 presents IV estimates of the effect of the number of jurisdictions on our two air quality measures. These estimates use, as an instrumental variable for logged county governments, the number of miles of small streams in an MSA. As in our OLS results, the results vary little according to the set of topographic and climate controls included: the coefficient on the logged number of county governments is positive and statistically significant at the 1% level in all specifications. However, compared to the OLS results, it is now somewhat larger in magnitude.

For the AQI measure of air quality, the coefficient on logged county governments in the baseline specification of Column (4) is 10.6. Hence, doubling the number of county governments is associated with a $\ln(2) \times 10.6 = 7.4$ point increase in the AQI. This is a sizable, half of a standard deviation increase in the AQI. Furthermore, doubling the number of county governments is associated with an additional $\ln(2) \times 5.1 = 3.5$ percent of days having an AQI above 100, which is equal to an additional 13 days per year with unhealthy air. A more modest, 50% increase in the number of jurisdictions—such as would result in going from two to three county governments—leads to an approximate 4.3 point increase in the AQI, and an additional 7.5 days per year with an AQI over 100. We take this as evidence of a robust, causal effect of having more jurisdictions on air quality, which may be underestimated when failing to account for the endogeneity of the number of jurisdictions. It is also a large increase when compared against the metropolitan area average of three weeks per year with unhealthy air.

The OLS and IV results are not statistically distinguishable, but the IV results are somewhat larger in magnitude. In the case of the AQI, the IV coefficient is about 30% larger than the OLS coefficient; in the case of the percent of days with unhealthy air ($\text{AQI} > 100$), the IV coefficient is about 22% larger than the OLS coefficient. The difference between the OLS and IV results may be explained by a number of potential sources of omitted variable bias. For example, areas with a larger number of jurisdictions may attract wealthier and more-educated citizens, and these citizens may demand a higher level of environmental quality.[26] Estimates that fail to take into account this source of endogeneity would likely be downward-biased.

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[26] See Hatfield and Kosec (2012) for some evidence that this is the case.

Several other factors seem to have some impact on air quality. In particular, having a larger land area is associated with lower air quality on both metrics, as is having rougher terrain (as measured by the standard deviation of elevation). Being on the Pacific Ocean is associated with better air quality on both metrics. In neither of the specifications does being on the Atlantic Ocean or the Great Lakes, the number of cooling degree days, hours of sunshine, or monthly rainfall have a statistically significant effect on air quality.

Table 5 shows that these findings are robust to the inclusion of a number of controls. In Column (1), we see that including a control for logged earnings by place of work per employee in 2000 has a very small effect on the coefficient on county governments; in the specification for which the AQI is the dependent variable, it goes from 10.65 to 10.69. Further including a control for population (Column 3) only drives the coefficients slightly upward, to 10.85. Controls for logged water area (in square miles) and the number of miles of major national rivers also have little effect on the coefficient. And finally, the coefficient is still similar—10.99—when controlling for the founding year of an MSA's earliest-founded county. A specification that includes all of these controls yields an even larger but still similar and still statistically significant coefficient of 12.06. These controls similarly have little effect on the results when our dependent variable is the percent of days with an unhealthy AQI. In general, our effects seem to come from having more county governments, and not from any correlation of having many county governments with these other factors.

3.4 IV Results: Effects on Toxic Air Pollutants

Table 6 presents OLS and IV estimates of the effect of the number of jurisdictions on the ambient concentrations of ten air pollutants associated with more non-cancer health problems and eight air pollutants associated with higher rates of cancer. These are pollutants classified by the EPA as being the most significant and dangerous airborne pollutants for human health. The concentrations of each of these pollutants are their average ambient concentrations (in micrograms per cubic meter) over the period 1999-2002; our dependent variables are the logarithms of these average concentrations. All specifications include our full set of topographic and climate controls, $\mathbf{X}_i$. The excluded instrument in the IV specification is 100s of miles of small streams, as before.

We find—in both the OLS and IV specifications—that there are higher concentrations of nearly all of these pollutants in areas with more jurisdictions. From the IV results—our preferred specification—we see that doubling the number of counties increases the concentrations of pollutants associated with greater non-cancer health problems by between 17% (in the case of manganese compounds) and 78% (in the case of chlorine). Only in the case of hexamethylene diisocyanate are more jurisdictions associated with no statistically significant increase in the pollutant's ambient concentration.[27] More jurisdictions are also associated with higher concentrations of pollutants known to cause cancer. Specifically, doubling the number of jurisdictions increases the concentrations of these pollutants by between 19% (in the case of benzene) and 250% (in the case of coke oven emissions). We take this as evidence of a robust, causal effect of the number of jurisdictions on the prevalence of air pollutants known to harm health.

To assess the overall cancer effects of having more jurisdictions, we can combine the information from the eight cancer-causing pollutants by multiplying the concentration of each by its unit risk estimate, defined as the "excess lifetime cancer risk estimated to result from continuous exposure to an agent at a concentration of 1 g/m^3 in air." We then sum these normalized variables (called cancer risks) across all eight pollutants; the resulting variable is the net cancer risk collectively posed by the eight cancer-causing pollutants. When we regress a logged variant of this variable on the logged number of county governments, we find that doubling the number of counties increases average cancer risk posed by pollution by 23%. As the EPA estimates that the rate of cancer due to air pollution in the U.S. is $\frac{1}{27{,}000}$, a back of the envelope calculation implies that doubling inter-jurisdictional competition within

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[27] The ambient concentration of hexamethylene diisocyanate is 0 in over 40% of MSAs, which contributes to the smaller sample size for this pollutant.

an MSA increases the rate of cancer due to air pollution by roughly $\frac{1}{117{,}000}$.[28] That is, our results imply that, statistically, an additional one in 117,000 people will develop air pollution-induced cancer (a 23% increase over the average) as a result of having double the number of county governments (e.g., two instead of one).

To assess the overall non-cancer health effects of having more jurisdictions, we can combine the information from the ten non-cancer pollutants by dividing the concentration of each by it reference concentration, defined as "the highest amount likely to be without an appreciable risk of deleterious effects." We then sum these normalized variables (called hazard quotients) across all ten pollutants. When we regress a logged variant of this variable on the logged number of county governments, we find that doubling the number of jurisdictions increases average non-cancer health hazards by 34%. This number is naturally harder to interpret than increased cancer risk given the multitude of possible non-cancer health impacts of pollution (e.g., asthma, bronchitis, emphysema, and heart problems). However, it suggests that these problems are significantly more prevalent in MSAs with more counties.

However, it may be the case MSAs with more jurisdictions may enhance the health of their residents through other means, such as higher incomes, better public and private health care systems, or better public awareness campaigns. Nevertheless, these results indicate that residents of areas with more jurisdictions are much more likely to breathe toxins associated with cancer and other health problems.

3.5 Placebo Analysis: Effects on Water Quality

A useful placebo analysis is to analyze whether the number of jurisdictions affects the quality of a publicly-provided, environmental good that does not have inter-jurisdictional spillovers. If, as we have hypothesized, air quality is lower in places with more jurisdictions due to spillovers (and not for some other reason), then we should not expect to see effects of the number of jurisdictions on an environmental good that lacks spillovers. Perhaps the most

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[28] The rate $\frac{1}{27{,}000}$ is likely a lower bound on the rate of cancer due to air pollution in our sample, which contains only metropolitan areas and not rural areas or smaller cities.

obvious candidate for such an analysis is public drinking water quality. Just as the EPA regulates air quality through the Clean Air Act, it regulates water quality through the Safe Drinking Water Act. However, we should expect no inter-jurisdictional spillovers in the case of drinking water, as local governments only provide water to residents in their own jurisdiction. In this way, the costs (benefits) of low-quality (high-quality) drinking water are borne entirely by residents and policymakers in the jurisdiction that provides them.

Table 7 presents the OLS and IV results from this placebo analysis, with and without the full set of controls. We use two measures of water quality: the number of maximum contaminant level violations for the average utility during 1999-2002, and the number of monitoring and reporting violations for the average utility during 1999-2002. Unlike the case of air quality, drinking water quality is unaffected by the number of jurisdictions in it. In none of the specifications is the number of jurisdictions significant at conventional levels; the point estimates imply that, if anything, water quality is higher in MSAs with a greater number of jurisdictions. In particular, the coefficients on the baseline IV specifications of Columns (4) and (8) (which include the full set of controls)—if significant—would imply that doubling the number of county governments is associated with $\ln(2) \times 0.045 = 0.03$ fewer maximum contaminant level violations, and $\ln(2) \times 0.555 = 0.39$ fewer monitoring and reporting violations for the average utility in the MSA during 1999-2002. This is a relatively modest, 16% reduction in the mean number of maximum contaminant level violations (0.2) and 13% reduction in the mean number of monitoring and reporting violations (2.9).

As these effects are not statistically significant, we conclude that people living in MSAs with many counties are just as likely to have high quality public drinking water as are people living in MSAs with few counties. Since both drinking water and air quality are publicly-provided, environmental goods regulated by the federal government, this is consistent with spillovers (present for air but not for drinking water quality) being a defining characteristic determining which goods are likely to be under-provided by local governments.

4 Mechanisms

4.1 Electric Power Generation

As our empirical analysis suggests that having more jurisdictions leads to lower air quality, we next consider what mechanisms may help explain the results. A natural first question is what factors lead to higher concentrations of the five pollutants on which the AQI depends (ozone, particulate matter, carbon monoxide, sulfur dioxide, and nitrogen dioxide). Motor vehicle exhaust accounts for the majority of carbon monoxide, nitrogen dioxide, and ozone pollution, which is likely increasing mechanically in vehicles per land area. However, sulfur dioxide is a pollutant for which 75% is the direct result of a single industry: electric power generation (EPA 2008). This provides a valuable opportunity to focus our attention specifically on the effects of the number of county governments on sulfur dioxide, and to learn about whether these effects are due to MSAs with more counties having a bigger power industry.

Table 8 examines the effect of the number of jurisdictions on power generation, total sulfur dioxide emissions (tons), and sulfur dioxide emissions coming specifically from electric power generation (tons). Table 8, Column (1) reveals that doubling the number of county governments is associated with 65% higher employment per land area in electric power generation, transmission, and distribution, implying that the number of jurisdictions in an MSA has a robust, positive impact on employment in the power industry.

Columns (2) and (4) suggest that doubling the number of county governments is associated with 40% higher sulfur dioxide emissions and 126% higher sulfur dioxide emissions from electric power generation. However, columns (3) and (5), respectively, reveal a sizable decrease in these two coefficients after controlling for total employment in electric power generation, transmission, and distribution per land area. Both coefficients drop significantly in magnitude—from 40% to 13% in the case of sulfur dioxide emissions, and from 126% to 27% for sulfur dioxide emissions from electric power generation—and become statistically insignificant. This suggests that a large majority (70-80%) of the effect of the number of county governments on the concentration of sulfur dioxide comes through the propensity of places with more county governments to have more electric power generation.

4.2 Chemical Manufacturing

Finally, we examine what share of the increase in toxic air pollutants due to more jurisdictions can be explained by these areas attracting more chemical manufacturing activity. Controlling for employment in chemical manufacturing per square mile allows us to recover that part of the effect of more jurisdictions that is *not* due to more activity in this industry. Table 9, Panel A reveals that doubling the number of county governments is associated with 101% higher employment per land area in chemical manufacturing, which is statistically significant at the 1% level.

Table 10 shows that employment per land area in these two industries is indeed associated with higher concentrations of toxic air pollutants. We consider the same 17 toxic air pollutants considered in the previous section, but exclude two that are unrelated to chemical manufacturing: coke oven emissions and diesel engine emissions. We find that doubling the number of employees in chemical manufacturing per land area is associated with higher ambient concentrations of nearly all of these toxic air pollutants. Most strikingly, it is associated with 55% more chlorine, 22% more chromium, and 22% more hydrazine. Only in the case of hexamethylene diisocyanate does greater employment in chemical manufacturing not have a positive impact on the pollutant which is statistically significant at the 1% level or higher.[29]

Table 9, Panel B examines whether the effect of the number of jurisdictions on toxic air pollutants—the non-cancer hazard drivers and cancer risk drivers—varies when we control for the number of employees in chemical manufacturing per square mile. Panel B suggests that doubling the number of county governments is associated with significantly higher concentrations of every one of these toxic air pollutants except hexamethylene diisocyanate.

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[29] As mentioned in Footnote 27, the ambient concentration of hexamethylene diisocyanate is 0 in over 40% of MSAs, which contributes to the smaller sample size for this pollutant.

Most strikingly, it is associated with 78% more chlorine, 60% more hydrazine, 43% more acrolein, and 35% more chromium. However, there is a sizable decrease in these effects after controlling for total employment in chemical manufacturing per land area. All coefficients drop significantly in magnitude—from 78% to 30% in the case of chlorine (a 62% drop), from 60% to 46% for hydrazine, from 33% to 20% for 2,4-toluene diisocyanante, and from 35% to 16% for chromium. In the cases of chlorine, hydrazine, and chromium, these coefficients also become statistically insignificant. It seems that a sizable share of the effect of logged county governments on the concentration of these toxic air pollutants was due to the propensity of MSAs with more county governments to have more chemical manufacturing.

5 Conclusion

In this work, we have used exogenous variation in the natural topography of U.S. metropolitan areas to estimate the causal impact of the number of jurisdictions on the quality of local, publicly-provided, environmental goods. We find that increasing the number of jurisdictions leads to a significant degradation of air quality, a publicly-provided good subject to significant spillovers. By contrast, we find that increasing the number of jurisdictions has led to no significant changes in public drinking water quality, a publicly-provided good not subject to significant spillovers. We further find that the differences in pollution levels between MSAs can largely be explained by differences in levels of industrial activity which produce such pollutants.

These results imply not only that local decisionmaking is important in determining local environmental quality, but also that the degree of jurisdictional segmentation, i.e., the number of local jurisdictions, is important in determining local decisionmaking. In particular, our results imply that public goods with significant spillovers (like air quality) will be under-provided by small local governments and, in such circumstances, it may be beneficial to centralize the provision of such goods. In the case of air quality, this would imply a greater centralization of regulatory authority on decisions affecting air pollution.

This paper demonstrates one of the costs of a greater number of jurisdictions: greater environmental pollution. In our earlier work, Hatfield and Kosec (2012), we showed that a greater degree of inter-jurisdictional competition leads to higher wages and higher economic growth, as well as higher taxes. Hence, this body of work demonstrates both the costs and benefits of a greater degree of inter-jurisdictional competition. Future research may help us to understand more fully the effects of inter-jurisdictional competition, as well as how to better assign policymaking authority to local governments.

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A Tables

Table 1: Summary Statistics

Variable	**Mean**	**Std. Dev.**
Average Air Quality Index (AQI), 1999-2002	44.35	14.44
Percent of days with an unhealthy AQI (greater than 100), 1999-2002	5.87	7.98
# maximum contaminant level violations for average water utility, 1999-2002	0.19	0.39
# monitoring and reporting violations for average water utility, 1999-2002	2.91	9.61
Number of county governments	2.53	2.50
100s of miles of streams (ESRI GIS Data)	2.92	2.68
Dummy - on pacific ocean	0.04	0.20
Dummy - on atlantic ocean	0.12	0.33
Dummy - on great lakes	0.07	0.25
Dummy - on major river	0.23	0.42
Log land area (1970, 1000s square miles)	1.50	1.37
Cooling degree days, 1970-2000 average	1.17	0.81
Heating degree days, 1970-2000 average	3.71	1.95
Hours of sunshine, average in January (1940-1970)	1.52	0.39
Monthly rainfall, 1970-2000 average	3.32	1.19
Standard deviation of elevation	0.11	0.17
Employment in chemical manufacturing (NAICS code 325) per sq. mile	0.73	1.00
Employment in electric power industry (NAICS code 2211) per sq. mile	0.52	0.63
Sulfur dioxide emissions in 2008 (tons)	8.94	19.20
Sum of non-cancer hazard quotients (over 10 pollutants)	421.68	435.89
Sum of average cancer risks (over 8 pollutants)	29.57	30.11
Ambient concentration of acrolein in 2002	4.78	3.65
Ambient concentration of 2,4-toluene diisocyanate in 2002	0.02	0.06
Ambient concentration of chlorine in 2002	0.78	2.59
Ambient concentration of chromium compounds in 2002	0.11	0.24
Ambient concentration of diesel engine emissions in 2002	78.94	41.50
Ambient concentration of formaldehyde in 2002	148.10	47.41
Ambient concentration of hexamethylene diisocyanate in 2002	0.01	0.15
Ambient concentration of hydrochloric acid in 2002	27.69	76.01
Ambient concentration of manganese compounds in 2002	0.20	0.32
Ambient concentration of nickel compounds in 2002	0.12	0.18
Ambient concentration of benzene in 2002	125.67	33.80
Ambient concentration of 1,3-butadiene in 2002	8.02	2.40
Ambient concentration of arsenic compounds in 2002	0.05	0.03
Ambient concentration of coke oven emissions in 2002	0.18	0.75
Ambient concentration of hydrazine in 2002	0.00	0.00
Ambient concentration of tetrachloroethylene in 2002	12.89	8.82
Ambient concentration of naphthalene in 2002	3.73	3.14
Number of observations	209	

Table 2: OLS Results, Showing the Effect of the Logged Number of County Governments on Two Measures of Air Quality

	Dep. Var.: Average Air Quality Index (AQI), 1999-2002				Dep. Var.: Percent of days with unhealthy AQI, 1999-2002			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log # of county governments	7.39	8.47	8.40	8.21	3.67	4.41	4.34	4.16
	(1.21)***	(1.54)***	(1.43)***	(1.37)***	(0.80)***	(1.04)***	(0.90)***	(0.85)***
Dummy - on pacific ocean			-5.70	-11.15			-6.20	-7.36
			(7.15)	(6.47)*			(4.40)	(3.17)**
Dummy - on atlantic ocean			0.97	-2.43			1.49	0.67
			(2.42)	(2.75)			(1.35)	(1.59)
Dummy - on great lakes			6.85	6.94			3.85	3.99
			(4.63)	(4.89)			(2.46)	(2.69)
Dummy - on major river			3.22	2.43			4.44	3.78
			(3.03)	(3.05)			(1.78)**	(1.71)**
Log land area				2.31				1.55
				(1.56)				(0.85)*
Cooling degree days				-3.68				-0.95
				(6.99)				(3.37)
Heating degree days				-9.43				-2.85
				(4.10)**				(1.84)
Hours of sunshine				-0.58				0.20
				(7.46)				(3.52)
Monthly rainfall				-0.22				-0.54
				(2.15)				(1.10)
Standard deviation of elevation				29.00				21.48
				(7.24)***				(3.89)***
State fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	209	209	209	209	209	209	209	209
R-squared	0.13	0.43	0.45	0.54	0.11	0.38	0.44	0.55

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates $p<.01$; ** indicates $p<.05$; * indicates $p<.10$. The same sample is used for all regressions. Dummy - on pacific ocean, Dummy - on atlantic ocean, and Dummy - on great lakes are indicators for bordering the Pacific Ocean, Atlantic Ocean, and Great Lakes, respectively. Dummy - on major river is an indicator for bordering a major river. Log land area is the log of the area of the (C)MSA in 1970, excluding area covered with water (in 1000s of square miles). Each day, heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2000, over 100. Hours sunshine is the average hours of sunshine in January, during 1941-1970 (in 100s). Monthly rainfall is average monthly precipitation during 1970-2000, in inches. The standard deviation of elevation is in 1000s of feet.
Sources: EPA (1999-2002), NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

Table 3: IV First Stage Results, Showing the Effect of Miles of Small Streams on the Logged Number of County Governments

Dep. Var.: Log # of county governments	(1)	(2)	(3)	(4)
100s miles of small streams	0.14	0.21	0.21	0.22
	(0.02)***	(0.02)***	(0.02)***	(0.02)***
Dummy - on pacific ocean			0.00	-0.36
			(0.23)	(0.23)
Dummy - on atlantic ocean			0.01	0.09
			(0.14)	(0.15)
Dummy - on great lakes			-0.07	-0.10
			(0.20)	(0.20)
Dummy - on major river			0.04	0.09
			(0.10)	(0.09)
Log land area				0.01
				(0.07)
Cooling degree days				-0.80
				(0.22)***
Heating degree days				-0.35
				(0.14)**
Hours of sunshine				-0.01
				(0.25)
Monthly rainfall				-0.01
				(0.10)
Standard deviation of elevation				-0.50
				(0.25)**
State fixed effects	No	Yes	Yes	Yes
Observations	209	209	209	209
R-squared	0.30	0.66	0.66	0.69
First stage F-stat, excluded instrument	59.93	190.38	191.75	162.82

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates p<.01; ** indicates p<.05; * indicates p<.10. The same sample is used for all regressions. 100s miles of small streams comes from a computation using ESRI (2008) GIS data that show all streams *not* classified as major national rivers as line features on a map. Dummy - on pacific ocean, Dummy - on atlantic ocean, and Dummy - on great lakes are indicators for bordering the Pacific Ocean, Atlantic Ocean, and Great Lakes, respectively. Dummy - on major river is an indicator for bordering a major river. Log land area is the log of the area of the (C)MSA in 1970, excluding area covered with water (in 1000s of square miles). Each day, heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2000, over 100. Hours sunshine is the average hours of sunshine in January, during 1941-1970 (in 100s). Monthly rainfall is average monthly precipitation during 1970-2000, in inches. The standard deviation of elevation is in 1000s of feet.
Sources: EPA (1999-2002), NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

Table 4: IV Second Stage Results, Showing the Effect of the Logged Number of County Governments on Two Measures of Air Quality

	Dep. Var.: Average Air Quality Index (AQI), 1999-2002				Dep. Var.: Percent of days with unhealthy AQI, 1999-2002			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log # of county governments	12.20	11.71	11.67	10.65	6.44	6.04	6.01	5.09
	(2.73)***	(1.55)***	(1.47)***	(1.38)***	(1.67)***	(1.04)***	(0.90)***	(0.83)***
Dummy - on pacific ocean			-6.94	-11.48			-6.83	-7.49
			(6.67)	(5.80)**			(4.06)*	(2.79)***
Dummy - on atlantic ocean			0.62	-2.81			1.31	0.53
			(2.08)	(2.41)			(1.20)	(1.40)
Dummy - on great lakes			6.36	6.63			3.60	3.87
			(4.30)	(4.46)			(2.31)	(2.43)
Dummy - on major river			2.83	2.05			4.24	3.63
			(2.68)	(2.67)			(1.53)***	(1.47)**
Log land area				2.10				1.47
				(1.27)*				(0.72)**
Cooling degree days				-2.17				-0.37
				(5.97)				(2.87)
Heating degree days				-8.83				-2.62
				(3.57)**				(1.61)
Hours of sunshine				0.35				0.56
				(6.57)				(3.05)
Monthly rainfall				-0.38				-0.60
				(1.85)				(0.97)
Standard deviation of elevation				28.17				21.16
				(6.36)***				(3.46)***
State fixed effects	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	209	209	209	209	209	209	209	209
First stage F-stat, excluded instrument	59.93	190.38	191.75	162.82	59.93	190.38	191.75	162.82

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates $p<.01$; ** indicates $p<.05$; * indicates $p<.10$. The same sample is used for all regressions. The instrumental variable is hundreds of miles of small streams in the MSA. Dummy - on pacific ocean, Dummy - on atlantic ocean, and Dummy - on great lakes are indicators for bordering the Pacific Ocean, Atlantic Ocean, and Great Lakes, respectively. Dummy - on major river is an indicator for bordering a major river. Log land area is the log of the area of the (C)MSA in 1970, excluding area covered with water (in 1000s of square miles). Each day, heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2000, over 100. Hours sunshine is the average hours of sunshine in January, during 1941-1970 (in 100s). Monthly rainfall is average monthly precipitation during 1970-2000, in inches. The standard deviation of elevation is in 1000s of feet.

Sources: EPA (1999-2002), NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

Table 5: IV Second Stage Results, Showing that the Effect of the Logged Number of County Governments on Air Quality is Robust to Inclusion of Numerous Controls

	Dep. Var.: Average Air Quality Index (AQI), 1999-2002						Dep. Var.: Percent of days with unhealthy AQI, 1999-2002					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log # county governments	10.69	8.08	10.85	10.62	10.99	12.06	5.56	4.33	5.61	5.56	5.30	6.59
	(2.39)***	(1.64)***	(2.42)***	(2.45)***	(1.45)***	(3.49)***	(1.29)***	(0.94)***	(1.30)***	(1.55)***	(0.87)***	(1.98)***
Log earnings per employe	-1.53		-22.44			-23.43	-3.09		-10.37			-11.02
	(11.21)		(11.72)*			(12.33)*	(5.70)		(5.88)*			(6.08)*
Log population per sq. mi.		5.28	6.85			7.68		1.66	2.38			2.76
		(1.74)***	(1.80)***			(1.81)***		(0.95)*	(0.99)**			(1.00)***
Log of water area (sq. mi.)				-0.06		-0.36				-0.17		-0.32
				(1.36)		(1.45)				(0.80)		(0.85)
Founding year, over 100					3.27	7.64					2.03	3.19
					(3.92)	(3.60)**					(1.93)	(2.09)
100s miles of major rivers				-0.68		-1.68				-1.42		-1.83
				(2.33)		(2.41)				(1.69)		(1.78)
Observations	207	207	207	206	209	206	207	207	207	206	209	206
First Stage F-Stat	63.75	113.12	74.64	61.05	149.41	36.45	63.75	113.12	74.64	61.05	149.41	36.45

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates p<.01; ** indicates p<.05; * indicates p<.10. The instrumental variable is hundreds of miles of small streams in the MSA. All specifications include dummies for bordering the pacific ocean, atlantic ocean, the Great Lakes, and a major river. They additionally controls controls for log land area, heating degree days, cooling degree days, hours sunshine in January, rainfall, and the standard deviation of elevation.

Sources: BEA (1969-2006), Census of Governments (1962-2002), NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

Table 6: OLS and IV Results, Showing the Effect of the Logged Number of County Governments on the Ambient Concentrations of Toxic Air Pollutants Associated with Higher Rates of Non-cancer Health Problems and Cancer

Dependent Variable (Pollutant):	OLS Coeff. on # county governments	OLS S.E. on # county governments	IV Coeff. on # county governments	IV S.E. on # county governments	N
Panel A: Non-cancer hazard drivers (log of concentration)					
Acrolein	0.355	(0.036)***	0.433	(0.043)***	226
2,4-toluene diisocyanate	0.301	(0.088)***	0.335	(0.116)***	226
Chlorine	0.621	(0.318)*	0.784	(0.301)***	212
Chromium compounds	0.373	(0.080)***	0.351	(0.086)***	226
Diesel engine emissions	0.268	(0.031)***	0.303	(0.042)***	226
Formaldehyde	0.172	(0.022)***	0.190	(0.021)***	226
Hexamethylene diisocyanate	0.747	(0.563)	0.982	(0.618)	126
Hydrochloric acid	0.22	(0.077)***	0.291	(0.084)***	226
Manganese compounds	0.159	(0.062)**	0.171	(0.059)***	226
Nickel compounds	0.404	(0.079)***	0.309	(0.091)***	226
Log of sum of non-cancer hazard quotients (over 10 pollutants)	0.264	(0.038)***	0.336	(0.045)***	226
Panel B: Cancer drivers (log of concentration)					
Benzene	0.179	(0.021)***	0.187	(0.025)***	226
1,3-butadiene	0.193	(0.021)***	0.220	(0.025)***	226
Arsenic compounds	0.273	(0.041)***	0.242	(0.046)***	226
Chromium compounds	0.373	(0.080)***	0.351	(0.086)***	226
Coke oven emissions	1.573	(4.371)	2.502	(1.026)**	17
Hydrazine	0.373	(0.177)**	0.595	(0.268)**	226
Tetrachloroethylene	0.253	(0.037)***	0.312	(0.041)***	226
Naphthalene	0.288	(0.036)***	0.321	(0.047)***	226
Log of sum of average cancer risks (over 8 pollutants)	0.228	(0.039)***	0.229	(0.036)***	226

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates p<.01; ** indicates p<.05; * indicates p<.10. The same sample is used for all regressions. All specifications include state group fixed effects, ocean and Great Lakes access controls, weather controls, and a control for the S.D. of elevation. The instrumental variable is hundreds of miles of small streams in the MSA. Each pollutant is entered in the regression as the log of its ambient concentration in the MSA (in micrograms per cubic meter), using measurements where available and emissions estimates and air dispersion models otherwise. A non-cancer hazard quotient for a pollutant is its concentration divided by a reference concentration (RfC), which is defined as the highest amount " likely to be without an appreciable risk of deleterious effects during a lifetime." A cancer risk for a pollutant is its concentration multiplied by a unit risk estimate (URE), which is "the upper-bound excess lifetime cancer risk estimated to result from continuous exposure to an agent at a concentration of 1 g/m^3 in air."
Sources: EPA (1999-2002), NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

Table 7: IV Second Stage Placebo Results, Showing the Effect of the Logged Number of County Governments on Two Measures of Water Quality

	# maximum contaminant level violations, 1999-2002				# monitoring and reporting violations, 1999-2002			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log # of county governments	-0.033	-0.037	-0.050	-0.045	-0.820	-1.007	-0.499	-0.555
	(0.031)	(0.036)	(0.034)	(0.035)	(0.593)	(0.665)	(0.381)	(0.411)
Dummy - on pacific ocean		-0.243		-0.242		-1.455		-1.538
		(0.112)**		(0.099)**		(1.883)		(1.677)
Dummy - on atlantic ocean		0.005		0.007		0.393		0.314
		(0.073)		(0.065)		(0.519)		(0.431)
Dummy - on great lakes		0.095		0.097		1.111		1.014
		(0.175)		(0.155)		(2.524)		(2.254)
Dummy - on major river		-0.042		-0.041		0.841		0.775
		(0.061)		(0.053)		(1.526)		(1.323)
Log land area		0.002		0.003		-0.029		-0.075
		(0.031)		(0.028)		(0.571)		(0.494)
Cooling degree days		-0.241		-0.245		-4.555		-4.314
		(0.193)		(0.173)		(2.168)**		(1.883)**
Heating degree days		-0.125		-0.126		-2.859		-2.761
		(0.100)		(0.089)		(1.653)*		(1.444)*
Hours of sunshine		0.006		0.002		-1.966		-1.774
		(0.117)		(0.104)		(2.274)		(2.062)
Monthly rainfall		0.010		0.010		-0.705		-0.726
		(0.041)		(0.036)		(0.793)		(0.696)
Standard deviation of elevation		0.077		0.080		2.493		2.330
		(0.226)		(0.200)		(1.556)		(1.339)*
Observations	226	226	226	226	226	226	226	226
First Stage F-Stat			199.59	172.24			199.59	172.24
R-squared	0.29	0.30			0.72	0.73		

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates p<.01; ** indicates p<.05; * indicates p<.10. The same sample is used for all regressions. All specifications include state group fixed effects. The instrumental variable is hundreds of miles of small streams in the MSA. Dummy - on pacific ocean, Dummy - on atlantic ocean, and Dummy - on great lakes are indicators for bordering the Pacific Ocean, Atlantic Ocean, and Great Lakes, respectively. Dummy - on major river is an indicator for bordering a major river. Log land area is the log of the area of the (C)MSA in 1970, excluding area covered with water (in 1000s of square miles). Each day, heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2000, over 100. Hours sunshine is the average hours of sunshine in January, during 1941-1970 (in 100s). Monthly rainfall is average monthly precipitation during 1970-2000, in inches. The standard deviation of elevation is in 1000s of feet.

Sources: EPA (1999-2002), NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

Table 8: IV Second Stage Results, Showing How the Effect of the Logged Number of County Governments on Sulfur Dioxide (SO_2) Emissions Changes When Controlling for Employment in Electric Power Generation, Transmission, and Distribution Per Square Mile

	Log # employees in electric power generation, transmission, & distribution per sq. mile	Log of total SO_2 emissions (tons)		Log of total SO_2 emissions from electric power generation (tons)	
	(1)	(2)	(3)	(4)	(5)
Log number of county governments	0.65	0.40	0.13	1.26	0.27
	(0.10)***	(0.14)***	(0.16)	(0.43)***	(0.52)
Log # employees in electric power per sq. mile			0.42		1.45
			(0.12)***		(0.36)***
Dummy - on pacific ocean	-0.24	-0.39	-0.29	-4.97	-5.24
	(0.37)	(0.45)	(0.48)	(2.14)**	(1.99)***
Dummy - on atlantic ocean	0.49	0.99	0.78	0.28	-0.33
	(0.22)**	(0.40)**	(0.38)**	(0.92)	(0.87)
Dummy - on great lakes	0.44	1.13	0.94	2.31	1.53
	(0.30)	(0.36)***	(0.39)**	(1.24)*	(1.30)
Dummy - on major river	-0.29	0.26	0.39	1.16	1.46
	(0.20)	(0.28)	(0.28)	(0.80)	(0.77)*
Log land area	-0.09	0.26	0.29	0.90	0.94
	(0.10)	(0.14)*	(0.13)**	(0.44)**	(0.42)**
Cooling degree days	-0.31	-1.54	-1.41	-5.31	-5.32
	(0.38)	(0.50)***	(0.46)***	(1.83)***	(1.63)***
Heating degree days	-0.45	-0.86	-0.67	-3.53	-3.13
	(0.23)*	(0.30)***	(0.29)**	(1.34)***	(1.21)***
Hours of sunshine	0.83	0.69	0.34	0.56	-1.23
	(0.48)*	(0.65)	(0.64)	(2.26)	(2.14)
Monthly rainfall	-0.04	0.48	0.49	0.60	0.42
	(0.16)	(0.20)**	(0.21)**	(0.83)	(0.83)
Standard deviation of elevation	-0.86	-0.19	0.17	-2.75	-1.92
	(0.49)*	(0.62)	(0.65)	(2.07)	(1.94)
Observations	225	225	225	190	190
First Stage F-Stat	172.13	172.13	139.46	149.27	113.96

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates p<.01; ** indicates p<.05; * indicates p<.10. The same sample is used for all regressions. The instrumental variable is hundreds of miles of small streams in the MSA. Dummy - on pacific ocean, Dummy - on atlantic ocean, and Dummy - on great lakes are indicators for bordering the Pacific Ocean, Atlantic Ocean, and Great Lakes, respectively. Dummy - on major river is an indicator for bordering a major river. Log land area is the log of the area of the (C)MSA in 1970, excluding area covered with water (in 1000s of square miles). Each day, heating degree days equal $\max\{0, 65 - \text{mean temperature}\}$, cooling degree days equal $\max\{0, \text{mean temperature} - 65\}$, and the heating and cooling degree variables are the average monthly total during 1970-2000, over 100. Hours sunshine is the average hours of sunshine in January, during 1941-1970 (in 100s). Monthly rainfall is average monthly precipitation during 1970-2000, in inches. The standard deviation of elevation is in 1000s of feet. Data show that 75% of sulfur dioxide pollution is due to electricity generation, motivating this analysis.
Sources: EPA (1999-2002), EPA (2008) NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

Table 9: IV Results, Showing the Effect of the Logged Number of County Governments on Ambient Concentrations of Toxic Air Pollutants When Controlling for Employment in Chemical Manufacturing

	Log # county govts		Log # employees in chemical manufacturing per sq. mile		N	% Change in coeff. on log # county govts
	IV Coeff.	IV S.E.	IV Coeff.	IV S.E.		
Panel A: Effects of log # county governments on log # employees in chemical manufacturing per sq. mile						
Log # employees in chemical manufacturing per sq. mile	1.01	(0.15)***			224	
Panel B: Effects of log # county governments on log concentration of toxic air pollutants						
Acrolein	0.43	(0.04)**				
Acrolein	0.38	(0.05)**	0.05	(0.02)**	224	12%
2,4-toluene diisocyanate	0.33	(0.12)**				
2,4-toluene diisocyanate	0.20	(0.13)	0.13	(0.04)**	224	39%
Chlorine	0.78	(0.30)**				
Chlorine	0.30	(0.36)	0.49	(0.16)**	211	62%
Chromium compounds	0.35	(0.09)**				
Chromium compounds	0.16	(0.10)	0.19	(0.05)**	224	54%
Formaldehyde	0.19	(0.02)**				
Formaldehyde	0.15	(0.03)**	0.04	(0.01)**	224	21%
Hexamethylene diisocyanate	0.98	(0.62)				
Hexamethylene diisocyanate	0.95	(0.72)	0.03	(0.26)	126	3%
Hydrochloric acid	0.29	(0.08)**				
Hydrochloric acid	0.12	(0.09)	0.17	(0.03)**	224	59%
Manganese compounds	0.17	(0.06)**				
Manganese compounds	0.07	(0.08)	0.10	(0.03)**	224	59%
Nickel compounds	0.31	(0.09)**				
Nickel compounds	0.15	(0.11)	0.16	(0.05)**	224	52%
Benzene	0.19	(0.02)**				
Benzene	0.15	(0.03)**	0.03	(0.01)**	224	21%
1,3-butadiene	0.22	(0.03)**				
1,3-butadiene	0.18	(0.03)**	0.04	(0.01)**	224	18%
Arsenic compounds	0.24	(0.05)**				
Arsenic compounds	0.16	(0.05)**	0.08	(0.02)**	224	33%
Hydrazine	0.60	(0.27)*				
Hydrazine	0.46	(0.30)	0.14	(0.08)	224	23%
Tetrachloroethylene	0.31	(0.04)**				
Tetrachloroethylene	0.26	(0.04)**	0.05	(0.02)**	224	16%
Naphthalene	0.32	(0.05)**				
Naphthalene	0.29	(0.05)**	0.03	(0.02)	224	9%

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates p<.01; ** indicates p<.05; * indicates p<.10. All specifications include state group fixed effects, ocean and Great Lakes access controls, weather controls, and a control for the S.D. of elevation. The instrumental variable is hundreds of miles of small streams in the MSA. Each pollutant is entered in the regression as the log of its ambient concentration in the MSA (in micrograms per cubic meter), using measurements where available and emissions estimates and air dispersion models otherwise. A non-cancer hazard quotient for a pollutant is its concentration divided by a reference concentration (RfC), which is defined as the highest amount " likely to be without an appreciable risk of deleterious effects during a lifetime." A cancer risk for a pollutant is its concentration multiplied by a unit risk estimate (URE), which is "the upper-bound excess lifetime cancer risk estimated to result from continuous exposure to an agent at a concentration of 1 g/m^3 in air." Employment in chemical manufacturing is employment in NAICS code 325.
Sources: EPA (1999-2002), NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

Table 10: OLS Regressions, Showing the Effect of Employment in Chemical Manufacturing Per Square Mile on Ambient Concentrations of Toxic Air Pollutants

	Log # employees in chemical manufacturing per sq. mile		N	R-squared
Dep. Var. (toxic air pollutant):	OLS Coeff.	OLS S.E.		
Acrolein	0.12	(0.02)***	224	0.67
2,4-toluene diisocyanate	0.17	(0.04)***	224	0.76
Chlorine	0.55	(0.14)***	211	0.52
Chromium compounds	0.22	(0.05)***	224	0.52
Formaldehyde	0.07	(0.01)***	224	0.55
Hexamethylene diisocyanate	0.23	(0.26)	126	0.42
Hydrochloric acid	0.19	(0.03)***	224	0.81
Manganese compounds	0.11	(0.03)***	224	0.55
Nickel compounds	0.18	(0.05)***	224	0.60
Benzene	0.06	(0.01)***	224	0.49
1,3-butadiene	0.08	(0.01)***	224	0.53
Arsenic compounds	0.11	(0.02)***	224	0.63
Hydrazine	0.22	(0.07)***	224	0.62
Tetrachloroethylene	0.10	(0.02)***	224	0.72
Naphthalene	0.09	(0.02)***	224	0.70

Notes: Each observation is an MSA (or a CMSA in the case of larger metropolitan areas). Robust standard errors appear in parentheses below the coefficient. *** indicates p<.01; ** indicates p<.05; * indicates p<.10. All specifications include dummies for bordering the pacific ocean, atlantic ocean, the Great Lakes, and a major river. They additionally controls controls for log land area, heating degree days, cooling degree days, hours sunshine in January, rainfall, and the standard deviation of elevation. Employment in chemical manufacturing is employment in NAICS code 325.

Sources: EPA (1999-2002), EPA (2008), NCDC (2002), ESRI (2008), NCDC (2008), and NOAA (2008).

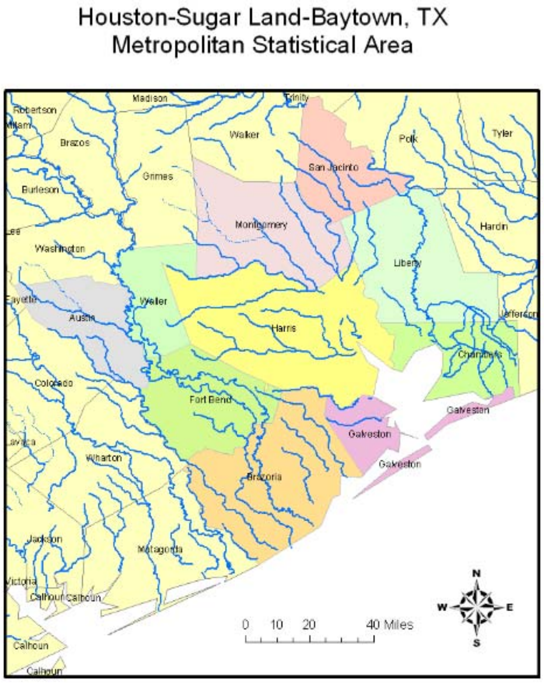

Figure 1: Map of the counties comprising the Houston-Sugar Land-Baytown MSA, and the MSA's streams