Power Plants, Air Pollution, and Health in Colombia

Abstract

The negative effects of air pollution on respiratory and cardiovascular health have been widely documented, but the evidence on the effects on mental health is much more limited. In this paper I provide the first estimates of the effects of air pollution on mental health, in addition to respiratory and cardiovascular health, in a developing country. I use the river flows that feed hydroelectric power plants as instruments for electricity generation from fossil fuel power plants, to estimate its effect on PM10, and the effect of PM10 on health. I find that 42 GWh of electricity generation increase the concentration of PM10 by 1 μg/m^3. For mental health, I find that a 1% increase in PM10 (0.45 μg/m^3 at the mean) leads to an increase in the rate of health services per 100,000 residents of 1.2% and of 2.1% for respiratory health, as well as a 1.7% increase in the rate of patients for the respiratory conditions. The health costs from 1 μg/m^3 of PM10 for the three health conditions in this study, are equal to 40.1 million USD per year for the total population in my sample.

1 Introduction

Air pollution is the leading environmental cause of death in the world, responsible for 4.9 million deaths per year and 147 million years of healthy life lost (Health Effects Institute, 2019). While the effects of air pollution on respiratory and cardiovascular health have been well documented, despite suggestive results from recent epidemiological studies, evidence of its effects on mental health is thinner (Buoli et al., 2018; Power, Adar, Yanosky, & Weuve, 2016). Much of this air pollution is produced by power plants, and fossil-fuel generation is expected to grow to meet increasing electricity demand in developing countries. However, existing studies do not estimate the direct effect of emissions from power plants on air pollution, and the effects of this air pollution on health.

This study focuses on the effect of thermal power plants' emissions on air pollution in Colombia, and the effects of exposure to pollution on mental, respiratory and cardiac health. I use the exogenous variation in the river flows used for hydropower generation to instrument for electricity generation from fossil fuel power plants. Current installed capacity for generation in Colombia is 70% hydro, and 30% thermal (gas, coal, diesel, and fuel oil, in order of importance). When river flows are low, hydropower generation becomes comparatively more expensive, and thermal power plants are turned on (or ramped up) to meet demand. Additionally, most hydroelectric power plants and the rivers that feed them are located in different regions to where the fossil fuel power plants are. Thus, this variation in river flows provides an exogenous shock to electricity generation from thermal power plants, that allows me to estimate the generation's effects on air pollution and health in surrounding areas.

The estimation of the effect of electricity generation on emissions will suffer from omitted variable bias if there are any confounding factors correlated with both these two variables. Two likely confounders are unobservable local weather conditions and economic activity. While I try to flexibly control for both in my model by including rainfall, temperature and total regional electricity demand, there is no guarantee that other confounders do not exist. The use of river flows as instruments allows me to get an unbiased estimate of this effect, subject to the assumptions that electricity generation effectively responds to changes in river flows, and that river flows only have an effect on emissions through their effect on electricity generation.

The use of these instrumental variables proves to be even more necessary when estimating the effect of PM10 on health. In this case, there are the two main concerns. One is that there are unobservable confounding factors that are both correlated with exposure to air pollution and health outcomes. A second one is that exposure to air pollution is likely to be measured with error, in which case the estimated effects will suffer from attenuation bias, and I would be underestimating the true effects on health. The use of river flows as instruments for PM10 allows me to overcome these challenges, since we expect them to be correlated with PM10 through their effect on electricity generation, but uncorrelated to health, to the exposure to air pollution and to the measurement error in PM10.

First, I construct a monthly panel of municipalities, by matching each municipality to the closest power plants in a 100 km radius, and aggregate the total electricity generation in that area, by fuel source and month. I then match the municipalities to all the pollution monitors in a 30 km radius, creating a buffer of 2827 km^2 from the centroids, which is enough to cover the area of the most populous municipalities and matches all the pollution monitors to at least one municipality. I use the data from these pollution monitors to calculate the monthly average concentration of PM10 by municipality and month. I use river flows as instrumental variables for the thermal electricity generation and estimate its effect on ambient concentrations of PM10. I find that a 1% increase in electricity generation from thermal power plants leads to a 0.06% increase in average PM10 concentrations, which evaluated at the mean value in my sample, implies that 42 GWh of electricity from these power plants increases the monthly average ambient levels of PM10 by 1 g/m^3.

To explore the effects of air pollution on health, I estimate a similar model, where the outcome variables are different measures of health events by municipality. I use the rate of monthly patients and health services per 100,000 residents for respiratory, mental and cardiovascular health conditions. I then estimate how ambient levels of PM10 affect these health outcomes, and find that a 1% increase in PM10, increases the total rate of services for respiratory health by 2.1%, the rate of patients by 1.8%, and the rate of services for mental health by 1.2%. With these effects I estimate the economic costs associated with PM10, and find that the highest costs are for respiratory conditions, followed by mental and cardiovascular health conditions. The total health costs from 1 g/m^3 of PM10 for these three health conditions in the average municipality in my sample is 14,057 USD per 100,000 residents per month. For the whole sample of 245 municipalities with a total population of 24.2 million, the total health costs per year are 40.9 million USD. The inclusion of the costs from mental health conditions increases the total costs by 9%.

This paper offers three contributions to the existing literature. The first one is the focus on mental health. Mental health disorders are currently considered as the leading contributor to the global burden of disease, accounting for 32.4% of years lived with disability, on par with cardiovascular and circulatory diseases in terms of disability adjusted years (Vigo, Thornicroft, & Atun, 2016). This paper contributes to our understanding of how air pollution affects mental health and is the first paper to estimate the effects of air pollution on contemporaneous mental health, using administrative data that includes all mental health episodes where patients sought attention through the health system. This study complements the findings from Bishop, Ketcham, & Kuminoff (2018), who focus on the long-term effects of exposure to PM2.5 on dementia. They use Medicare data to follow patients through time and place of residence (population aged 65 or older). They find that an increase in average exposure to PM2.5 over a decade significantly increases the probability of being diagnosed with dementia, and estimate that the reduction in PM2.5 as a result of the Clean Air Act led to $240 billion saved from the lower costs of dementia. The only other economic study to estimate the effect of pollution on mental health uses self-reported measures of happiness and depression. Zhang, Zhang, & Chen (2017) find that lower levels of air quality reduce hedonic happiness for Chinese households, and increase the rate of depressive symptoms. From the epidemiological literature, several studies find that exposure to higher levels of air pollution can contribute to a deterioration of mental health, with the important caveat that the estimated associations cannot be interpreted causally (Buoli et al., 2018; Power et al., 2016).

Second, this is the first paper to establish a causal link between electricity generation from fossil fuels, air pollution and health. Previous studies have focused on the negative externalities from electricity generation using coal, but due to data availability constraints, have not been able to estimate the effects of this generation on air pollution, and then estimate the effect of air pollution on health. Clay, Lewis, & Severnini (2016) use the timing of coal-fired power plants in the US to estimate the effect that coal burning for electricity generation has on infant mortality, and find that there is an increase in infant mortality and a decrease in property values, but that these are concentrated in counties with almost universal electrification. Importantly, they cannot estimate the effect of coal-fired power plants on any measure of air pollution, due to the low availability of monitor data during their sample period. Using a similar strategy, Barrows, Garg, & Jha (2019) examine the effects of coal-fired power plant openings on infant mortality in India, and find that installed capacity in coal increases infant mortality. Unlike previous studies, they use satellite pollution data to show that these effects are due to changes in air pollution, but do not directly estimate the effect of air pollution on infant mortality. In another study in India, Gupta & Spears (2017) estimate the effect from new coal plants on health (reported cough by households), and find that there is a positive and significant increase in households reporting cough.

The importance of being able to link electricity generation from fossil fuels to air pollution and health is twofold. One is that the electricity sector is a major emitter of GHG. In 2016, GHG emissions from electricity generation represented 30% of the total GHG emissions in the world, and generated 14% of the total emissions in Latin America (World Resources Institute, 2019). The second one is that the identification strategy used in this study make my results relevant in terms of both their policy implications, and the external validity, as the dependence in hydroelectric power generation is higher in developing than in developed countries. Specifically, for low income countries, hydropower generation represents 44% of total electricity generation, compared to 19% for middle income countries and 12% for high income countries.[1]

Finally, this study contributes to the growing literature assessing the effects of air pollution in developing countries, which has focused on mortality effects (Arceo, Hanna, & Oliva, 2016; He, Fan, & Zhou, 2016; Heft-Neal, Burney, Bendavid, & Burke, 2018; Jayachandran, 2009; Pullabhotla, 2018), labor productivity and supply (Aragón, Miranda, & Oliva, 2017; Hanna & Oliva, 2015), and the long-term effects from in-utero exposure (Bharadwaj, Gibson, Zivin, & Neilson, 2017). In this case, my main contribution is that this is the first study examining the effects of air pollution in Colombia, a setting that serves as an interesting case study: it has nearly universal health insurance coverage and a high rate of urbanization, which means that access to healthcare is higher and so the health effects can be more accurately measured. It also has similar levels of air pollution to other upper middle-income countries, a category that includes China, Russia, Mexico and Brazil, and which currently accounts for 37% of the world population. Additionally, the topography of the country means that different areas will face very different emissions, which is helpful to identify the effects of local pollution shocks.

The paper is organized as follows. The next section provides background information of air pollution in Colombia, together with the current environmental regulations and their relationship to the electricity sector, and also explains how the health system operates. Section 3 presents the data used for the analysis, together with summary statistics. Section 4 presents the empirical strategy used, followed by results in section 5, and an estimation of the economic costs associated to air pollution and electricity generation. As additional analyses, I present some robustness tests in section 6. The conclusions for the paper are in section 7.

[1] https://ourworldindata.org/energy using data from IEA (accessed July 28, 2020).

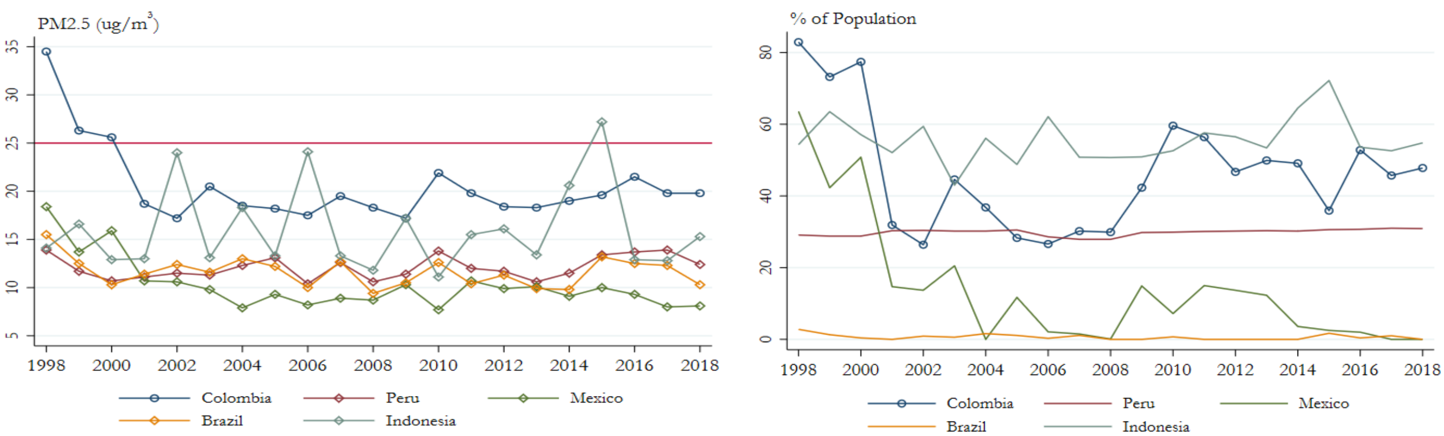
2 Background

2.1 Air Pollution and the Electricity Sector

The levels of air pollution in Colombia in the last 20 years have decreased (Figure 1, Panel A)[2], although compared to other developing countries with similar income levels, the country underperforms in terms of both the current levels and their reduction. At 47%, the percentage the country's population that is exposed to concentrations of PM2.5 above 25 g/m^3 (the current threshold set by the environmental authority in Colombia), is higher than that of most other countries, with the exception of Indonesia (Figure 1, Panel B).

Figure 1. PM2.5 in Colombia and Selected Countries (1998 – 2018)

Panel A. Panel B.



Environmental policies for air quality control in Colombia have focused on the technical aspects regarding the measurement of air pollution, and the definition of air quality standards. These policies delegate the enforcement of these standards to local environmental authorities, who are also in charge of approving the environmental licenses and emissions permits that all industrial facilities, including power plants, are required to have in order

[2] These data comes from Hammer et al., (2020), who use satellite data together with chemical transport models and ground based measures of PM2.5 to produce global time series of yearly PM2.5 concentrations, at different spatial resolutions that allow comparisons between countries and years.

to operate. A new regulation from 2008[3] set the emission standards for stationary sources such as power plants, where the standards depend on the total installed capacity, the fuel used, and the date of construction. Power plants that use coal and diesel have to meet a similar standard in terms of particulate matter, but diesel fueled plants face more stringent standards for SO2 and NOx, and all plants built after 2008 have to meet stricter standards. The characteristics of power plants in Colombia will therefore vary with type of fuel used and year of construction (Table 1). On average, coal power plants are older and less efficient than both gas and diesel, and they are also the ones with the lower installed capacity, despite being the most common type of power plant.

Table 1. Power plant characteristics by fuel type

	Average value by fuel source (t-statistic of the difference in parentheses)			
	Coal	Gas	Diesel	All power plants
Heat rate (MBTU/MWh)	10.81	9.14	7.05	9.73
	(-3.03)**	-1.28	(2.55)**	
Capacity (MW)	115.9	200.1	269.0	166.6
	(1.73)*	(-0.96)	(-1.20)	
Year of construction	1988	1996	2003	1993
	(1.84)*	(-1.00)	(-1.28)	
Obs.	14	12	3	29

These power plants are also an important source of air pollution and greenhouse gas (GHG) emissions, even though the proportion of emission from the electricity sector in Colombia is lower than that of other regions. In 2016, GHG emissions from electricity generation represented 12% of the total GHG emissions, which is lower than the weight this sector has in Latin America (14%) and in the world (30%) (World Resources Institute, 2019). This lower weight is due to the fact that the electricity generation sector is highly

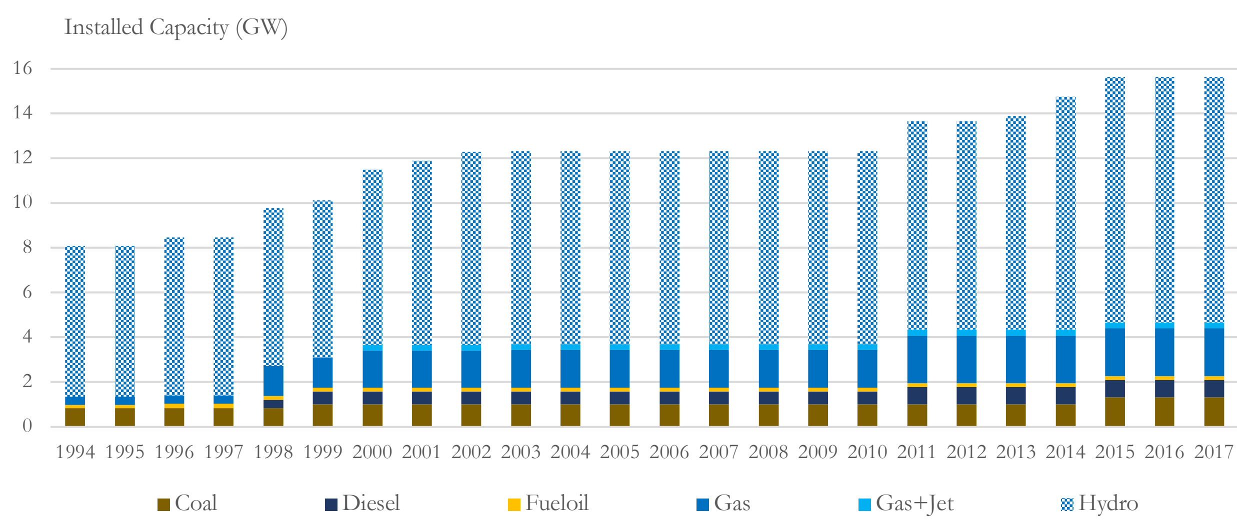
[3] "Resolución 0909 de 2008"
(available from https://minas.medellin.unal.edu.co/convenios/redaire/images/normatividad/Res_0909.pdf)

reliant on hydroelectric generation, despite being reformed to allow the entry of fossil fuel generators into the system.

The reforms started in 1994, after the country suffered from programmed blackouts in 1992 and 1993, as a consequence of El Niño, the climatic phenomenon associated with a warming of the waters in the central Pacific Ocean. In Colombia, El Niño is associated with an increase in average temperature, a decrease in rainfall and river flows, and the subsequent decrease in the reservoir levels. Before 1994, 83% of the country's electricity generation capacity came from hydro generation. The reforms implemented in 1994, deregulated the market and allowed the entry of new generators, and lead to the expansion of the installed capacity (Arango, Dyner, & Larsen, 2006; Larsen, Dyner, Bedoya V, & Franco, 2004). The installed generation capacity has practically doubled since 1994, although it is still highly dependent on hydroelectric power plants (

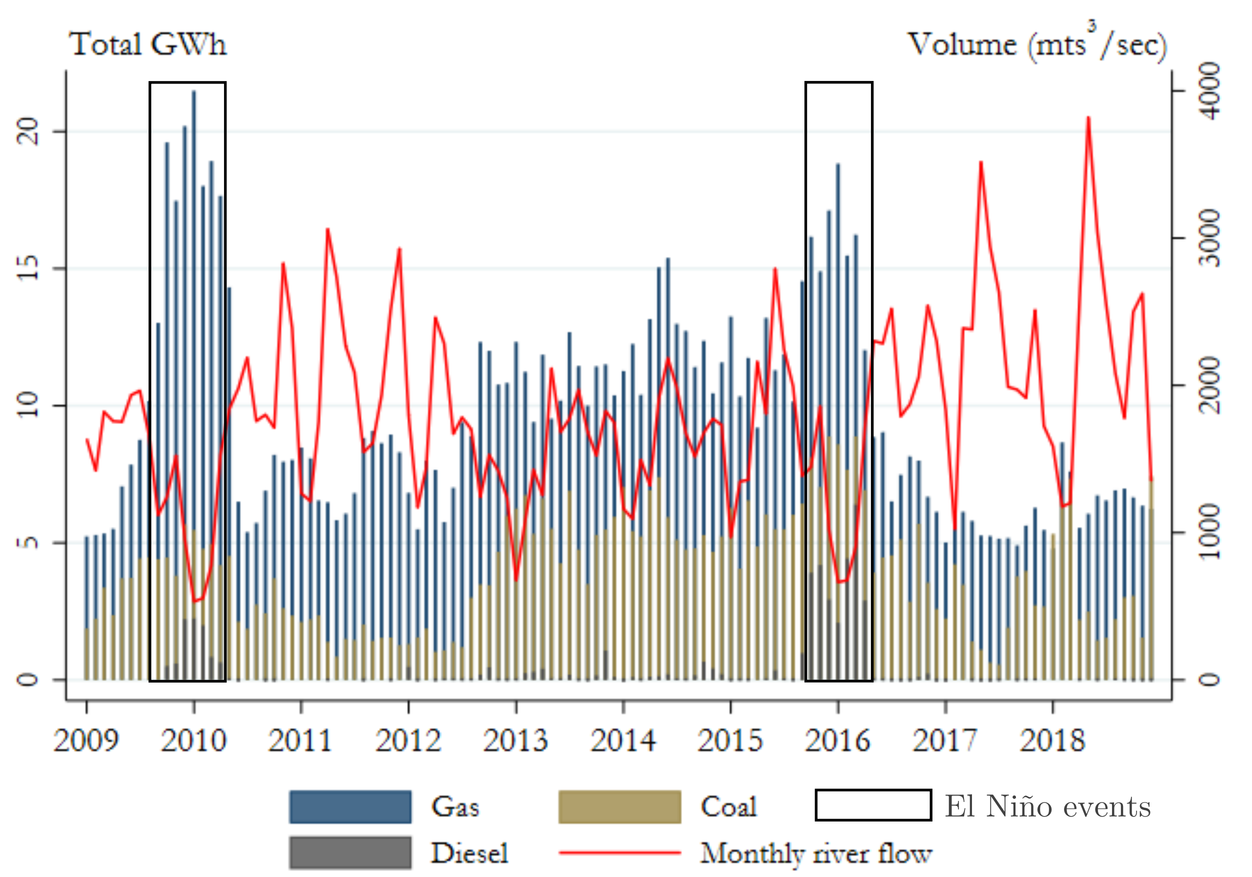
Figure 2). As of 2017, hydro represented 70% of the total installed capacity, gas represented 14%, coal 9%, diesel 5% and fuel oil 2%.

Figure 2. Total installed capacity by source (2000 – 2017)



Since the implementation of these reforms, the country has not experienced any new blackouts, despite experiencing several dry periods due to El Niño. However, changes in river flows still lead to shifts in the generation mix. The generation mix is determined by a market where daily bids are submitted by generators for the following day. The bids include a price for the following day, as well as the total electricity to be supplied each hour of the day. The allocation of generation by the system operator is determined based on the total demand and the bids submitted, such that the last generator to provide electricity to the system, will be one with the highest bid. Thus, when river flows are low, hydropower generation becomes comparatively more expensive, and this leads to a shift in the electricity generation mix (Figure 3).

Figure 3. Monthly generation by fossil fuel



2.2 Colombia's Healthcare System

Since 1993, the health system is divided into two types of insurance regimes: subsidized and contributive. The contributive regime provides mandatory coverage to all legally employed workers, and the insurance premiums are divided between the employers and employees. The insurance also covers the workers' dependents (spouse and children). The subsidized regime provides insurance to the segment of the population whose income is below a given threshold, and to those that are unemployed. Under the current system, the health insurance coverage is nearly universal, with 95% of the population under either one of the two regimes, about equally split between each (49% of the population is under the contributive regime, and 46% is under the subsidized one).

The almost universal coverage enables the access to health services for most of the population, especially since the copayments are fixed, and relatively low. Those insured under the contributive regime have copayments per consultation that depend on their level of income, with those who make less than two monthly minimum wages paying 1 USD, those who make between 2 and 5 minimum wages 3.5 USD, and those who make more than 5 minimum wages paying 9.3 USD per consultation. Those who are in the subsidized regime make no payments for medical consultations, but have to make payments of up to 10% (capped at a certain value) for hospitalizations (Camacho & Mejía, 2017). Additionally, some services that are considered essential are not subject to copayments. These services include: pregnancy, child birth, care of the newborn, care of children under 5 years of age, high blood pressure, diabetes, and initial emergency care. For all other procedures, a copayment is required, although current rulings by the Colombian Constitutional Court have determined that service cannot be denied if patients do not make the payments (Hernán, Moreno, Julieta, & Martinez, 2017). Consequently, out-of-pocket health expenditures in Colombia represent 14% of the total health expenditures (1% of GDP), one of the lowest in Latin America, below the 30% average for middle-income countries (Mills, 2014), and below the OECD average of 20% (Organisation for Economic Co-operation and Development, 2016).

Given these low costs and high rates of coverage, access to health services by those who need it, is fairly common. The Colombian Quality of Life Survey (QLS) shows that in 2013, 66% of those who had a health problem went for a consultation under their insurance coverage, 9% went to a private consultation, and 17% either self-medicated or used home-made remedies. These figures are in line with what Camacho & Mejía (2017) find from the Demographic and Health Survey (DHS) of 2005, where 70% of the population that had a health problem attended a formal health service. Additionally, when asked about the quality of their health service provider, users have a favorable view, with 80% reporting that it is ‘very good’ or ‘good’, and very similar for the two regimes, with 77% those under the contributive regime and 80% under the subsidized regime having a favorable opinion of the quality of the service (QLS 2017).

3 Data

The data for this paper merges datasets on electricity generation, air pollution and health, with most datasets available at a monthly frequency, and with the municipality as the unit of observation. First, I use plant level electricity generation data for all power plants in Colombia. For each power plant, I aggregate the total generation at the monthly level, so that I have a geolocated panel with monthly observations of electricity generation by thermal power plants: gas, coal and diesel. Additionally, I have data on the river flows for all the rivers that feed into the reservoirs that are used by hydroelectric power plants. All of these data are publicly available and come from the Colombian market operator XM[4].

Pollution data come from the network of pollution monitors across the country, that are managed by the different regional environmental authorities. The national meteorological authority (IDEAM) is in charge of compiling and organizing the data from all the different pollution monitoring stations, with daily data for PM10 from 2009 to 2018, which I average to a monthly level. From IDEAM I also get monthly rainfall and temperature data, from ground-based weather stations.

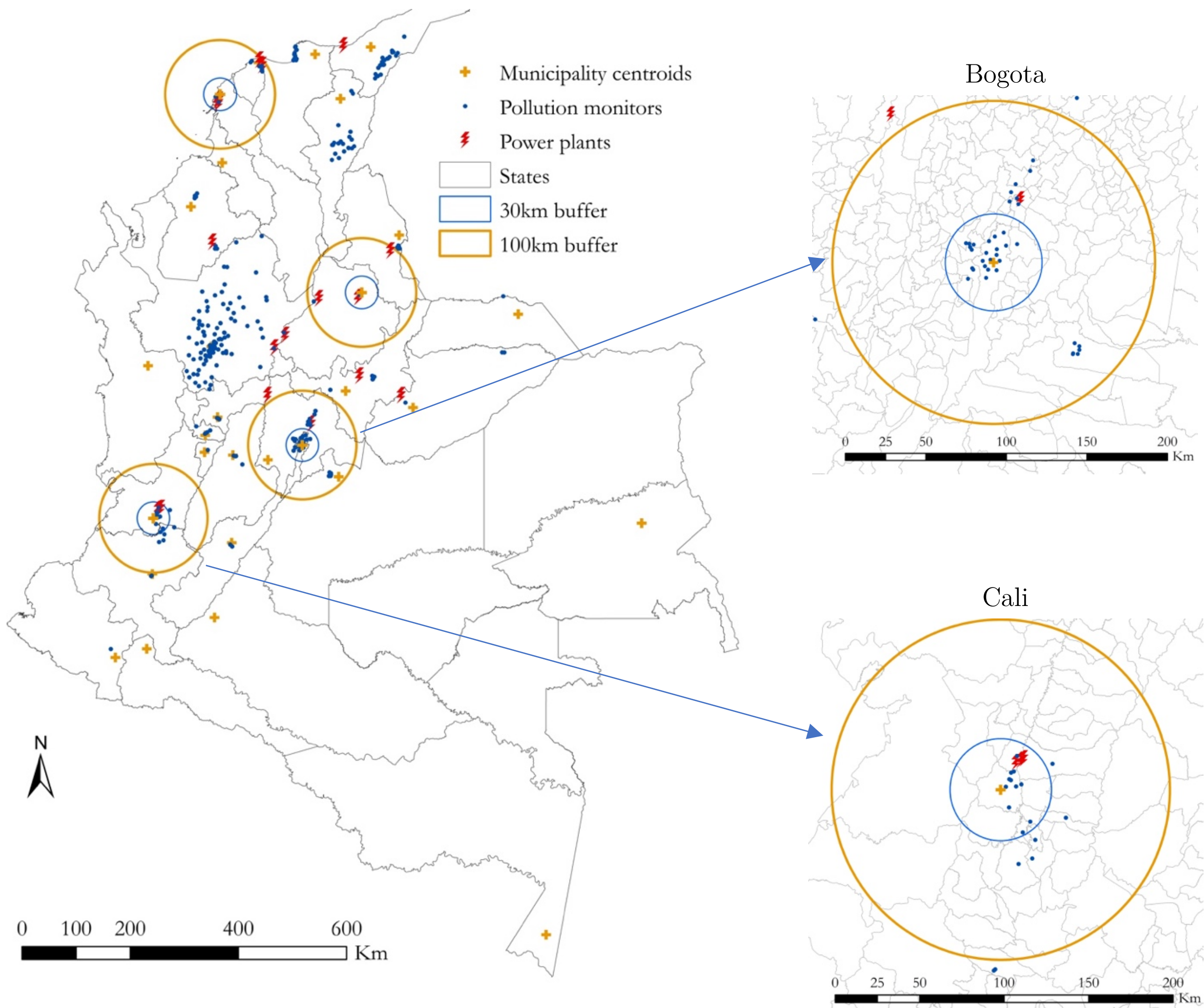
I match municipalities to all the pollution monitors in a 30 km radius, to capture the exposure of the population to air pollution in all the municipality, and then calculate a monthly average for each municipality (similar to the clustering procedure for pollution monitors by Deryugina, Heutel, Miller, Molitor, & Reif, 2019). This radius creates a circle with an area of 2827 km2, which is an area that covers the most populous municipalities, and one for which every monitor is matched to at least one municipality. It is possible that for some months and municipalities, the number of data points from which the average daily value is calculated is very low, in which case the measure of PM10 I would be using could potentially be a very inaccurate measure of the true levels of PM10 in a municipality. In the most extreme case, this average is given by only one daily observation from one monitor. To prevent this, for my main specification I restrict my sample to include only those months and municipalities for which there at least 10 daily values in the month. Additionally, I flexibly control for the number of data point days by including data point bins as part of my control variables, where each bin is a 5 observation interval, so that an average constructed using between 10 and 14 observations will be in bin 10, if it is calculated from 15 to 19 observations it will be in bin15, and so on until bin 75, which includes all

[4] http://portalbissrs.xm.com.co/Paginas/Home.aspx

the averages constructed from 75 or more observations. This allows for a different mean for each group of observations, depending on the number of data points used to calculate the average daily mean per month.

I then match municipalities to all the fossil fuel power plants in a 100 km radius (Figure 4), and aggregate the total electricity generation by the type of fuel used around each municipality. Several studies have used atmospheric modeling techniques to model the dispersion of pollutants in a region, and have found that for the case of power plants, the effects are significant for up to 300 km (up to 500 km for a study in China by Zhou, Levy, Evans, & Hammitt, 2006), although most of the effects occur within a 50 km radius (Levy, Spengler, Hlinka, Sullivan, & Moon, 2002). In a study on the effects of the opening of coal power plants in the US, Clay, Lewis, & Severnini (2016) use a 50 km distance buffer. I use a 100 km buffer because the evidence shows that the effects on air pollution are still significant at this distance, and this is the distance that captures the exposure to air pollution for all the biggest cities in Colombia, with the exception of Medellin.

Figure 4. Municipalities, pollution monitors and power plants*



* For visual clarity, I show the buffers for the four biggest municipalities in my sample. However, the sample I use for estimating the models, includes 245 municipalities.

I also include data from different time series at the national level. First, I include data on fuel prices. Of all the fuels used by power plants in Colombia, coal is the only one that is unregulated. I have data on the average cost of fuels paid by all the power plants every month, with data on the cost of coal, and data for gas and diesel averaged together[5]. All of these are in Colombian pesos per kWh. Additionally, given that most of the coal produced is exported, I also have data on the price of Australian and South African coal, as well as

[5] Provided by XM upon request.

an international price index for natural gas[6] (Figure 9 in the appendix). I include all price series in my regressions. Second, I include the total demand for electricity at the national and department level (departments are the administrative level above of municipalities in Colombia, similar to states in the US).

For the outcome variables, I focus on three health outcomes: mental, respiratory and cardiac health. The health data I use, come from the Individual Registry of Health Services Provision (RIPS, per its acronym in Spanish). It is constructed using the individual-level records for medical consultations, emergency room (ER) visits, hospitalizations and procedures that took place in any health service institution in Colombia (Camacho & Mejía, 2017). All the health services provided have information about the date and municipality where it took place, the diagnosis (using the ICD-10[7]), as well as the total cost (including any co-pays); it also includes information about the patient, such as the age, gender, municipality of residence, and type of health insurance. I use the publicly available data, aggregated at the municipality and month level, for every month since January 2009. However, it is important to note that these data tell us nothing about the health effects for people who did not attend a health service institution, which based on estimations from the 2005 DHS, account for 30% of the population (Camacho & Mejía, 2017). Data from the most recent census (2018) shows that of those who faced a health problem that did not require hospitalization in the previous month, 75% attended the services provided by their health insurance, 7% attended a private physician, 7% used home remedies, 4% went to a pharmacist, 4% self medicated, and the remaining 3% did nothing. Only the 75% who attended the services from their health insurance and the 7% who attended a private physician will be included in the RIPS data.

The quality of this data has been evaluated, and although there is evidence of underreporting, the quality has been improving over time (Martínez Ramos & Pacheco García, 2013; Méndez-Ayala, Nariño, & Rosselli, 2015). Furthermore, there is no indication of systematic underreporting in municipalities that are more exposed to the pollution from fossil fuel power plants, and so my estimated results could be considered as a lower bound of the true effects. The health data can be disaggregated by age, gender, type of insurance and municipality of residence. The three types of diagnoses I focus on (mental, respiratory

[6] All these international prices come from the World Bank's commodity prices series.

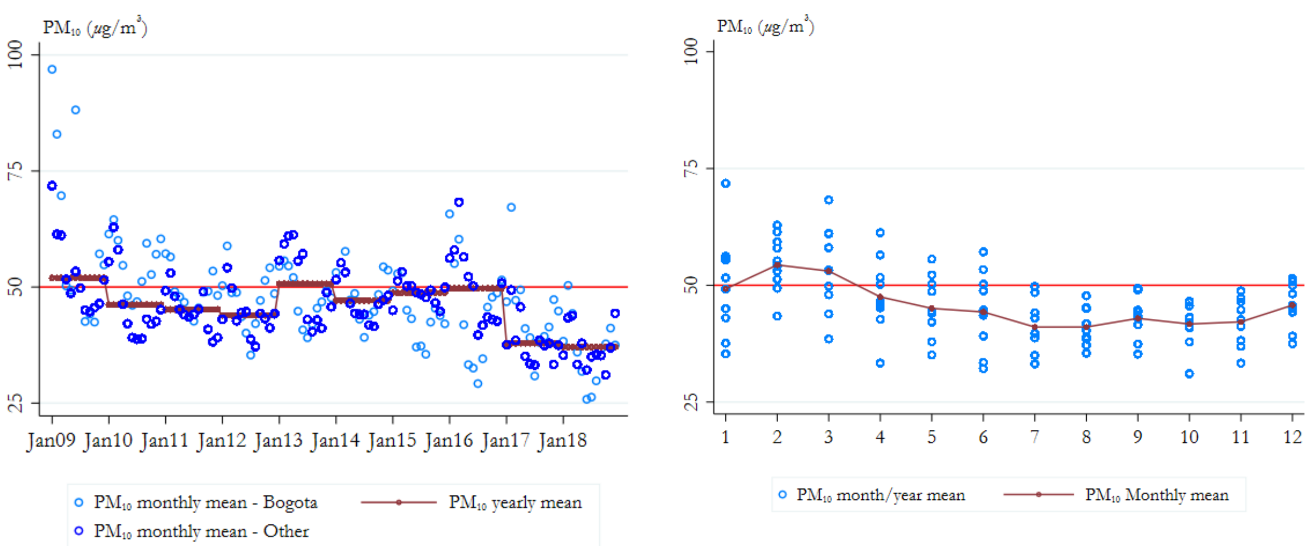
[7] ICD-10 is the International Statistical Classification of Diseases and Related Health Problems, version 10.

and cardiac), are classified as chapters 5, 10 and 9 in the ICD-10. I match these data with the municipality panel with PM10 and electricity generation data, so that the complete dataset I use for the estimations is a monthly panel of municipalities, with data on health, PM10, electricity generation, from January 2009 to December 2018.

3.1 Summary Statistics

The average concentration of PM10 has been relatively constant since 2009 and up to 2016, with a decreasing trend in the last two years (Figure 5). The daily average per month has been under the World Health Organization guidelines of 50 μg/m3 (World Health Organization, 2005), for most months. However, it is clear that in some places, the average concentrations are above the WHO guidelines, highlighting the very high variability in air pollution across different regions. Additionally, there is a clear seasonal pattern, with the highest levels on PM10 occurring in February, and the lowest level occurring in August.

Figure 5. Average PM10 concentrations



From Table 2, we have the summary statistics for PM10 and for the total electricity generation by fuel source. For the whole sample period, the daily average per month level of PM10 is 46, below the WHO guidelines. In terms of electricity generation, total generation by fuel source around a municipality varies greatly by month and municipality, as evidenced by the high standard deviation for all the fuel sources. Furthermore, it is clear that despite gas being the main source of electricity generation for the whole country (after hydro), for the municipalities in my sample (ie. the ones with data from pollution monitors, and near power plants), coal is the main source of electricity generation. On average, electricity generation from coal is 77.7 GWh per month, which represents 70.7% of the total average, followed by gas (28%) and diesel (1.3%).

Table 2. Summary statistics

	Mean	Min	Max	SD	Obs.
PM10	45.9	1.59	148.6	18.38	16,910
GWh Coal	77.7	0.0	369.5	89.4	16,910
GWh Gas	30.7	0.0	1054.5	94.9	16,910
GWh Diesel	1.4	0.0	461.5	12.8	16,910
GWh Total	109.8	0.0	1054.5	119.1	16,910
Installed capacity GW Coal	0.255	0.0	0.6	0.2	16,910
Installed capacity GW Gas	0.170	0.0	2.1	0.4	16,910
Installed capacity GW Diesel	0.099	0.0	0.9	0.2	16,910
Installed capacity GW Total	0.404	0.0	2.1	0.3	16,910

The final sample includes 245 of the 1122 municipalities in the country, with a total population of 24.2 million (50% of the country's population), where 88% of these are urban residents (Table 3). The municipalities in my sample include very large cities with a total population of over 8.1 million people (Bogota), to small towns with only 980 residents, and some municipalities with almost no urban population to municipalities with exclusively urban populations. It also includes municipalities with very different climates, as is clear from the wide range in both rainfall and temperature.

In terms of health outcomes, we can see that cardiac health conditions are the ones that have a higher weight, both in the number of patients and the number of health services, followed by respiratory conditions and finally by mental health ones. In terms of mental health, the rate of mental health patients in Colombia is higher than the global average (99.1 per 100,000 population), and even higher than countries with a similar level of income (117.2 per 100,000 population) (WHO - World Health Organization, 2017).

Table 3. Summary statistics on health outcomes by municipality

Characteristics for all the municipalities	Total				
Number of municipalities	245				
Total population - 2018	24,238,655				
Urban as a percentage of total - 2018	88%				
Municipality characteristics - Average	**Mean**	**Min**	**Max**	**SD**	**Obs.**
Total population	112,388	980	8,182,739	677,147	16,910
% Urban population	49%	2%	100%	26%	16,910
Yearly per capita expenditure, local government (USD)	414	70	2,694	248	16,910
Monthly rainfall (cubic mm)	109	0	727	88	16,910
Monthly temperature (degrees Celsius)	23	5	40	5	16,910
Health Outcomes - Rates per 100,000 inhabitants					
Respiratory - Number of patients	727	0	6,388	561	16,910
Respiratory - Number of services	1,502	0	97,058	1,778	16,910
Mental - Number of patients	153	0	2,921	180	16,910
Mental - Number of services	354	0	43,674	886	16,910
Cardiac - Number of patients	1,041	0	6,343	875	16,910
Cardiac - Number of services	2,224	0	57,290	2,431	16,910

4 Methods

4.1 Electricity Generation and Air Pollution

The first step in the analysis is to estimate the effect of electricity generation from fossil fuels on the average level of PM10 in the air. I use a fixed effects model, where I regress local PM_{10} levels on electricity generation from gas, coal and diesel. The estimating equation is:

$$PM10_{it} = \beta_1 Gas_{it} + \beta_2 Coal_{it} + \beta_3 Diesel_{it} + X_{it}\beta + \alpha_y + \alpha_m + \alpha_i + \varepsilon_{it} \qquad (1)$$

where i indexes a municipality in month t, and Gas_{it}, $Coal_{it}$ and $Diesel_{it}$ denote the total electricity generated by each fuel type within a 100 km radius around the municipality. I also include a set of controls for the weather conditions, that include quadratic terms for both rainfall and temperature (at the municipality, the pollution monitor and the power plant levels), the total load for the whole system and the state, year and month fixed effects, to control for the seasonality in both electricity generation and pollution, and linear trends at the state level. The aim of these differential trends, is to control for any shocks within a region, that could affect both the level pollution and the electricity generation.

The underlying assumption for the unbiasedness of $_1$, $_2$, and $_3$, is that conditional on the control variables, and the month and year fixed effects, there are no unobserved time varying factors correlated both with the electricity generation from fossil fuel sources, and the levels of PM10. However, there are possibly many unobservable factors that are correlated to both the ambient concentration of pollutants, and the generation of electricity from fossil fuels, such as changes in local economic activity, or local environmental factors that increase the demand for electricity. Therefore, I use an instrumental variable approach, where I use the interaction between installed capacity from thermal power plants and river levels, to estimate the effect from fossil fuel electricity generation, on ambient levels of PM10.

The first stage of the two stage least squares model is given by:

$$Coal_{it} = \theta_{\mathrm{jf}} \sum_{f}^{3} \sum_{j}^{n} Capacity_{if} \times River_{t-1} + X_{it}\beta + \alpha_y + \alpha_m + \varepsilon_{it} \tag{2}$$

$$Gas_{it} = \theta_{\mathrm{jf}} \sum_{f}^{3} \sum_{j}^{n} Capacity_{if} \times River_{t-1} + X_{it}\beta + \alpha_y + \alpha_m + \varepsilon_{it} \tag{3}$$

$$Diesel_{it} = \theta_{\mathrm{jf}} \sum_{f}^{3} \sum_{j}^{n} Capacity_{if} \times River_{t-1} + X_{it}\beta + \alpha_y + \alpha_m + \varepsilon_{it} \tag{4}$$

where (2), (3) and (4) are the first stage equations for Gas, Coal and Diesel, respectively. Subscript i indexes a municipality, so that $Coal_{it}$ corresponds to the total electricity generation from all power plants that use coal, around municipality i, in month t. The same applies for the other fossil fuels. The river flow variable is the average river flow, aggregated at a national level. Additionally, I interact the river levels with the percentage availability of the installed capacity for each fuel source for each month. This allows me to more accurately estimate the effect that changes in river flows has on local electricity generation by fuel source. For example, a municipality that has no coal fired power plants around it, would see no changes on electricity generation from coal as river flows change. This allows me to more precisely estimate both the first stage relationship, and the effect from electricity generation on pollution. I include the same control variables as in equation (1).

From the estimation of the system of equations (2), (3) and (4), I get the predicted electricity generation from each fuel source, so that in the second stage I can estimate their effects on the average concentrations of PM10:

$$PM10_{it} = \beta_1 \overline{Gas_{it}} + \beta_2 \overline{Coal_{it}} + \beta_3 \overline{Diesel_{it}} + X_{it}\beta + \alpha_y + \alpha_m + \alpha_i + \varepsilon_{it} \qquad (5)$$

Two assumptions are necessary for river levels to be a valid instrument for thermal generation. The first assumption is that river flows have a direct effect on the amount of electricity that is generated by the hydroelectric power plants, thus changing the amount of electricity that has to be generated from fossil fuels. This effect can be seen in Figure 3. When the average river flows are low, the total generation of electricity from fossil fuel sources goes up in order to compensate the decrease in electricity generation from hydroelectric. Figure 10 in the appendix also shows that as the level of river flows increase, there is a decrease in the generation of electricity from both gas and coal (

Figure 11 shows a similar relationship for electricity generation from diesel).

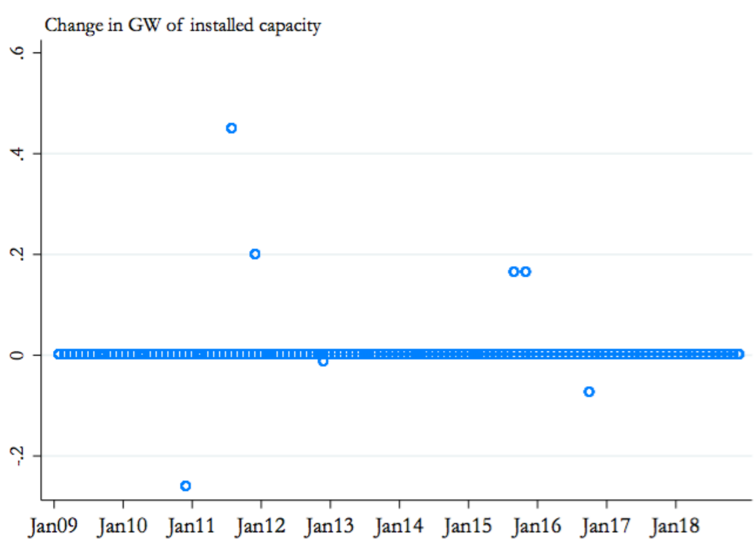
The second assumption is the exclusion restriction, which implies that the river flows will affect the ambient concentrations of PM10, only through the effect they have on the generation of electricity from fossil fuels. I believe that this assumption holds in this case. As before, one major concern could be that economic activity is correlated with both river flows, possibly through rainfall, and with electricity generation. Perhaps periods where river flows are high are also periods where there is usually more economic activity and more electricity generation. To account for this, I include the same controls as in (1), for the regional electricity demand, and I also include monthly linear trends by state, which would effectively control for any time trends within each region, that affect both river levels and electricity generation.

Relatedly, given that the river flows are interacted with the installed capacity in the first stage equations, another concern is that differences in installed capacity around each municipality are correlated with time varying unobservable characteristics at the municipality level, that affect both PM10 concentrations and health. The first thing to note is that the installed capacity is relatively constant over the sample period (see Figure 6 for the average change and

Figure 2 for the total installed capacity). These differences are likely due to structural factors that do not change during this period, and thus can be controlled for with the municipality fixed effects. I also check whether municipalities with more installed capacity are different from those with lower installed capacity, and find that there are significant differences in most characteristics (

Table 8 in the Appendix), and unsurprisingly they also have higher levels of PM10. In terms of the health outcomes, the differences are significant for half of these: the rate of mental health patients, and both the rates of patients and services for cardiovascular health are significantly higher in municipalities with more installed capacity. Given that I control for all of these factors in my model, and that conditional on the existing installed capacity, the variation in river flows provide an exogenous source of variation in electricity generation and in PM10, I believe the differences between the municipalities with different installed capacity do not pose a threat to my identification strategy.

Figure 6. Changes in installed capacity



4.2 Electricity, Air pollution, and Health

The estimation of the effects of electricity generation on health, follows a similar procedure as the one explained above. However, in this case the first stage equation estimates how changes in river flows affect the average concentration of PM10 at the municipality level, conditional on the installed capacity for electricity generation by fuel source:

$$PM10_{it} \ = \theta_{\mathrm{jf}} \sum_{f}^{3} \sum_{j}^{n} Capacity_{if} \times \ River_{t-1} + X_{it}\beta + \alpha_y + \alpha_m + \varepsilon_{it} \tag{6}$$

The outcome variable $PM10_{it}$ represents the average monthly concentration of PM10 in municipality i in month t. The vector of controls X_{it} is the same as before, and the standard errors are also clustered at the municipality level. Using the predicted level of PM10 from (6), the second stage equation is given by:

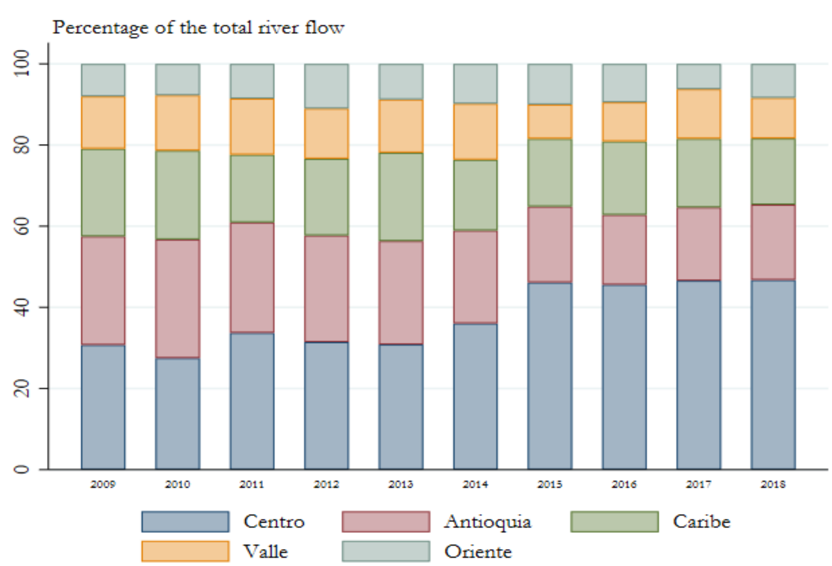
$$H_{it} = \beta_1 \overline{PM10_{it}} + X_{it}\beta + \alpha_y + \alpha_m + \alpha_i + \varepsilon_{it} \tag{7}$$

where H_{it} is a health outcome for municipality i in month t. There 6 outcome variables that I evaluate: the monthly rate of patients and of health services per 100,000 residents for respiratory, cardiac and mental health conditions. We can think of the rate of patients for each condition as measuring the health effects at the extensive margin, while the rate of health services provided as measuring the effects at the intensive margin, given that the same patient can require multiple services.

In this case, the exclusion restriction required for the unbiasedness of the estimated effects implies that the only channel through which river flows can affect health, is through the air pollution produced by the emissions from electricity generation by fossil fuel power plants. As before, I believe this to be a reasonable assumption, conditional on controlling for local weather conditions, and other explanatory variables that could have an effect on health. There are two additional concerns I need to address, but for both of these, it is important to note that most of the rivers are concentrated in a very specific region of Colombia (Centro and Antioquia account for 65% of the total volume, Figure 7). Thus, their effects are unlikely to be felt in other regions, other than through the effect they have on electricity generation, and that I flexibly control for the precipitation and temperature at the municipality level. The first concern is that rivers could potentially have an effect on health, through the effect they have on the income of rural households. However, I do not believe this to be a major concern in my sample, given that 88% of the total population in my sample is urban, and that I include the percentage of the urban population with respect to the total population per municipality as part of my control variables. Furthermore, according to the latest agricultural census (2014), 43% of rural households use no irrigation, and of those who do, 55% use water from local rivers and aqueducts, so that the rural population who would be likely to be affected by changes in the river flows of these rivers is potentially very small.

The second concern is that low river levels can be associated with low access to water for both rural and urban households, which could ultimately affect the population's health. To check whether access to water changes with the level of river flows, I use data from the agency that regulates public utilities in Colombia[8]. These are data for the average number of hours per day for which there was water available, by state and year since 2014. From these it seems that there is very little change in the number of hours with water available per state, and it seems like the variation in river flows is not associated with changes in water availability (Figure 12 in the Appendix).

Figure 7. Percentage of total river flows volume by region



Finally, it is important to note that PM10 is likely be correlated with other pollutants that are also affected by thermal electricity generation, so that the estimated effect from PM10 on health, where PM10 is instrumented for by river flows, could be biased because it

[8] https://www.superservicios.gov.co/publicaciones (accessed July 28, 2020).

could also capture the effect from the other pollutants that result from the emissions of thermal power plants. If these are positively correlated, then the estimated effects from PM10 will most likely be larger than the true effects of PM10 alone. The use of PM10 is common in studies of air pollution in developing countries (Aragón et al., 2017; Ebenstein, Fan, Greenstone, He, & Zhou, 2017), given that it is the pollutant that is more commonly monitored. Additionally, given the composition of PM10, it can seen as an indicator pollutant that captures the presence of other pollutants. For example, the composition of PM10 for Bogota shows that organic material represents 42% of the total mass, while sulfates and nitrates represent approximately 11% of the total mass (from SOx and NOx, respectively), and elemental carbon represents 9% (Ramírez et al., 2018).

5 Results

5.1 Effects on Air Pollution

The results from the estimation of (2), (3), (4) and (5) for PM10 are in Table 4. The fixed effects model (columns 1 and 2, Table 4) shows that a 1% increase in electricity generation from diesel (0.014 GWh, with respect to the mean), increases the average level of PM10 by 0.025%. The effect from coal is positive but not significant and from gas is negative and significant at the 10% level. The results when estimating the effect from the total electricity generation, show that the effect is lower than that of diesel, but it is still positive and significant. The results from the IV models (columns 3 and 4, Table 4) show much larger effects than the fixed effects model, highlighting the importance of addressing the omitted variable bias in the estimation of these effects. The results show that a 1% increase in electricity generation from coal, increases the average level of PM10 by 0.05% and for diesel generation a 1% increase, increases PM10 by 0.24%.The effect from total electricity generation is positive and significant, and is approximately equal to the average of the effects from coal, gas and diesel, with an increase in total electricity generation of 1% leading to a 0.06% increase in average PM10 concentrations. This effect is three times higher than the estimated effect from the fixed effects regression. The first stage regression results show that the instruments are strong and have predictive power for electricity generation (

Table 9 in the Appendix), although these seem to be weaker when predicting electricity generation from diesel, which could partially explain why the estimated effect is so much larger than that of coal, and then the one when using all the sources combined. However, the model seems to perform very well when using the total electricity generation from all three sources combined, in which case there is only one endogenous variable and three instruments.

Table 4. PM_{10} and electricity generation

	Coefficients (std. errors in parentheses)			
	Dependent variable: IHS(Monthly average PM10)			
	FE	FE - Total	IV	IV - Total
	(1)	(2)	(3)	(4)
IHS(Coal generation GWh)	0.013***		0.047***	
	(0.004)		(0.017)	
IHS(Gas generation GWh)	0.001		-0.102**	
	(0.003)		(0.049)	
IHS(Diesel generation GWh)	0.025***		0.237**	
	(0.004)		(0.098)	
IHS(Total electricity generation GWh)		0.020***		0.057***
		(0.003)		(0.012)
Observations	16,910	16,910	16,910	16,910
R-Squared	0.35	0.35		

Notes: Table reports the results from OLS and IV estimation of equation (5). The dependent variables are inverse hyperbolic sine transformation (IHS) of the monthly levels of PM10, and so the results can be interpreted as elasticities. All regressions include year, and month fixed effects, as well as state by year linear trends, and flexible specifications of rainfall and temperature. The significance levels are: *** (1%), ** (5%) and * (10%). The standard errors are clustered at the municipality level and reported in parentheses.

5.2 Air Pollution and Health

The previous results show that increases in electricity generation cause significant increases in average levels of PM10. I then estimate how changes in the average levels of PM10 affect the respiratory, cardiovascular and mental health of the population in municipalities exposed to this air pollution. In this case, the first stage equation uses the interaction between river levels and installed electricity generation capacity as the instrumental variables, in order to predict the daily average per month level of PM10, which I then use in the second stage to estimate the effect of PM10 on health.

The effects from air pollution on health, are estimated from equations (6) and (7). I find that for respiratory conditions, the concentrations of PM10 have a positive and significant effect on the rate of patients and of services (Table 5). Given that both the dependent and the explanatory variable are transformed using the inverse hyperbolic sine transformation, we can interpret these estimated effects as elasticities, so that a 1% increase in the average monthly concentration of PM10, leads to an increase in the rate of patients for respiratory conditions of 1.8% and of 2.1% in the rate of health services. Evaluated at the mean value of both of these variables, an increase in the concentration of PM10 of 0.046 ug/m^3, leads to an increase of 12 patients and 31 services per 100,000 residents in the municipality. For mental health conditions, an increase in PM10 of 1% leads to an increase in mental health services of 1.23%, which implies an increase of 4 services per 100,000 residents. It is important to highlight that the estimated effects using 2SLS are orders of magnitude bigger than the OLS estimates (Panel A, Table 4), which points to the possibility that the attenuation bias leads to an underestimation of the health effects.

Table 5. Respiratory, mental and cardiovascular health

	Coefficients (std. errors in parentheses)					
	Respiratory		Mental		Cardiovascular	
	Patients	Services	Patients	Services	Patients	Services
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - OLS estimates						
IHS(PM10)	0.0386	0.0888*	0.0843*	0.115*	0.0346	0.0727
	(0.0257)	(0.0304)	(0.0331)	(0.0387)	(0.0284)	(0.0307)
Observations	16,910	16,910	16,910	16,910	16,910	16,910
R-squared	0.203	0.202	0.35	0.343	0.25	0.252
Panel B - IV estimates						
IHS(PM10)	1.755***	2.123***	0.788	1.227*	0.0420	0.328
	(0.615)	(0.701)	(0.555)	(0.644)	(0.472)	(0.493)
Observations	16,910	16,910	16,910	16,910	16,910	16,910

Notes: Table reports the results from OLS and IV estimation of equation (7). The dependent variables are inverse hyperbolic sine transformation (IHS) of the rate of patients and health service per 100,000 residents, and so the results can be interpreted as elasticities. All regressions include year, month fixed effects, as well as state by year linear trends, and flexible specifications of rainfall and temperature. The significance levels are: *** (1%), ** (5%) and * (10%). The standard errors are clustered at the municipality level and reported in parentheses.

To understand the magnitude of the effect, I compare it to the estimated effects from the most similar study I could find. In a study that explores the effect of air pollution on COPD (chronic obstructive pulmonary disease) in Italy, Lagravinese, Moscone, Tosetti, & Lee (2014) find that a 10 ug/m^3 increase in PM10, increases hospital admissions for children by 6.2% (2 new admissions per 10,000 children). Their effects are lower than the ones than the ones I find. However, there are important differences that can explain this. First, they focus on COPD only, and do not consider other respiratory health conditions. Second, their effects are at yearly level. Third, their estimated effects are only for children, whereas I include the whole age distribution in my sample. Fourth, the ambient concentration on PM10 in Italy is 33.3 ug/m^3, which is 27% lower than the ambient concentration in Colombia for my sample period.

5.3 Economic Costs

The estimated health effects allow me to do back-of-the-envelope calculations of the costs associated to PM10. First, I get the total cost for consultations and procedures by health condition, and the calculate the average cost per patient and condition. With the estimated effects and based on the mean rates of patients and services per health condition, I can estimate the number of people affected and the number of health services required. Thus, I can get an estimate of the total health costs for 1 g/m^3 of PM10 for a given population (Table 6). I estimate that the cost of 1 g/m^3 of PM10 to be highest for cardiovascular conditions, with the total cost per 100,000 residents per month equal to approximately 10,370 USD, while that respiratory conditions is 2,510 USD and for mental health conditions it is 1,178 USD. The total costs associated to these three conditions amount to 14,057 USD per 100,000 residents.

The costs are much higher when considering bigger cities. For example, Bogota in 2018 had a population of 8,182,739, so that the health costs associated with 1 g/m^3 of PM10 are equal to 1,150,263 USD per month. The costs for entire sample of 245 municipalities, with a total population in 2018 of 24,238,655 are then equal to 3,407,273 USD per month for 1 g/m^3 of PM10, and 40.9 million USD annually, equivalent to 31% of the investment budget from the ministry of health in 2018, and 41% of the 2018 tax collections from the carbon tax that came into effect in 2016 (5 USD per ton of CO2).

Table 6. Estimated costs (in USD) by population size

Costs per 1 ug/m of PM10	Total per 100,000 residents	Total for Bogota (8.2 mill.)	Total for whole sample (24.2 mill)
Mental health*	1,178.2	96,410.9	285,585.3
Cardiovascular health	10,369.5	848,507.8	2,513,423.6
Respiratory health*	2,509.5	205,344.2	608,264.3
Total per month	14,057.19	1,150,262.93	3,407,273.18
Total per year	168,686.25	13,803,155.19	40,887,278.20

* Costs estimated from significant effects

It is important to highlight that these costs only represent a fraction of the total health costs. The estimated costs are only for three health conditions, and therefore if PM10 affects other health conditions, these costs only provide a lower bound of the total health costs. Additionally, the estimated effects stem from contemporaneous exposure to PM10, and it is expected that exposure to air pollution can also have significant effects on health in the long run. It is also important to remember that I am only estimating the effects for the population that goes for consultations within the health system, so that the total health effects (and costs) are potentially larger when considering the effects on the entire population. Finally, in terms of the link between electricity generation and health, here this is mediated by the effects of generation on PM10. However, given the ample evidence of the emission of other pollutants by power plants (Jaramillo & Muller, 2016), if these are not strongly correlated to PM10, then these would not be included in this analysis.

6 Robustness Tests

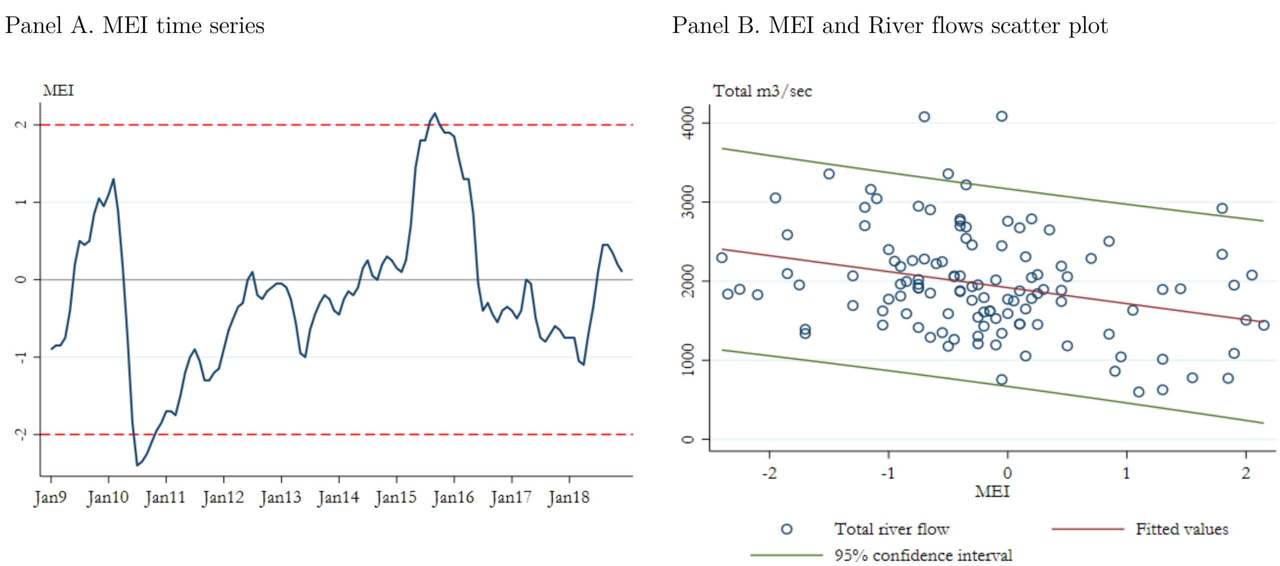
6.1 Excluding El Niño Events

El Niño Southern Oscillation (ENSO) Events are climatic events that reflect a cycle in sea surface temperatures and air pressure of the atmosphere. In Colombia, ENSO events are associated with higher than average temperatures and lower precipitation, whereas La Niña events are associated with lower than average temperatures and higher precipitation (Cai et al., 2020; Puertas Orozco & Carvajal Escobar, 2011). It is expected that these macro weather fluctuations will simultaneously affect river flows, temperature, air pollution, and other factors that also affect the health outcomes examined here, in which case the exclusion restriction would be violated if these factors are not controlled for appropriately. It is also possible that the validity of my instruments is restricted to periods associated to extreme ENSO events, limiting the generalizability of my results.

ENSO events can be captured through different indices, but the most commonly used is the Multivariate ENSO Index (MEI), which is constructed from the principal components of six variables, and aims to provide a more complete measure of ENSO events (Wolter & Timlin, 2011). In order to test whether the estimated effects from PM10 are driven by extreme El Niño events, I estimate the same equations as before, excluding the months where the MEI is above 2 (El Niño) or below -2 (La Niña). Out of the 120 months in my sample, there are 6 months where the MEI is outside the [-2, 2] range (Figure 8), which correspond to the last months of 2010 and beginning 2011, where an extreme La Niña led to extreme rainfall and floods, and to the end of 2015, where an El Niño severely affected rainfall and river flows. The results show that the estimated effects are statistically significant, and similar to the ones I report above (

Table 10 and Table 11 in the Appendix).

Figure 8. MEI and river flows



It is important to highlight that in my main specification I control for both rain and temperature at the pollution monitors, the power plants and the municipalities, and that I also included squared terms of both of these variables at these three levels to control for non-linear effects from weather on air pollution and health. Thus, I can control for the main channel through which El Niño events could affect air pollution and health. Additionally, given that ENSO events have different local effects, I include a state by MEI interaction terms, which effectively capture how macro weather changes, affect local conditions at the state level. The results from these regressions show that there is still a positive and significant effect from electricity generation on PM10, and that there is a positive and significant effect of PM10 on respiratory health, although these effects are smaller than the ones I reported above. Finally, the effects on mental health are still positive, but they are smaller and no longer significant (Table 12 and

Table 13 in the Appendix).

6.2 Days with pollution monitor data

My main sample is constructed by using the average daily PM10 values for all the pollution monitors in a 30 km radius around each municipality, and limiting the sample to include only those months and municipalities for which there at least 10 daily values in the month. However, it is possible that estimated effects are more precise when using measures of PM10 that more accurately capture the average level to which the population is exposed. Therefore, to check whether my results change when using more accurate measures of PM10, I restrict my sample to those observations where the average was calculated using at least 15 data points, and at least 25 data points. I find that the effects do not change dramatically, especially for respiratory health conditions. When I restrict the sample to those with at least 15 data points for the average PM10, I find that the effects of PM10 on mental health are positive but no longer significant. On the other hand, when I restrict the sample to those with at least 25 data points, I find that the effects of PM10 on mental health for both the number of patients and health services, are both positive and significant. Additionally, using a sample that includes all observations for which the daily average per month concentration of PM10 can be calculated, while still controlling for the number of data points, yields very similar results.

6.3 Simulated River Flows Data

Following a similar procedure as Deryugina et al. (2019), I conduct a placebo test where I generate a set of random river flows, with the same mean and standard deviation as the actual river flows, such that the distribution of the simulated and actual river flows is very similar, and I estimate the same equations as before, using the simulated river flows as the instrumental variables. I find that none of the results are significant (results available upon request).

6.4 Effects on other health conditions

As an additional placebo test, I estimate the effect of PM10 on health conditions which we would expect to not be affected by air pollution (Schlenker & Walker, 2016). Following similar tests in the literature, I estimate the effect on appendicitis, and find that the effects of PM10 are positive but not statistically significant.

Table 7. Patients and health services for appendicitis

	Coefficients (std. errors in parentheses)	
	Dependent variable: IHS(Appendicitis per 100,000)	
	Number of patients	Number of health services
	(1)	(2)
IHS(PM10)	0.0314	0.849
	(0.497)	(0.644)
Obs.	16,910	16,910
Weather, Prices, Total load, state linear trend	Y	Y
Month and Year effects	Y	Y
Clustered Std. Errors at municipality	Y	Y

Significance levels: *** (1%), ** (5%) and * (10%)

7 Conclusion

Understanding the negative consequences from air pollution on multiple health conditions is important to fully quantify the health costs associated with it. It is especially important to understand its effects on health conditions that have not been studied until now, such as mental health conditions. Furthermore, power plants as sources of air pollution play a prominent role in most countries, especially in developing ones. However, establishing a causal effect from electricity generation to air pollution, and from air pollution to health can be challenging given all the possible confounding factors, but necessary in order to understand the negative externalities on health of the pollution from electricity generation.

This study presents evidence on the negative effects of electricity generation on air pollution, and on air pollution on mental, respiratory and cardiovascular health. I find that electricity generation increases the ambient levels of PM10, and that evaluated at the mean, 42 GWh of electricity generation increase the concentration of PM10 by 1 $\mu g/m^3$. In terms of the effects on health, I find significant effects on mental and respiratory health. For mental health, I find that 1% increase in PM10 (0.45 $\mu g/m^3$ at the mean) leads to an increase in the rate of health services per 100,000 residents of 1.2% and of 2.1% for respiratory health, as well as a 1.7% increase in the rate of patients for the respiratory conditions. These estimated effects are robust to several different specifications. Importantly, the estimates are slightly lower when excluding extremes El Niño event months from my sample, with the effect of a 1% increase PM10 increasing the rate of health services by 1% for mental conditions and by 1.8% for respiratory ones. From the estimated effects from my main specification, I estimate that the health costs from 1 $\mu g/m^3$ of PM10 for the three health conditions in this study, are equal to 40.1 million USD per year for the total population in my sample.

The effects I estimate and the health costs derived from these, are based on short term health effects of PM10. These effects only account for conditions for which people seek assistance through the health system, and so they do not included effects on health that could be considered as minor, but that could be much more common and frequent. They also do not include any loss of income as a consequence of ill health. Additionally, exposure to air pollution can have long-term health effects that are not fully included here. However, the estimated effects provide a lower bound of the total costs associated with PM10, and thus should be considered as an important input by policy makers.

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8 Appendix

Figure 9. Price series used in the estimating equation

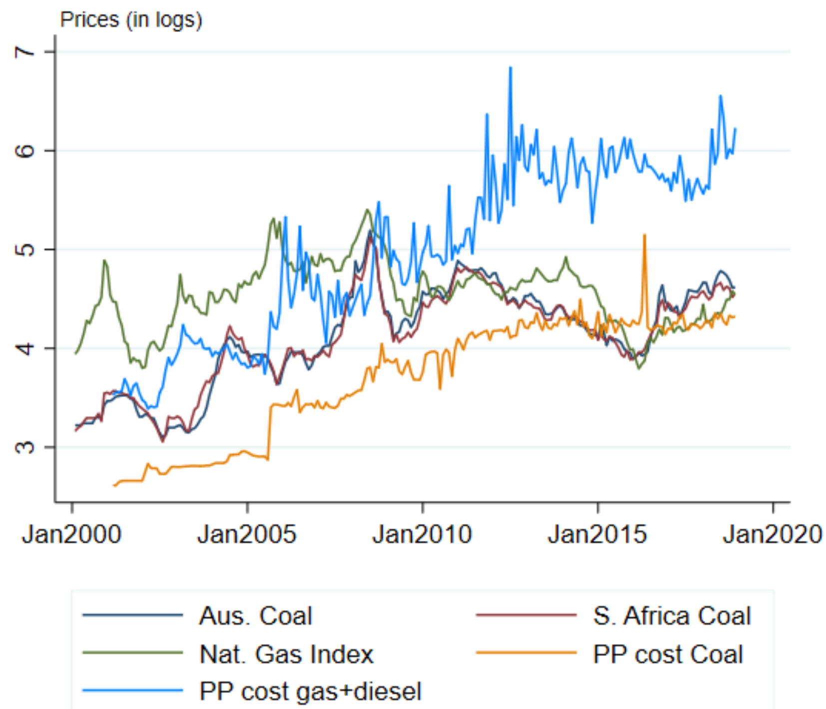

Figure 10. Scatterplot of gas and coal generation, and total river flows

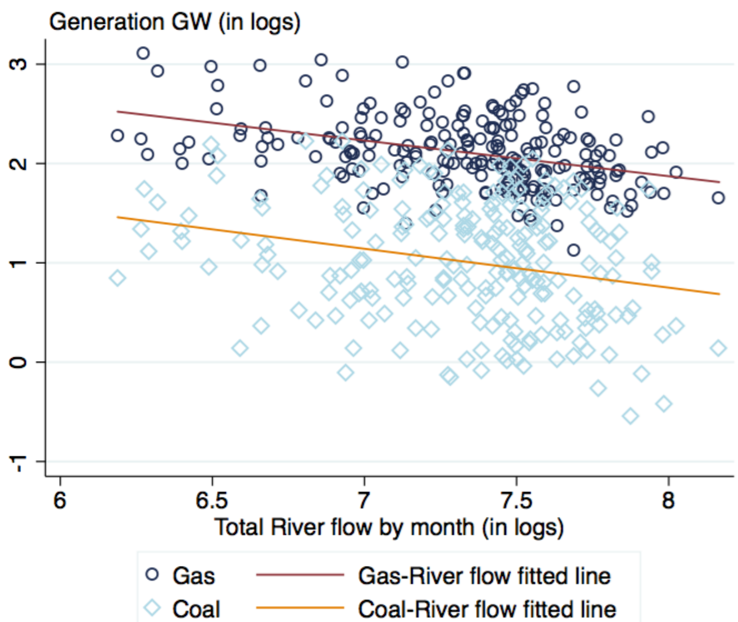

Figure 11. Scatterplot of diesel generation, and total river flows

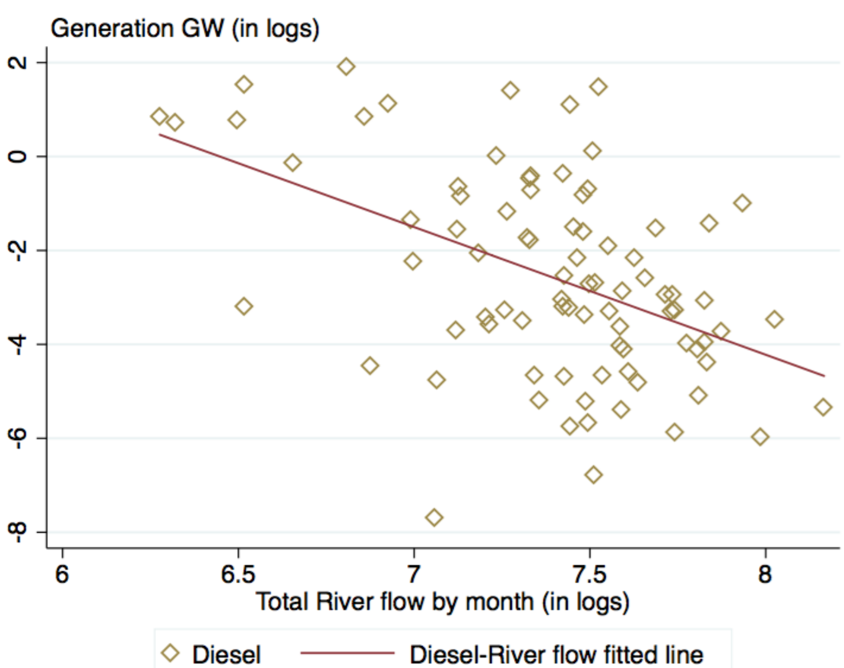

Figure 12. Availability of water services by region

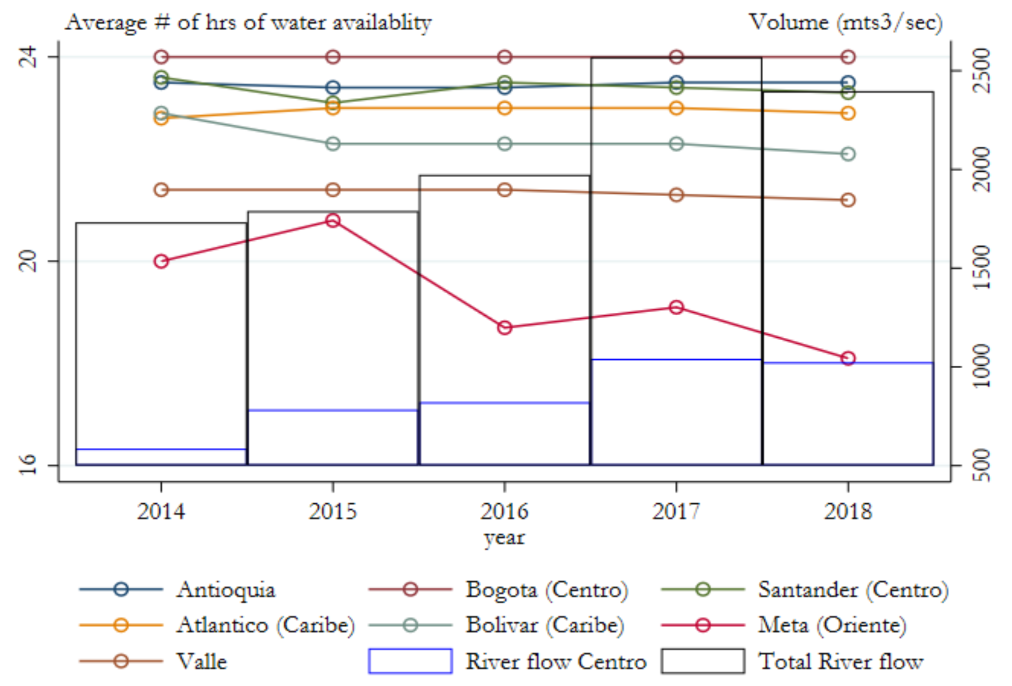

Table 8. Summary statistics by installed capacity

Municipality characteristics - Average	Low Installed Capacity (GW) (1)	High Installed Capacity (GW) (2)	Difference (3)
PM10	43.3	50.1	6.8***
Total Population	106,870	75,615	-31,255***
Regional Electricity Demand (GWh)	718	652	-66.6***
Percent Urban	50.3%	52.2%	1.9%***
Yearly per cap. expend. local government (USD)	402	370	-31.6***
Monthly rainfall (cubic mm)	124	138	14.4***
Monthly temperature (degrees Celsius)	23	25	1.81***
Rates per 100,000 inhabitants			
Respiratory - Number of patients	676	664	-11.6*
Respiratory - Number of services	1,368	1,348	-19.7
Mental - Number of patients	132	140	7.4***
Mental - Number of services	310	301	-8.7
Cardiac - Number of patients	875	1,144	269***
Cardiac - Number of services	1,894	2,439	544.6***

Notes: This table shows the means by the installed capacity, where low installed capacity refers to municipalities where the installed capacity is lower than the median of 0.36 GW. The third column shows the difference between the means of these two groups, and the significance levels of t-test of the differences in the means. The significance levels are: *** (1%), ** (5%) and * (10%)

Table 9. First stage regression for electricity and PM10, and for PM10 and Health

Coefficients (std. errors in parentheses)					
	Dependent variables (IHS transformation):				
	Electricity from Coal	Electricity from Gas	Electricity from Diesel	Total electricity	PM10
	(1)	(2)	(3)	(4)	(5)
Perc. Gas x Total River Flows	-0.000***	0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Perc. Coal x Total River Flows	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Perc. Diesel x Total River Flows	-0.000*	-0.000***	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	16,486	16,486	16,486	16,486	16,486
Cragg-Donald 1st stage F-statistic	40.86	40.86	40.86	285.68	27.75

Significance levels: *** (1%), ** (5%) and * (10%)

Table 10. Electricity Generation and PM10 excluding ENSO Events

Coefficients (std. errors in parentheses)				
Dependent variable: IHS(Monthly average PM10)				
	FE	FE - Total	IV	IV - Total
	(1)	(2)	(3)	(4)
IHS(Coal generation GWh)	0.014***		0.052***	

	(0.004)		(0.017)	
IHS(Gas generation GWh)	0.002		-0.101**	
	(0.003)		(0.045)	
IHS(Diesel generation GWh)	0.025***		0.234**	
	(0.005)		(0.091)	
IHS(Total electricity generation GWh)		0.022***		0.058***
		(0.004)		(0.011)
Obs.	16,049	16,049	16,049	16,049
Controls: Weather, Prices, Total load, state linear trend	Y	Y	Y	Y
Month and Year effects	Y	Y	Y	Y
Clustered Std. Errors at municipality	Y	Y	Y	Y

Significance levels: *** (1%), ** (5%) and * (10%)

Table 11. PM10 and Health excluding ENSO Events

Coefficients (std. errors in parentheses)				
Panel A - Dependent variable: IHS(Patients per 100,000)				
	Respiratory (1)	Mental (2)	Cardiovascular (3)	Appendicitis (4)
IHS(PM10)	1.592***	0.654	0.0164	0.00878
	(0.544)	(0.500)	(0.429)	(0.452)
Panel B - Dependent variable: IHS(Services per 100,000)				
IHS(PM10)	1.854***	1.045*	0.233	0.724
	(0.605)	(0.576)	(0.440)	(0.579)
Obs.	16,049	16,049	16,049	16,049
Weather, Prices, Total load, state linear trend	Y	Y	Y	Y
Month and Year effects	Y	Y	Y	Y
Clustered Std. Errors at municipality	Y	Y	Y	Y

Significance levels: *** (1%), ** (5%) and * (10%)

Table 12. Electricity and PM10 (no ENSO events, and MEI and state effects)

Coefficients

(std. errors in parentheses)

Dependent variable: IHS(Monthly average PM10)				
	FE (1)	FE - Total (2)	IV (3)	IV - Total (4)
IHS(Coal generation GWh)	0.012*** (0.004)		0.056*** (0.019)	
IHS(Gas generation GWh)	-0.005* (0.003)		-0.074** (0.034)	
IHS(Diesel generation GWh)	0.011** (0.005)		0.176 (0.108)	
IHS(Total electricity generation GWh)		0.013*** (0.003)		0.054*** (0.011)
Obs.	16,049	16,049	16,049	16,049
Controls: Weather, Prices, Total load, state linear trend	Y	Y	Y	Y
Month and Year effects	Y	Y	Y	Y
MEI and state effects	Y	Y	Y	Y
Clustered Std. Errors at municipality	Y	Y	Y	Y

Significance levels: *** (1%), ** (5%) and * (10%)

Table 13. PM10 and Health (no ENSO events, and MEI and state effects)

Coefficients

(std. errors in parentheses)

Panel A - Dependent variable: IHS(Patients per 100,000)				
	Respiratory (1)	Mental (2)	Cardiovascular (3)	Appendicitis (4)
IHS(PM10)	1.300** (0.506)	0.469 (0.506)	0.00780 (0.443)	-0.00227 (0.503)
Panel B - Dependent variable: IHS(Services per 100,000)				
IHS(PM10)	1.411*** (0.545)	0.746 (0.562)	0.132 (0.448)	0.575 (0.644)
Obs.	16,049	16,049	16,049	16,049

Weather, Prices, Total load, state linear trend	Y	Y	Y	Y
Month and Year effects	Y	Y	Y	Y
MEI and state effects	Y	Y	Y	Y
Clustered Std. Errors at municipality	Y	Y	Y	Y

Significance levels: *** (1%), ** (5%) and * (10%)