Power Plants, Air Pollution, and Health in Colombia

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Abstract

In this paper I estimate how electricity generation from fossil fuel power plants affects air pollution in Colombia, and how that air pollution affects the mental, respiratory and cardiovascular health of the population around them. I use the river flows that feed hydroelectric power plants as instruments for electricity generation from fossil-fuel plants, to estimate increases on particulate matter (PM10) and associated health effects. I find that the electricity necessary to meet the monthly demand for 1 million people (116 GWh), is responsible for 2.75 ug/m^3 of PM10, leading to an increase in mental health patients of 6%, and of 9% for respiratory health patients. I show that this has significant economic effects, highlighting that the inclusion of mental health effects increases the total costs by 13%. The total health costs for the 24 million people in my sample, amount to 22 million USD per year, for 1 ug/m^3 of PM10. A cost-benefit analysis of the replacement of coal power plants around Bogota by solar generation, shows that the health benefits outweigh the cost of the tax incentives, with a benefit-cost ratio of 6:1.

JEL: Q53, O15, I10, Q40

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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, evidence of its effects on mental health is scarcer, despite suggestive results from epidemiological studies (Buoli et al., 2018; Power, Adar, Yanosky, & Weuve, 2016). Understanding these effects is important given that mental health disorders are currently considered the leading contributor to the global burden of disease, accounting for 32% of years lived with disability, and on par with cardiovascular and circulatory diseases (Vigo, Thornicroft, & Atun, 2016). Additionally, from a policy perspective, the source of air pollution matters. Fossil-fuel power plants are significant contributors to air pollution, and their contributions are expected to grow, as electricity generation and demand increase in developing countries (Wolfram, Shelef, & Gertler, 2012). However, existing studies in the developing context do not estimate the direct effect of electricity generation on air pollution, and the effects of this air pollution on health.

This study investigates how thermal power plants' affect air pollution, mental, respiratory and cardiac health in Colombia. 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. Most hydroelectric generation and the rivers that feed their reservoirs are located in different regions from where the fossil fuel power plants are. Thus, the variation in river flows provides an exogenous shock to electricity generation from fossil fuel power plants, and to the pollution they create.

The use of instrumental variables is necessary in this context since direct estimation of the effect of electricity generation on emissions will likely suffer from omitted variable bias. There may exist unobservable confounders that correlate with both generation and emissions. For example, two likely confounders are unobservable local weather conditions and economic activity. While I flexibly control for both of these in my model by including rainfall, temperature and regional electricity demand, there is no guarantee that other confounders do not exist. The use of river flows as instruments allows unbiased estimation of this effect, given that they shift electricity generation from hydro to thermal, and that the only channel through which they affect air pollution is through their effect on electricity generation.

The use of instrumental variables proves to be even more necessary when estimating the effects of particulate matter (PM10) on health. In this case, there are the two main concerns. First, there are unobservable confounding factors that are correlated with both exposure to air pollution and with health outcomes. Second, exposure to air pollution is often measured with error, in which case the estimated effects will suffer from attenuation bias, thus 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 with health, with the exposure to air pollution, and with the measurement error in PM10.

Therefore, to estimate the effect from electricity generation on PM10, I construct a monthly panel of municipalities, matching them to the closest power plants in a 100 km radius. I aggregate the total electricity generation in that area, by fuel source and month, and match the municipalities to all the pollution monitors in a 30 km radius. I use the data from these pollution monitors to calculate the daily average concentration of PM10 by municipality and month. I use river flows as instrumental variables for thermal electricity generation, and find that a 1% increase in electricity generation from thermal power plants leads to a 0.06% increase in the average PM10 concentrations. Evaluated at the average generation in my sample, this implies that 42 GWh of electricity from these power plants, enough to meet the demand of 370,000 people for a month, increase the monthly average ambient levels of PM10 by 1 $u\text{g/m}^3$ for municipalities in a 100 km radius.

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 mental, respiratory, and cardiovascular health conditions. I then estimate how ambient levels of PM10 affect these health outcomes, and find that an increase in PM10 of 1 $u\text{g/m}^3$ increases the rate of mental health patients by 1.4% (3 patients per 100,000 residents), and the rate of respiratory health patients by 1.8% (24 patients per 100,000 residents). With these estimates, I calculate the economic costs associated with increases in PM10. My results highlight the importance on accounting for mental health effects. The inclusion of the mental health costs increases the total costs by 13%. The total health cost from 1 $u\text{g/m}^3$ of PM10 for all health conditions for the whole sample of 245 municipalities, with a total population of 24.2 million, are 21.7

million USD per year. These health costs are net of avoiding behavior and measurement error, and so following Alberini & Krupnick (2000) and Moretti & Neidell (2011), can be interpreted as the willingness-to-pay (WTP) to reduce ambient concentration of PM10 by 1 ug/m^3 in Colombia. I estimate the WTP per capita per year to be of $0.87, lower than the estimated WTP for PM10 of $1.34 per year for China (Ito & Zhang 2020), a country with roughly the same level of per capita GDP but with ambient levels of PM10 that are 124% higher. I use this to evaluate a tax incentive policy for renewable energy from the Colombian government, and I find that the health benefits from a reduction in PM10 vastly outweigh the cost of the tax incentives, with a benefit-cost ratio of 5.9.

Furthermore, I decompose the health effects from PM10 for two distinct groups of the population with different socioeconomic status: those under the contributive health insurance regime (higher SES) and those under the subsidized regime (lower SES). It is usually assumed that people from lower SES are both more vulnerable and more exposed to air pollution, and thus will be more affected from changes in its ambient levels. I test this hypothesis here, by estimating separate effects for these two groups. Surprisingly, I find that the effects are higher for those under the contributive regime, when compared to those from the subsidized regime, and to the entire population in my sample. I find that the most likely explanation to these results is that those under the contributive regime are on average older and in worse health than those under the subsidized regime, and that their level of exposure to air pollution, as measured by yearly PM2.5, is also higher.

This paper offers three contributions to the existing literature. The first one is its focus on mental health. Epidemiological studies have found that exposure to higher levels of air pollution are associated with a deterioration of mental health, although these cannot be interpreted causally (Buoli et al., 2018; Power et al., 2016). The exact mechanisms are not known, but evidence suggests an association with neurological effects on the central nervous system, with neuroinflammation and neurotoxicity (Block et al., 2012; Jia et al., 2018), and with a reduction in sleep (Harvey, 2011; Heyes & Zhu, 2019). Mental health disorders are not limited to a small group of people, since it is expected that 50% of the population in middle- and high-income countries will suffer a mental health disorder at some point in their lives (Trautmann, Rehm, & Wittchen, 2016). This is the first paper to estimate the causal effects of air pollution on contemporaneous mental health, using administrative data that includes all instances where patients sought attention through the health system. The results from this study complement the findings from Bishop, Ketcham, & Kuminoff (2018), who focus on the long-term effects of exposure to PM2.5 on dementia. Using Medicare data (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 that through the effect it had in PM2.5, the Clean Air Act led to $240 billion saved from the lower costs of dementia. The only other study to estimate the causal effect from air pollution on mental health uses self-reported measures of happiness and depression, and finds that lower air quality reduces hedonic happiness for Chinese households and increases the rate of depressive symptoms (Zhang, Zhang, & Chen, 2017).

Second, this paper effectively links electricity generation, air pollution and health, whereas others, due to lack of available data, have focused on the electricity to health link. Previous studies have focused on the negative externalities from electricity generation using coal, but do not directly link generation to air pollution and health. Clay, Lewis, & Severnini (2016) use the timing of the installation of coal-fired power plants in the US to estimate the effect that coal burning for electricity generation had on infant mortality. They find an increase in infant mortality and a decrease in property values, but do not estimate the effect of coal-fired power plants on any measure of air pollution, due to the lack of pollution monitor data. 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. 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 reported cough by households, and find a positive and significant increase in households reporting cough.

The importance of linking electricity generation from fossil fuels to air pollution and health is threefold. First, the electricity sector is a major emitter of GHG, with emissions accounting for 30% of the total GHG emissions in the world in 2016 (World Resources Institute, 2019). Second, 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 generation is higher in developing than in developed countries. For low income countries, hydroelectric generation represents 44% of total electricity generation, compared to 19% and 12% for middle- and high-income countries[1], respectively. Third, the

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

direct estimation of the effect of electricity generation on ambient levels of air pollution and health is helpful in that it allows policy makers to correctly price the negative externalities from generation. These effects can also be estimated using atmospheric transport models which simulate the dispersion of pollutants in the atmosphere (Gao et al., 2018). However, the results from these studies are sensitive to the assumptions used in the models and can lead to very different results (Y. Zhang, He, Zhu, & Gantt, 2016), resulting in uncertainty about the optimal policy response. Therefore, there is a distinct advantage in being able to directly link generation to ambient levels of PM10.

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 long-term effects from in-utero exposure (Bharadwaj, Gibson, Zivin, & Neilson, 2017). Here, my main contribution is that this is the first study examining the effects of air pollution in Colombia, which serves as an interesting case study. It has nearly universal health insurance coverage and a high rate of urbanization, which translates into higher access to healthcare, and a more accurate estimation of the health effects. Additionally, the topography of the country implies that different areas will face very different emissions, which is helpful to identify the effects of local pollution shocks. Finally, it also has similar levels of air pollution to other upper middle-income countries, a category that includes China, Russia, Mexico and Brazil, and currently accounts for 37% of the world population.

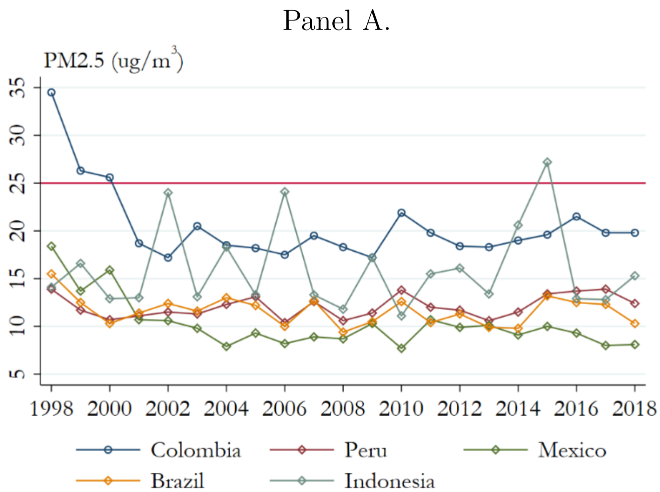
The paper is organized as follows. Section 2 provides background information of air pollution in Colombia, together with current environmental regulations and their relationship to the electricity sector, and also briefly explains how the health system operates. Section 3 presents the data used and summary statistics. Section 4 presents the empirical strategy and estimating equations, followed by results in section 5, and an estimation of the economic costs from air pollution and electricity generation. In section 6 I present an analysis on the heterogenous health effects by type of health insurance. I present some robustness tests in section 7, and then conclude in section 8.

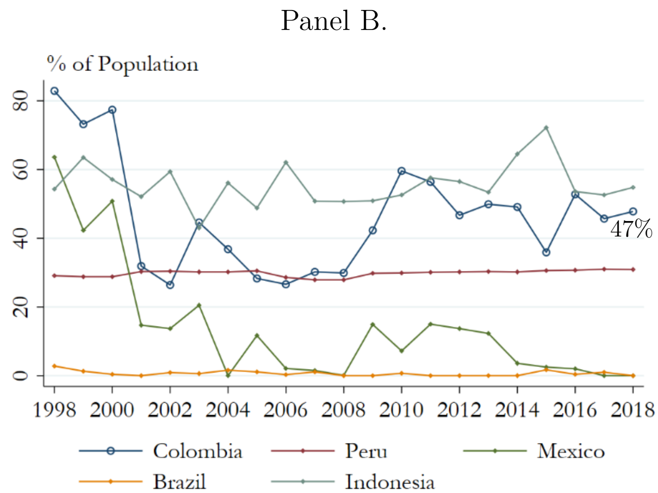
2 Background

2.1 Air Pollution and the Electricity Sector

The levels of air pollution in Colombia in the last 20 years have decreased, although the country underperforms with respect to other middle-income countries, in terms of both the current levels (Figure 1, Panel A)[2], and the percentage the country's population that is exposed to concentrations of PM2.5 above 25 ug/m^3, which is the current threshold set by the environmental authority in Colombia (Figure 1, Panel B).

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





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 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,

[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.

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

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.

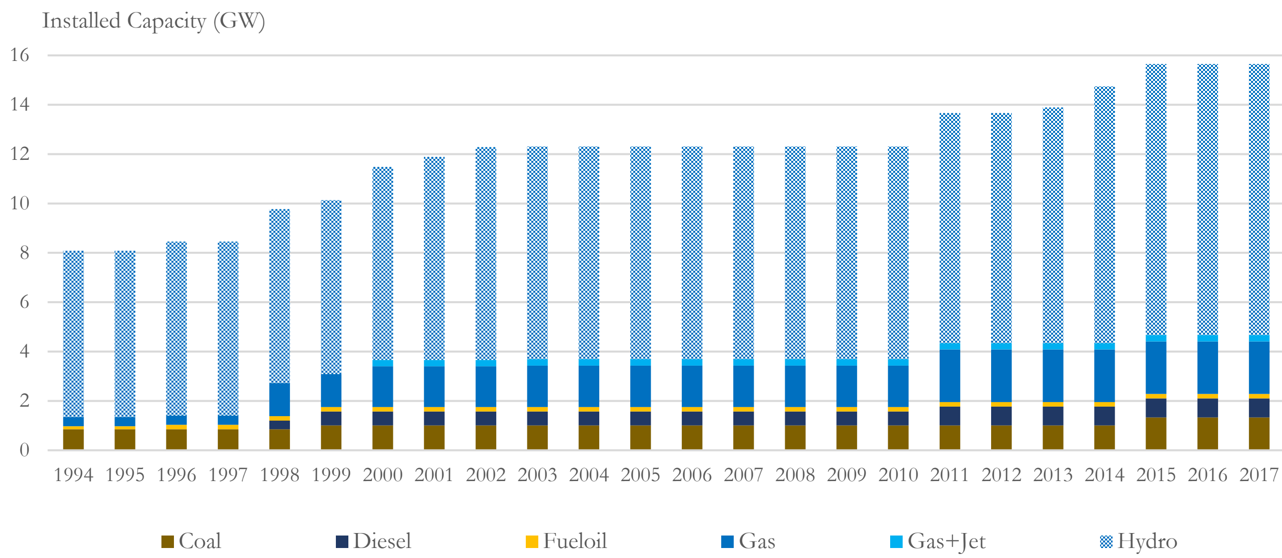
Table 1. Power plant characteristics by fuel type

	Average value by fuel source			
	Coal	Gas	Diesel	All power plants
Heat rate (MBTU/MWh)	10.81	9.14	7.05	9.73
Capacity (MW)	115.9	200.1	269.0	166.6
Year of construction	1988	1996	2003	1993
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 emissions 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 reliant on hydroelectric generation, despite being reformed to allow the entry of fossil fuel generators into the system.

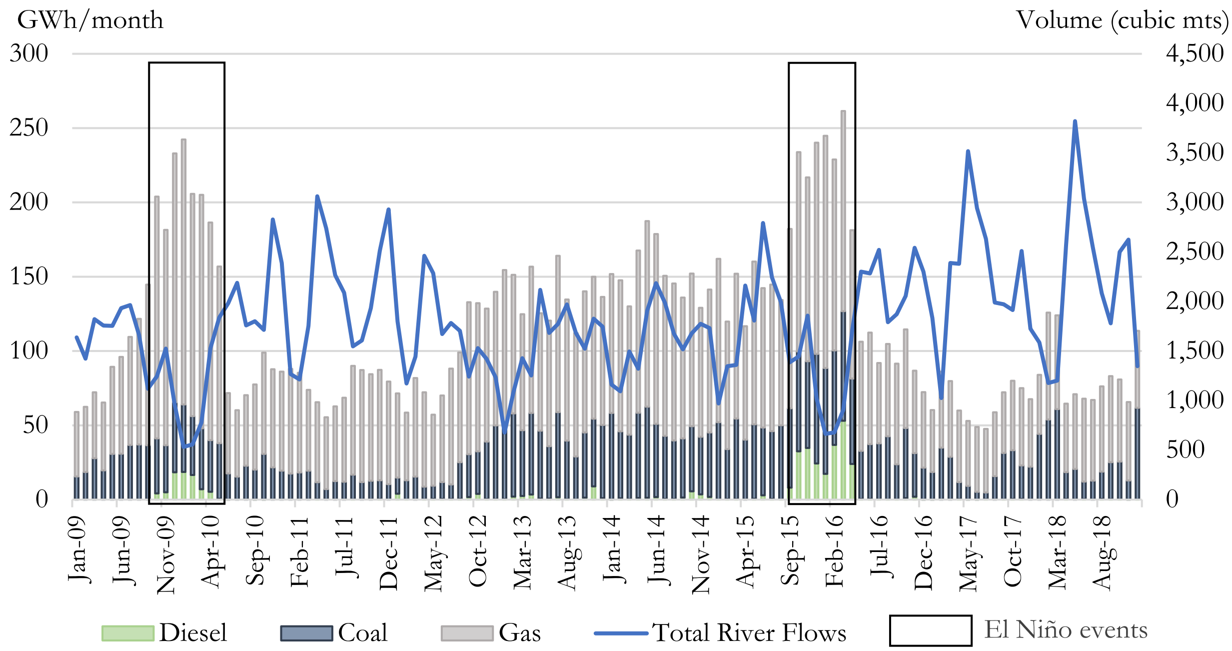
The reforms started in 1994, after the country suffered from programmed blackouts in 1992 and 1993, as a consequence of El Niño, the climatic phenomenon associated with a warming of the waters in the central Pacific Ocean. In Colombia, El Niño is associated with an increase in average temperature, a 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 large-scale 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

For the analysis in this paper, I merge 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.

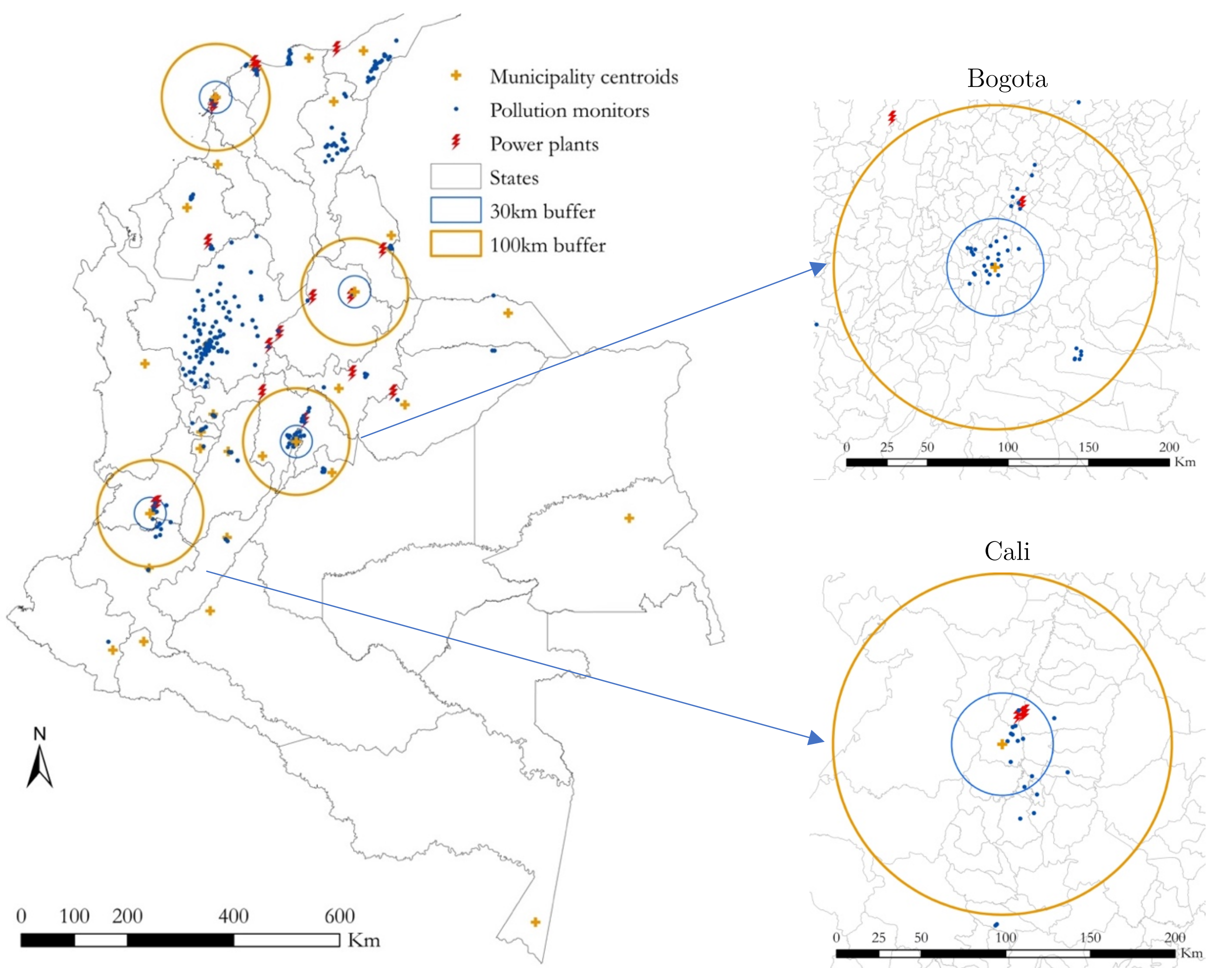
I match municipalities to all the pollution monitors in a 30 km radius, to capture the exposure of the population to air pollution in all the municipality, and then calculate a monthly average for each municipality (similar to the clustering procedure for pollution monitors by Deryugina, Heutel, Miller, 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 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

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

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, such that the price paid by power plants is the market price, and is not set by decree, like gas and diesel. 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 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,

[5] Provided by XM upon request.

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

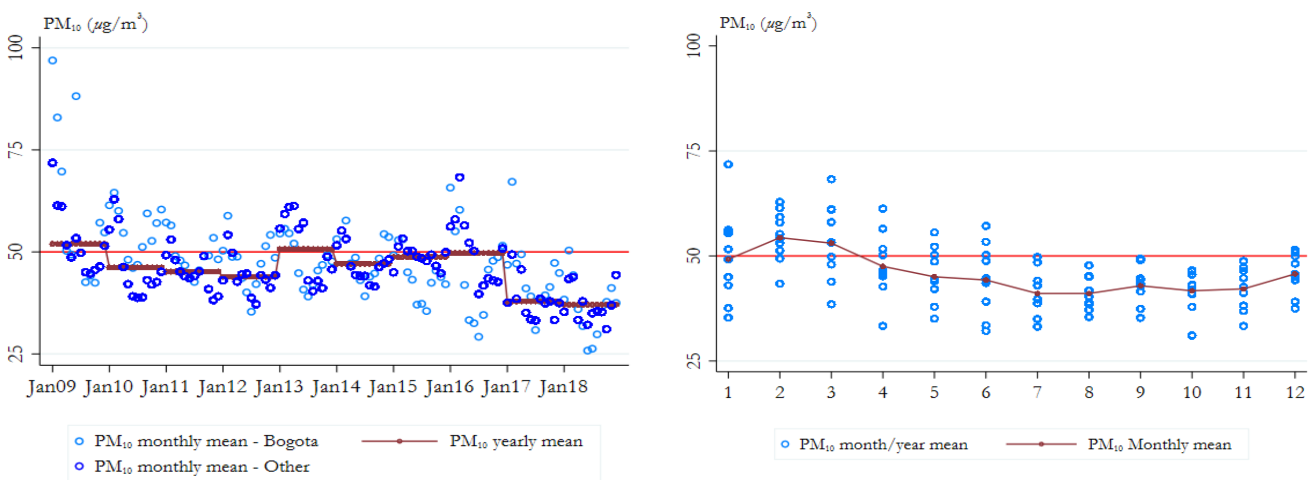
[7] ICD-10 is the International Statistical Classification of Diseases and Related Health Problems, version 10.

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 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 ug/m^3 (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 (49% 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, 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 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). The two most important mental health disorders in Colombia between 2009 and 2018 are "Neurotic, stress related and somatoform disorders" and "Mood affective disorders", with 26% and 19% (respectively) of all the mental health patients being diagnosed with either one of these disorders (Table 13 in the Appendix).

Table 3. Summary statistics on health outcomes by municipality

Characteristics for all the municipalities	Total				
Number of municipalities	245				
Total population in sample - 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 β_1, β_2, and β_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:

$$Coal_{it} = \theta_{\mathrm{jf}} \sum_{f}^{3} Capacity_{if} \times Rivers_{t-1} + X_{it}\beta + \alpha_y + \alpha_m + \varepsilon_{it} \qquad (2)$$

$$Gas_{it} = \theta_{\mathrm{jf}} \sum_{f}^{3} Capacity_{if} \times Rivers_{t-1} + X_{it}\beta + \alpha_y + \alpha_m + \varepsilon_{it} \qquad (3)$$

$$Diesel_{it} = \theta_{\mathrm{jf}} \sum_{f}^{3} Capacity_{if} \times Rivers_{t-1} + X_{it}\beta + \alpha_y + \alpha_m + \varepsilon_{it} \qquad (4)$$

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, and so $Capacity_{if}$ is the percentage of the installed capacity in fuel f that is available around municipality i. This allows me to more accurately estimate the effect that changes in river flows has on local electricity generation by fuel source, and the effect from electricity generation on pollution. 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. 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:

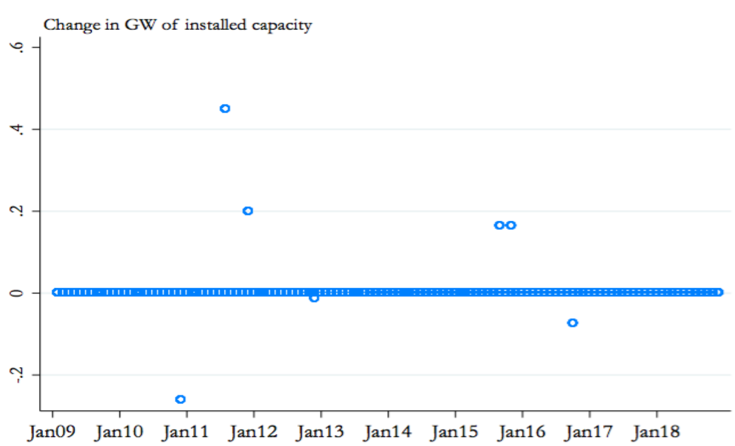
$$PM10_{it} = \beta_1 \widehat{Gas_{it}} + \beta_2 \widehat{Coal_{it}} + \beta_3 \widehat{Diesel_{it}} + X_{it}\beta + \alpha_y + \alpha_m + \alpha_i + \varepsilon_{it} \tag{5}$$

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. It is likely that this assumption holds conditional on my controls. 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 14 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, and therefore 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:

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

The outcome variable $\mathrm{PM10}_{\mathrm{it}}$ 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:

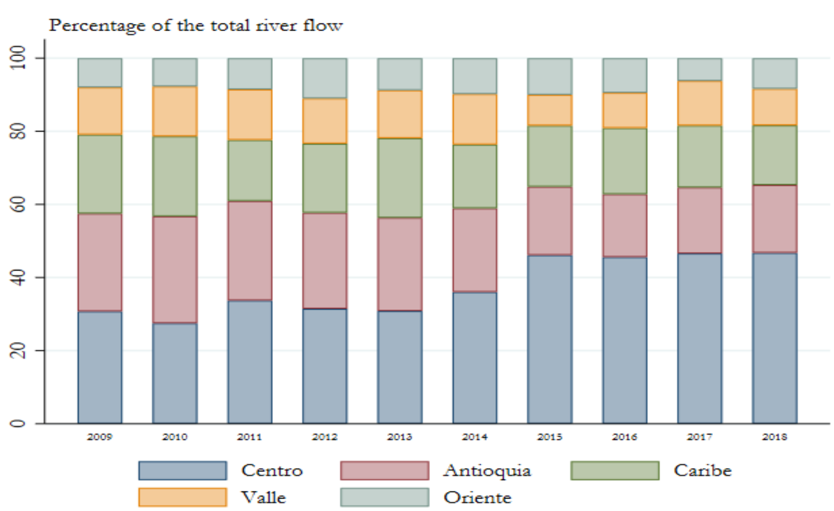
$$H_{it} = \beta_1 \widehat{PM10}_{it} + X_{it}\beta + \alpha_y + \alpha_m + \alpha_i + \varepsilon_{it} \tag{7}$$

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 number of patients for each condition as measuring the health effects at the extensive margin, while the amount 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, this is likely 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 0.033%. The effect from coal is positive and significant, with a 1% increase in electricity generation from coal leading to a 0.014% increase in PM10. 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 0.08% and for diesel generation a 1% increase, increases PM10 by 0.22%.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 16 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 than the one when using all the sources combined. However, the model seems to perform 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)	0.014***		0.078***	
	(0.004)		(0.014)	
IHS(Gas generation GWh)	0.001		-0.055	
	(0.003)		(0.040)	
IHS(Diesel generation GWh)	0.033***		0.216***	
	(0.005)		-0.078	
IHS(Total electricity generation GWh)		0.022***		0.057***
		(0.003)		(0.012)
Observations	16,903	16,903	16,903	16,903
R-Squared	0.63	0.63		
Kleibergen-Paap Wald F-stat. (1st stage)			51.3	331.0

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 generation capacity as the instrumental variables, to predict the daily average level of PM10 per month, 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 services (Table 5). Additionally, the estimated effects using 2SLS are orders of magnitude bigger than the OLS estimates (Panel A, Table 5), which points to the possibility that the attenuation bias leads to an underestimation of the health effects. Given that both the dependent and the explanatory variables 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 1.5% and of 1.8% in the rate of health services. Evaluated at the mean value of both of these variables, an increase in the concentration of PM10 of 0.46 ug/m3, leads to an increase of 11 patients and 26 services per 100,000 residents for respiratory conditions. For mental health conditions, an increase in PM10 of 1% leads to an increase in mental health patients of 1% and of services of 1.4%, which implies an increase of 1.5 patients and 5 services per 100,000 residents. For mental health disorders, I analyze the effects by the different classifications (according to the ICD-10), and focus on the two groups of disorders that have the higher prevalence rate: mood affective disorders (F30-39 in the ICD-10), and neurotic and stress related disorders (F40-49 in the ICD-10). I find that there is only a significant effect for mood affective disorders (Table 16 in the Appendix), a category which includes bipolar and depressive disorders, and which accounts for 19% of all the mental health patients during my sample period.

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)	0.0284	0.0822*	0.0650	0.0974	0.0274	0.0731
	(0.0453)	(0.0496)	(0.0534)	(0.0593)	(0.0465)	(0.0514)
Observations	16,903	16,903	16,903	16,903	16,903	16,903
R-squared	0.517	0.492	0.579	0.555	0.496	0.491
Panel B - IV estimates						
IHS(PM10)	1.502***	1.77***	0.961*	1.407**	0.139	0.424
	(0.529)	(0.588)	(0.537)	(0.640)	(0.437)	(0.451)
Observations	16,903	16,903	16,903	16,903	16,903	16,903
Kleibergen-Paap Wald F-stat. (1st stage)	13.97	13.97	13.97	13.97	13.97	13.97

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 put these estimated effects in context, I compare them to the estimated effects from the two most similar studies I could find. I scale the results from these studies to make them comparable to mine, such that they show the percentage change in the outcome variable from a 0.46 ug/m^3 change in PM10. 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 0.46 ug/m^3 increase in PM10, increases hospital admissions for children by 0.3% (rate per 10,000 children). Similarly, a study from Sweden finds that a 0.46 ug/m^3 increase in PM10, increases the rate of patients for respiratory conditions by 0.5% Jans, Johansson, & Nilsson (2018). In both cases, the estimated effects are lower than the ones I find. However, there are important differences that can explain this. For the case of the study in Italy, they focus on a narrower set of respiratory conditions (COPD) and only on hospitalizations, and their estimated effects are only for children. The study in Sweden also focuses on children, but their outcome variable includes all respiratory conditions. Additionally, in both cases the ambient concentrations of PM10 are lower than that of Colombia: 33.3 ug/m^3 in Italy and 21 ug/m^3 in Sweden (27% and 54% lower than the levels of PM10 in Colombia, respectively).

5.3 Economic Costs of Pollution

The estimated health effects allow me to quantify the economic costs associated with PM10. These can be interpreted as the slope of the dose response function, and so by multiplying these effects with the marginal value of illness, I can get an estimate of the willingness-to-pay (WTP) for reducing PM10 in Colombia (Alberini & Krupnick, 2000; Moretti & Neidell, 2011). The marginal value of illness includes the costs for medical attention, the costs due to the loss income from sick days, and the cost of the avoidance behavior. For the cost of medical attention, I get the total cost for consultations and procedures by health condition (including out-of-pocket payments by patients), and then calculate the average cost per patient and condition (Table 17 in the Appendix). 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. Additionally, I have data on the total number of sick days requested by year and health condition, such that I can get the average number of sick days per patient and health condition, which I multiply by the estimated number of patients that results from a 1 ug/m^3 increase PM10 and the average wage per day. The average number of sick days per patient is 0.8 for mental health conditions, 0.4 for respiratory health conditions and 0.3 for cardiovascular conditions, and the average income per day is $18 USD.

I estimate that the cost of 1 ug/m^3 of PM10 to be highest for respiratory conditions, with the total cost per 100,000 residents per month equal to approximately 5,374 USD, while that for cardiovascular conditions is 1,239 USD and for mental health conditions is 859 USD. The total costs associated to these three conditions amount to 7,471 USD per 100,000 residents (Table 6).

The costs are much higher when considering the exposure for bigger populations. For example, Bogota in 2018 had a population of 8.2 million, so that the health costs associated with 1 ug/m^3 of PM10 are equal to 611,367 USD per month. The costs for the entire sample of 245 municipalities, with a total population in 2018 of 24,2 million (49% of the country's population) are equal to 1,810,792 USD per month and 21.7 million USD per year, for 1 ug/m^3 of PM10. This is equivalent to 101% of the investments made in public hospitals by the ministry of health in 2018, and 22% of the 2018 tax collections from the carbon tax that came into effect in 2016 (5 USD per ton of CO2).

Furthermore, because I use an IV approach to estimate these effects, the estimated WTP is not affected by avoidance behavior and measurement error in pollution exposure. Thus, from this value I can then estimate the per capita WTP, which I estimate to be $0.89 per year for a unit of PM10. This is lower than the estimated WTP for PM10 of $1.34 per year for China (Ito & Zhang 2020), although the level of ambient PM10 in China in their study is of 103 ug/m^3 compared to 46 ug/m^3 in Colombia for this study.

It can also be useful to compare the value of the electricity generated, to the health costs of the air pollution associated with it. Per capita monthly demand for electricity in 2018 was 116 KWh, so that for a municipality with a population of 100,000, the total demand would be equivalent to 11.6 GWh. Using the average electricity prices from 2018, the value of that electricity would be $1.65 million USD and the health costs associated with the pollution generated represent 0.5% of the value of the electricity generated.

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

Costs per 1 ug/m^3 of PM10	Total per 100,000 residents	Total for Bogota (8 mill.)	Total for whole sample (24.2 mill)
Mental health	859	70,283	208,191
Cardiovascular health	1,239	101,364	300,258
Respiratory health	5,374	439,719	1,302,523
Total per month	7,471	611,367	1,810,972
Total per year	89,657	7,336,403	21,731,665

* Costs estimated from significant effects

It is important to highlight that the values used to calculate the marginal value of illness do not include all the necessary costs. Specifically, the cost per patient for each health condition is likely to be higher that the values I use, given that health providers are not required to enter the health condition when performing non-surgical procedures. Also, 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. Regarding the timing of the effects, the estimated effects stem from contemporaneous exposure to PM10. If exposure to air pollution also has significant effects on health in the long run, then these future costs would not be captured here. 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.

5.3.1 Cost-Benefit Analysis of Tax Incentives for Renewable Energy

The health costs that result from exposure to ambient PM10, can be considered as a benefit that arises from policies aimed at reducing air pollution. The objective of this simple analysis is to illustrate how the estimated health costs can be used to evaluate the cost effectiveness of environmental policies. I focus here on a specific policy that came into effect in 2014 ("Ley 1515 de 2014"), that created tax incentives to invest in renewable energy. The biggest tax incentive comes from the deduction of 50% of the amount invested as a cost that lowers the taxable profit for corporations. I do a cost-benefit analysis to evaluate the cost of replacing the installed capacity from coal power plants located near Bogota by solar photovoltaic capacity. The power plants near Bogota are located 42 km from the city, with a total installed capacity of 0.224 GW. Running at full capacity for a month (12 hours per day, as a solar PV power plant would), they can generate 80.64 GWh of electricity, which in turn would result in an increase in ambient levels of PM10 of 3.71 ug/m^3 per month. The health costs associated to that level of PM10 in Bogota, are 27.2 million USD per year, assuming a constant increase in PM10 for a whole year. The cost of installing solar powered capacity that could replace these power plants would be 224 million USD (the details of these calculations can be found in Table 22 in the Appendix)[9], and the cost of the tax incentives provided are 36.9 million USD. Using a 10-year horizon and a discount rate based on the rate of Colombia's government bonds, I find that the benefit-cost ratio of replacing existing coal power plants by solar, is of 5.9. This implies that the health benefits associated with a decrease in air pollution from replacing existing coal capacity with solar energy, vastly outweigh the cost from the government's tax incentives for renewable energy investments. Importantly, this analysis is based on the health benefits from the reduction in PM10, but a complete cost-benefit analysis should include other benefits, such as the mortality effects, the reduction in CO2 emissions, and the reduction in ambient levels of other pollutants.

6 Heterogeneous Health Effects

The health effects from the exposure to air pollution can be different for different groups of the population due to the composition of each group, which ultimately affects the level of exposure and vulnerability of each group. These differential effects mean that health costs associated with air pollution will vary by group, potentially leading to the most exposed and vulnerable groups in the population bearing most of the cost.

Most studies examining the effects of air pollution on health do not explicitly focus on the estimation of the effects across different groups based on socioeconomic status (SES), although most studies do control for income and other proxies of SES. To the best of my knowledge, there are only two studies that explicitly focus on health effects by SES, with both of these studies focusing on child health. Neidell (2004) estimates how different pollutants affect the rate of child hospitalizations for asthma, and how these effects vary by the zip code level SES. He finds that the effects of O_3 and CO are larger for low SES children. In a study of the effects of air pollution on Swedish children's health, Jans, Johansson, & Nilsson (2018) find that low SES children are more affected from changes in PM10, and that

[9] I use a cost per MW of solar of 1 million USD per MW, which is the cost of the last project developed in Colombia the uses solar PV technology (from https://www.celsia.com/es/accionistas-e-inversionistas/inicia-operaciones-celsia-solar-bol237var-la-nueva-granja-de-generaci243n-de-energ237a-solar-de-celsia-para-beneficio-de-los-colombianos, accessed Oct. 22 2020)

the effect for children from low income households is 10% larger than that of medium-income households, and 70% larger than that of high-income households. It is important to note that both these studies look at the health of children in developed countries, and that no study has explored the differential health effects in a developing country setting, where the differences between low and high-income households are more stark, and where the coping mechanisms available for low-income households are more limited.

I explore the heterogeneous health effects by estimating the health effects from PM10 on two distinct groups in the population: those under the subsidized and the contributive regimes. Affiliation to the insurance regimes is correlated with socioeconomic status. Those who are covered under the contributive regime are legally employed and receive full health and pension contributions from their employers, and those under the subsidized regime are usually informal workers with a lower income, such that the regime under which a person is covered is a good indicator of that person's socioeconomic status (SES). By estimating the health effects from PM10 for these two groups, this study contributes to the understanding of the differential effects across the SES gradient in a developing country.

6.1 Characteristics by Insurance Regime

The Ministry of Health has been doing yearly surveys to evaluate the users' perception regarding the quality of the health services received, and collecting information about the characteristics of the beneficiaries under each regime (Ministerio de Salud y Protección Social, 2012, 2014). In Colombia, the SES of a person is highly correlated to the stratum in which they live, with strata ranging from low (1) to high (6), so that lower income groups tend to live in strata 1 and 2, middle income in 3 and 4, and high income groups in 5 and 6. From the information collected by the Ministry of Health, we know that in 2012, 82% of the users from the subsidized regime live in strata 1 and 2 (same as in 2014), and 75% of those in the contributive regime live in strata 2 and 3 (76% in 2014). Furthermore, quality and access to healthcare services is comparable under both regimes, with 71% of those under the contributive regime (79% for the subsidized) reporting that the quality of the service they had received was very high, and 59% of those under the contributive regime (64% for the subsidized) reporting having to wait less than 3 days for a doctor's appointment (Ministerio de Salud y Protección Social, 2014).

Recent data from a nationally representative survey from 2017 (National quality of life survey) shows the differences between those under the subsidized and contributive regime (Table 7). As expected, those under the subsidized regime live in more numerous households, in a lower stratum, and have a total household income that is 57% lower than those in the contributive regime, and per capita income that is 66% lower. People in the subsidizes regime are younger than those in the contributive regime and their reported satisfaction with their life is lower. All the differences between these two groups are statistically significant.

Table 7. Characteristics by insurance regime

	Subsidized	Contributive	Difference
# Household members	4.3	3.6	0.65***
Total household income (USD)	491	1,149	-658***
Household's per capita income (USD)	128	372	-244***
Stratum	1.6	2.5	0.94***
Age	31.8	35.7	-3.86***
Life satisfaction (1=low,..., 10=high)	8.1	8.7	-0.56***
Health satisfaction (1=low,..., 10=high)	7.8	8.3	-0.51***

Note: The third column shows the differences between the two regimes, and reports the significance levels from a t-test in the difference of the means. The significance levels are: *** (1%), ** (5%) and * (10%).

6.2 Health Effects by Insurance Regime

I estimate the effects of PM10 on the rate of health services and patients under each regime per 100,000 residents in each municipality, using the same instruments as the ones I did for my main analysis. I find that the effects of PM10 on health are different for the populations under the two insurance regimes (Table 8). Those under the contributive regime, experience higher effects than the whole population in my sample, and higher effects than those under the subsidized regime. Additionally, the effects for those in the contributive regime are significant for all the health conditions and for all the outcomes considered. The effects for those under the subsidized regime are lower than for those in the contributive regime, and are also lower than the effects when considering the whole population in my sample.

These results highlight the importance of estimating the health effects separately for each group, since it allows me to decompose the effects for the total population. The estimated effects for the whole population in my sample (Table 5) is a weighted average of the estimated effects for the populations under each one of the insurance regimes.

Table 8. Health effects by type of insurance

Coefficients (std. errors in parentheses)						
	Respiratory		Mental		Cardiovascular	
	Patients	Services	Patients	Services	Patients	Services
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Contributive regime						
IHS(PM10)	1.848***	2.023***	1.126**	1.256**	1.381***	1.333***
	(0.464)	(0.503)	(0.542)	(0.610)	(0.492)	(0.489)
Panel B - Subsidized regime						
IHS(PM10)	0.970	1.349**	0.583	1.240	-0.214	0.268
	(0.590)	(0.669)	(0.596)	(0.757)	(0.597)	(0.632)
Observations	16,863	16,863	16,863	16,863	16,863	16,863
Kleibergen-Paap Wald F-stat. (1st stage)	13.28	13.28	13.28	13.28	13.28	13.28

Notes: 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.

A surprising result from this analysis is that the effects for the population with lower SES are smaller than those for the whole population, and are also not statistically significant. This runs against the results from other studies, and from what would be expected about both the vulnerability and exposure to pollution for low SES populations. Another important factor to consider is that of access to the health system, since lower SES populations might face higher barriers to access services in the health system.

In terms of vulnerability, there is suggestive evidence that this group of the population is not more vulnerable than those under the contributive regime. This population is younger than that under the contributive regime (Table 7), their self-assessed health status is higher and the prevalence of chronic illnesses is lower than those under the contributive regime (Table 9). Access to the health system seems to be the same for both regimes, and if anything it would appear the barriers are lower for those under the subsidized regime, given that the wait between a request for a doctor's appointment and the actual consultation is 47% lower, and the perception about the overall quality of the system. However, even if the proportion of those who fell ill in the last 30 days is higher for those under the subsidized regime, the proportion of those who effectively get treated is much lower, with 75% of those under the contributive regime receiving treatment, but only 62% of those in the subsidized regime receiving treatment through the health system.

Table 9. Health status and access by insurance regime

	Subsidized	Contributive	Difference
Health status (1=very good,…,4=bad)	2.09	1.95	0.143***
Chronic illnesses (1=yes, 0=no)	0.14	0.16	-0.01**
Ill in the last 30 days (1=yes, 0=no)	0.08	0.06	0.02***
Received treatment (1=yes, 0=no)	0.62	0.75	-0.12***
Due to this illness, number of days with no normal activities	4.83	5.36	-0.53
Visited the ER (1=yes, 2=no)	0.69	0.66	0.02
Treated in the ER (1=yes, 2=no)	0.95	0.93	0.02
Days between appointment request & consultation	2.27	4.27	-2.00***
General quality of the service (1=very good,…,4=very bad)	2.02	1.95	0.068*

When asked why they did not seek treatment through the health system, 70% of those in the subsidized regime report that the condition was mild, against 60% of those in the contributive regime (Table 10). The lack of treatment through the health system for those under the subsidized regime is compensated by a much higher proportion of treatment using home remedies and self-prescribed medications. All of this aligns with the possibility that those under the subsidized regime have better underlying health conditions, and suffer from milder health problems that do not require attention through the health system, even if access to the system and the perceived quality of service is better than for those under the contributive regime.

Table 10. Action taken by those who were ill in the last 30 days

	Subsidized	Contributive
Health system	62%	75%
Pharmacist	6%	5%
Traditional healer	0%	0%
Alternative therapies	0%	0%
Home remedies	14%	8%
Self-prescribed medications	15%	8%
Nothing	3%	5%
Reason to not get treated: mild condition	70%	60%

Finally, to explore whether exposure to pollution differs by SES I use the 2018 census microdata for the 3 main cities in my sample (Bogota, Cali and Barranquilla account for 49% of the population in my sample), together with yearly PM2.5 data at a 0.1 degrees resolution from Hammer et al., (2020), to get the average yearly concentration of PM2.5 by stratum for 2009 and 2018. I find that those in strata 2 and 3 are the ones who face the highest levels of pollution in 2009 and 2018, and those in strata 1 and 5 are the ones with the lowest levels of pollution (Table 11). Therefore, given the composition of each group, the weighted exposure for those under the contributed regime is higher in both 2009 and 2018 (22.2 and 24.4, respectively), compared to the exposure for the population in the subsidized regime (21 and 23.4, respectively). Furthermore, 64% of those in the contributive regime live in strata 2 and 3, the ones with the highest levels of pollution, compared to 45% of those under the subsidized regime.

Table 11. Yearly exposure to PM2.5 by stratum

Strata	Subsidized	Contributive	PM2.5 - 2009	PM2.5 - 2018
1	55%	20%	18.8	21.6
2	33%	35%	23.8	25.9
3	11%	28%	23.0	25.1
4	1%	10%	22.0	24.0
5	0%	5%	20.3	22.7
6	0%	2%	20.9	23.1

In sum, it is important to note that the evidence I just presented regarding the possible explanations for the different health effects from PM10 by health insurance regime is by no means conclusive. However, it seems likely that the higher health effects associated with PM10 for those under the contributive regime, can be explained by the different composition of the groups, with a younger and seemingly healthier population under the subsidized regime, and evidence of a higher level of exposure to air pollution for those under the contributive regime.

7 Robustness Tests

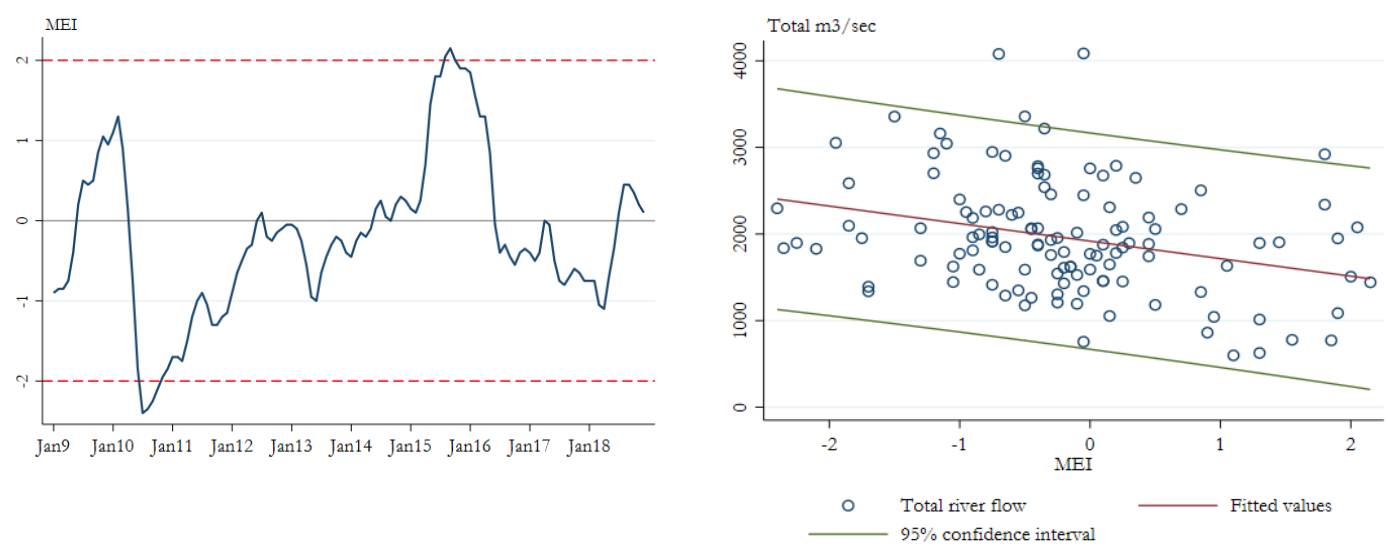
7.1 Excluding El Niño Events

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 18 and Table 19 in the Appendix).

Figure 8. MEI and river flows

Panel A. MEI time series   Panel B. MEI and River flows scatter plot



7.2 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.

7.3 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 12. 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%)

8 Conclusion

Understanding the negative consequences from air pollution on multiple health conditions, especially in those understudied ones like mental health, is important to fully quantify the health costs associated with it. Furthermore, power plants as sources of air pollution play a prominent role in most countries, especially in developing ones, where the expected growth in electricity demand will be met with generation from fossil fuel plants. However, establishing a causal effect from electricity generation to 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 of 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 ug/m^3 for municipalities within a 100 km of the power plants. In terms of the effects on health, I find significant effects on mental and respiratory health. I find that an increase in PM10 of 1 ug/m^3 leads to an increase in the rate of mental patients per 100,000 residents of 2.2% (3 patients per 100,000 residents) and of 3.3% for respiratory health patients (24 patients per 100,000 residents). These estimated effects are robust to different specifications, although they are marginally lower when excluding extreme El Niño event months from my sample. From these effects, I estimate that the health costs from 1 ug/m^3 of PM10 for the three health conditions in this study, are equal to 21.7 million USD per year for the total population in my sample (49% of the population in the country). The inclusion of mental health conditions increases the total costs by 13%. From these costs I estimate that the per capita WTP for a reduction in PM10 of 1 ug/m^3 is \$0.87 per year. I evaluate a tax incentive for renewable energy implemented by the Colombian government, and I find that the health benefits from the reduction in PM10 outweigh the cost of the tax incentives, with a benefit-cost ratio of 5.9.

Additionally, to explore health effects by SES, I estimate the effects by type of health insurance, since a person's SES is correlated with the health insurance regime to which they belong. I find that for those under the contributive regime (higher SES) there is a significant effect from PM10 on all the health conditions and outcomes. The effects are higher than for the total population in my sample, and higher than for those under the subsidized regime, which tend to be of a lower SES. I explain these set of results by examining the vulnerability and exposure of each group, and find that those in the contributive regime are older, have more chronic illnesses and are also exposed to higher levels of pollution. However, I note that these explanations are by no means conclusive.

As a concluding note, I want to highlight some limitations of my study, in the spirit of suggesting areas for future research. First, the only variable I use to measure air pollution is ambient levels of PM10, given the lack of data for any other pollutant. It has been documented that there is a positive correlation between PM10, PM2.5, and to a lesser degree SO2, and NOx, so that the effects estimated here will likely include the effects from other pollutants. However, efficient regulation of these pollutants requires the identification of the differential effects from each pollutant. Second, the estimated effects only account for conditions for which people seek assistance through the health system, excluding health conditions that could be considered minor, but that could be much more common and frequent. Finally, my estimates and the health costs derived from them, are based on contemporaneous health effects from PM10. This means that long-term effects are not fully included here, which offers an area for future research.

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Appendix

Table 13. Mental health conditions by number of patients

Condition (ICD10 Code in parentheses)	% of patients (2009-2018)
Organic, including symptomatic, mental disorders (F00-F09)	7%
Mental and behavioral disorders due to psychoactive substance use (F10-F19)	4%
Schizophrenia, schizotypal and delusional disorders (F20-F29)	6%
Mood [affective] disorders (F30-F39)	19%
Neurotic, stress-related and somatoform disorders (F40-F48)	26%
Behavioral syndromes associated with physiological disturbances and physical factors (F50-F59)	5%
Disorders of adult personality and behavior (F60-F69)	1%
Mental retardation (F70-F79)	5%
Disorders of psychological development (F80-F89)	13%
Behavioral and emotional disorders with onset usually occurring in childhood and adolescence (F90-F99)	13%
Unspecified mental disorder (F99)	0.2%

Figure 9. Price series used in the estimating equation

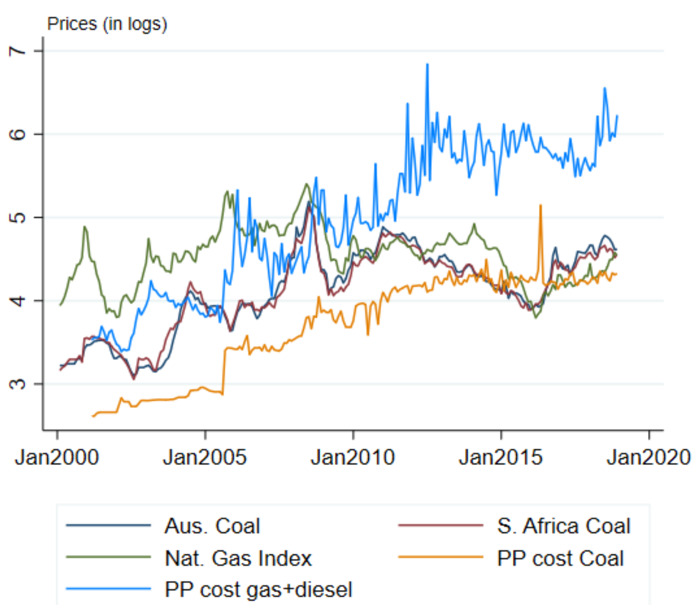

Figure 10. Scatterplot of gas and coal generation, and total river flows

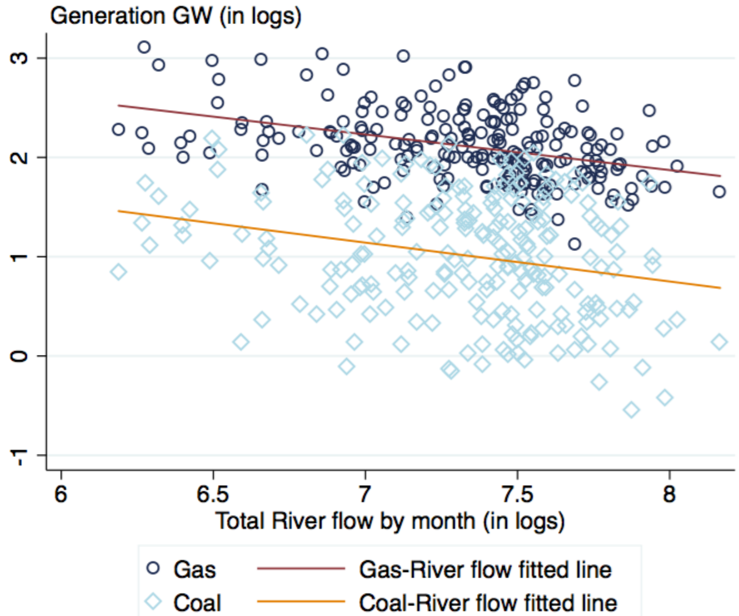

Figure 11. Scatterplot of diesel generation, and total river flows

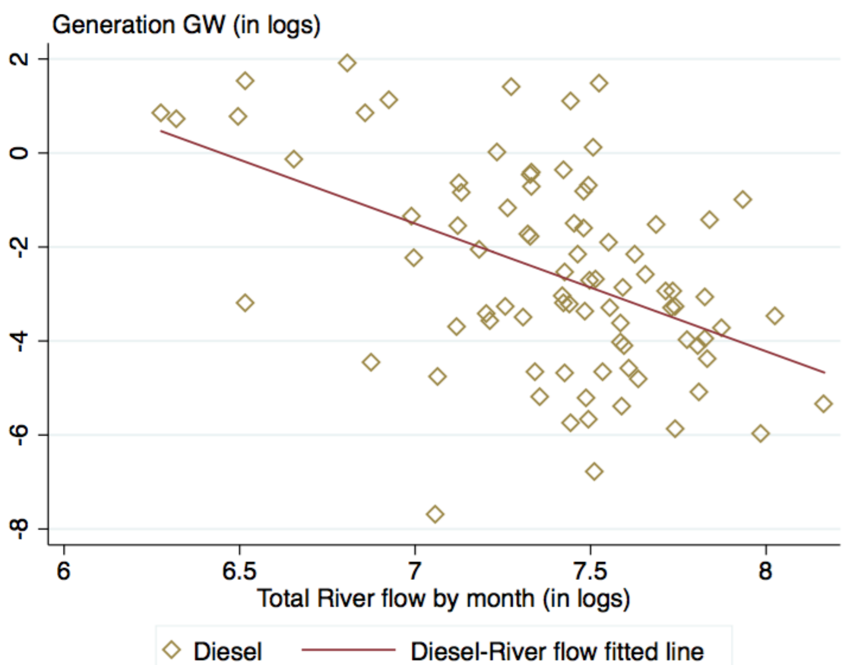

Figure 12. Availability of water services by region

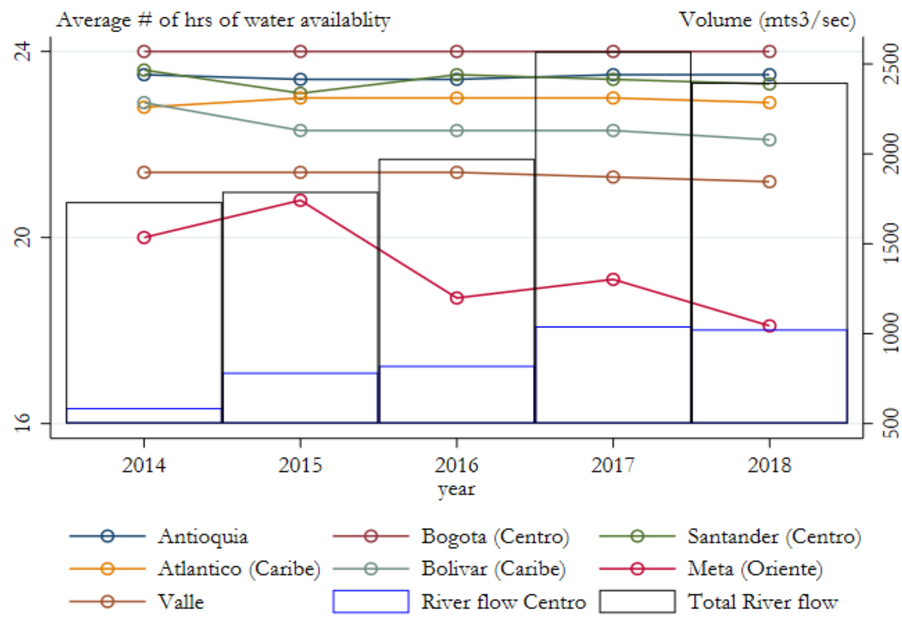

Table 14. Summary statistics by installed capacity

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 15. 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	-0.282***	-0.418***	-0.448***	-0.669***	-0.0955***
	(0.078)	(0.104)	(0.062)	(0.068)	(0.023)
Perc. Coal x Total River Flows	-0.632***	0.125***	0.038**	-0.594***	-0.048***
	(0.063)	(0.029)	(0.016)	(0.027)	(0.008)
Perc. Diesel x Total River Flows	-0.109	-0.844***	-0.364***	-0.932***	-0.040***
	(0.068)	(0.101)	(0.053)	(0.071)	(0.015)
Obs.	16,903	16,903	16,903	16,903	16,903
Sanderson-Windmeijer rk F statistic	264.7	120.3	61.95	189.56	13.97

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

Table 16. IV estimates for different mental health conditions

	Coefficients (std. errors in parentheses)					
	Mood affective disorders (F30-39)		Neurotic and stress related (F40-49)		All other mental disorders	
	Patients	Services	Patients	Services	Patients	Services
	(1)	(2)	(3)	(4)	(5)	(6)
IHS(PM10)	0.879*	0.912	0.601	0.669	0.00272	0.392
	(0.486)	(0.563)	(0.506)	(0.559)	(0.792)	(0.841)
Observations	16,903	16,903	16,903	16,903	16,903	16,903
Kleibergen-Paap Wald F-stat. (1st stage)	13.97	13.97	13.97	13.97	13.97	13.97

Table 17. Cost per patient and health condition (in USD)

	Consultation costs	Procedures costs	Out-of-pocket costs	Total cost per patient
Mental health	211.9	39.0	0.91	252
Cardiovascular health	90.3	292.9	0.8	384
Respiratory health	29.0	70.4	117.5	217

Table 18. 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)	0.015***		0.087***	
	(0.004)		(0.014)	
IHS(Gas generation GWh)	0.002		-0.050	
	(0.003)		(0.036)	
IHS(Diesel generation GWh)	0.034***		0.205***	
	-0.005		-0.072	
IHS(Total electricity generation GWh)		0.023***		0.075***
		(0.003)		(0.009)
Obs.	16,040	16,040	16,040	16,040
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

Table 19. PM10 and Health excluding ENSO Events

	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)	0.00721	0.0554	0.0601	0.0893	0.00202	0.0496
	(0.0453)	(0.0500)	(0.0529)	(0.0586)	(0.0467)	(0.0517)
Observations	16,040	16,040	16,040	16,040	16,040	16,040
R-squared	0.515	0.491	0.579	0.555	0.493	0.489
Panel B - IV estimates						
IHS(PM10)	1.397***	1.568***	0.866*	1.277**	0.11	0.33
	-0.483	-0.527	-0.494	-0.588	-0.409	-0.419
Observations	16,040	16,040	16,040	16,040	16,040	16,040
Kleibergen-Paap Wald F-stat. (1st stage)	15.68	15.68	15.68	15.68	15.68	15.68

Table 20. Response to illness

	Subsidized	Contributive
Health system	62%	75%
Pharmacist	6%	5%
Traditional healer	0%	0%
Alternative therapies	0%	0%
Home remedies	14%	8%
Self-prescribed medications	15%	8%
Nothing	3%	5%

Table 21. Labor force participation by insurance regime

	Subsidized	Contributive	Difference
Worked during the last week	0.88	0.97	-0.088***
Have a work contract	1.94	1.78	0.16***
Kind of contract (1=spoken, 2=written)	1.14	1.86	-0.72***
Length of contract (1=indefinite, 2=fixed)	1.19	1.29	-0.10***
Length of contract (months)	9.10	12.38	-3.27***
Affiliated to labor risk insurance (1=yes, 2=no)	2.00	1.16	0.85***
Time working in that job (months)	22.21	58.73	-36.52***
Payment in the last month (USD)	176.51	452.19	-275.69***
Time to get to workplace (minutes)	21.62	27.45	-5.83***
Hours/week household chores	6.13	5.46	0.67***
Hours/week caring for children	15.33	11.81	3.52***
Hours/week caring for other members	11.17	6.00	5.17***

Table 22. Cost-Benefit Analysis

	Bogota - Name of powerplants: "Zipaemg2,3,4,5" (Coal)
Corporate income tax rate	33%
Investment that's deductible	50%
Total Incentive	17%
Population	8,182,739
Cost per GW (USD 2018)	$1,000,000,000
Installed GW from coal power plant	0.22
PM10 generated from power plant (average per month)	3.71
Cost of replacing by solar (USD 2018)	$224,000,000
Health costs for 8.2 mill pop / Year (USD 2018)	$27,218,054
Interest rate in 2018	4.25%
Number of periods	10
NPV of health benefits (USD 2018)	$218,040,755
Tax deductions (USD 2018)	$36,960,000
Benefit/Cost Ratio	5.9