Power Production and Atmospheric Conditions

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Abstract

The production of energy has an impact on the environment and our own health. Different types of power plants emit varying amounts of air pollution into the atmosphere. Our group explored how data science could be used to identify relationships between power plant type and atmospheric conditions. Data from power plants around the world in conjunction with data about CO2 and particulate matter levels were collected. We chose PM 2.5 as our proxy for air pollution due to its impact on respiratory health. The atmospheric effects of different power plant types on particulate levels were estimated via OLS regression. We found that Coal, Gas, and Hydro power plants all increase average exposure to PM2.5. Specifically, this paper uses two separate models to approximate the effects of each power plant type. The first model estimates that a 1 percent increase in gas power plants causes a country's mean annual PM2.5 exposure to increase by 0.029 micrograms per cubic meter. It also suggests that a 1 percent increase in hydro power plants causes a country's mean annual PM2.5 exposure to increase by 0.0237 micrograms per cubic meter. The second model estimates that a 1 percent increase in coal power plants causes a countries mean annual PM2.5 exposure to increase by 1.3667 micrograms per cubic meter. Our results suggest that countries should curtail the development of Coal, Hydro and Gas power plants. The lack of statistical significance in power plant types such as Nuclear, Waste, Wind, and Solar leave room for more research questions.

Keywords: Particulate Matter, PM2.5, CO2, Energy, Power Plants

1. Introduction

Humanity's need for power drives us to use an array of energy production means. Solar, coal, nuclear, natural gas, hydro, and wind energy are all popular sources of energy. Each source has their own benefits and drawbacks when it comes to air pollution. Air pollution is known to kill one in eight people worldwide, the harmful effects of pollution is compounded when you account for its effects on crops. The World Health Organization claims that 92 percent of the global population lives in places with unhealthy air quality[8]. Air pollution is becoming a more severe concern to humans around the world, the power sources humans choose to utilize have an impact on our air quality and long term health. For example, looking at nuclear energy, a NASA study estimated that between 1976 and 2009, humans use of nuclear energy has saved 1.8 million lives through cleaner, less polluted air[4]. However the creation of a nuclear power plant requires intensive production of rare materials, which during construction create emissions.

Our group set out to determine which power source creates the most air pollution. We used the definition,"Air pollution consists of chemicals or particles in the air that can harm the health of humans, animals, and plants."[9] Power plants emit various different types of emissions and particulates. We chose PM 2.5 as our proxy for air pollution due to its impact on respiratory health. PM 2.5 stands for Particulate Matter at or below 2.5 micrometers. PM 2.5 levels are important as they can be inhaled deep into the lungs where gas exchange occurs with the bloodstream. PM 2.5 stays suspended in the atmosphere for weeks and may travel long distances. High PM 2.5 levels have been found to increase death rates from air pollution."If the particles are water soluble, they can pass into the bloodstream within minutes. If they are not water soluble, they remain in the alveolar portion of the lungs for a long time. However, when the small particles go deeply into the lungs and become trapped this can result in lung disease, emphysema and/or lung cancer in some cases." Drawing links between different power sources and the emissions in their surrounding areas is incredibly important. If we find strong relationships between these pollutants and a power source, we may be able to suggest legislation to dissuade the use of certain power plant types.

2. Data sets

Our project used the data from the Global Power Plant Database. The databases coalesces data about power plants from around the world. The goal of the Global Power Plant Database is to centralize power plant data to make it more accessible and easier to navigate so that anyone can perform their own analysis on it. Each power plant is geolocated with data entries containing information on plant capacity, power generation, ownership, and the fuel type. As of June 2018 the database includes statistics from around 28,500 power plants across 164 countries.[5] In conjunction with the power plant data set we used The World Banks publicly available dataset on CO2 emissions. The data set contains the metric tons of CO2 emitted per capita from the year 1960 through 2014 across 250 countries. The World Banks publicly available datasets also provided us with data on PM2.5 air pollution. The dataset contains the mean annual exposure of PM2.5 in micrograms per cubic meter for 250 countries from 1990 to 2016. The data sets can be found on the web at the following links.

Power Plant data set: http://datasets.wri.org/dataset/globalpowerplantdatabase
CO2: https://data.worldbank.org/indicator/EN.ATM.CO2E.PC
PM2.5: https://data.worldbank.org/indicator/en.atm.pm25.mc.m3

3. Previous Research

Researchers have asked similar questions about power plant emissions and their affects on the environment. However a robust peer reviewed paper on the subject is hard to find. A novel aspect of our paper is our choice to model PM2.5 rather than another pollutant. A somewhat similar study focused on CO2 emissions and its link to power plant types. In the paper written by the World Nuclear Association(WNA), Comparison of Lifecycle Greenhouse Gas Emissions of Various Electricity Generation Sources, the WNA came to the conclusion that Lignite, Coal, Oil, and Natural Gas created the most CO2 emissions, followed by Solar, Biomass, Hydroelectric, and Wind. Their comparison of emissions took into account lifecycle CO2 costs. This means the WNA calculated totals, based not only on operational costs, but on construction and decommissioning. The paper was detailed and it robustly estimated the effects of different power plant types on CO2 levels. However, the paper was certainly focused on nuclear power. Comparisons in the paper were relative to Nuclear plants and the benefits of nuclear power plants were emphasized. In the study there was a conscious choice for a lower emitting version of nuclear power production, "enrichment of nuclear fuel by gaseous diffusion has a higher electrical load, and therefore, lifecycle emissions are typically higher than those associated with centrifuge enrichment."[3] Perhaps calling into question their results. This paper took a detailed look at CO2 costs of building, decommissioning and using different power plants. Their emissions numbers show a more direct way of measuring emissions as opposed to our general emissions in the area.

One of the inspirations for our projects topic was a paper on historical air pollution levels and air pollution caused deaths; titled Air Pollution. In their paper they wrote about Sulfur Dioxide and PM2.5, while we focused mainly on PM2.5, "which is one of the most concerning air pollutants for human health".[2] In their paper they worked to show how elevated levels of Particulate Matter 2.5 microns or smaller leads to premature deaths. They found, "In many cases, air pollution exacerbates pre-existing cardiorespiratory illnesses."[2] The way they measured these premature deaths centered around Age Standardized Death Rates and Disability Adjusted Life Years(DALYs). Age Standardized Death Rates "measure reports the number of deaths attributed to air pollution per 100,000 people, and standardizes based on the age structure of the population. It therefore corrects for population size and age demographics (i.e. assumes the same population characteristics across all countries, and through time), allowing for a direct comparison of mortality risk between countries"[2]. However using only Age Standardized Death Rates, "a child who dies from an illness related to air pollution is counted exactly the same as an older individual who died a few months earlier than expected. To account for these differences, we also measure morbidity and mortality rates using a metric called Disability-adjusted life years (DALYs) lost. The DALYs lost metric measures the overall loss of healthy life as a result of air pollution, and is given as the sum of the total number of life years lost through premature death and disability. A child who dies from a pollution-related illness will therefore record a higher number of DALYs lost than an older individual."[2] Using these metrics they were able to come to more accurate estimations of death rates caused by air pollution.

In this groups research they were able to determine that, "Death rates from air pollution-across countries of all income levels have shown a general decline over the last few decades. For many countries, the death rate has declined by more than 50 percent."[2] However they also found that the total number of deaths caused by air pollution is increasing. This research on PM2.5 levels and resulting death rates is extremely important for public health and reveals how important limiting exposure to PM2.5 is. This research in conjunction with our research on possible air pollution creators can work as a guideline for cleaner air.

4. Methodology

All the datasets used were already fairly clean. The data for PM2.5 and CO2 emissions is incomplete prior to the 2000s, but the range of years we incorporated into our final data set (2005-2014) had no missing data. We decided to group the power plant data by country, to match with the emissions data. Not all the power plant data was included, only the total number of each type of power plant per country, as well as the country's cumulative annual power generation. Any power plant commissioned after 2014 was not included, as the emissions data did not go past that year. Once the plant types were categorized by country, the percent amount of each plant type was calculated for each country. The data was formatted in python and written to a csv file. For the model, we used ordinary least squares regression to compare power plant types to PM2.5 emission, using the CO2 emissions per capita data as a control variable. We ran our model on our entire data set, as well as data only from countries with 100 or more power plants.

5. Descriptive Statistics

The variables of interest are in percent terms and as follows Solar, Coal, Gas, Hydro, Oil, Wind, Waste, Biomass, Geothermal, Nuclear, Other. Table 1 displays all of the counties in our data set that have at least 100 power plants and their associated power plant types in percentage terms. Each variable represents the percent of power plants in a given country that utilize the type of fuel listed. Power sources such as Solar, Coal, Gas, Hydro, Oil, and Wind are well represented among all countries in the table; the same is true for the other 104 countries not listed in the table. Waste, Biomass, Geothermal, Nuclear and Other are sparsely represented. Cogenration and Petcoke are almost non existent, due to the lack of variation they were omitted from the model. Figure 1 displays a correlation matrix of all variables for all countries in the original data set. As expected all independent variables have relatively low correlations values except for Cogeneration and Petcoke, this is due to the lack of variation in the two variables. Our dependent variable 2014pm25, mean annual PM2.5 exposure(micrograms per cubic meter), is highly correlated with 2013pm25 but this will not cause issues in the model since 2014pm25 is the dependent variable and 2013pm25 is an independent variable.

6. Results

We used a multivariate OLS regression to analyze the effect of different power plant types on air quality. Variables with insufficient variation were removed from the model. Oil, Cogeneration, Other and Petcoke were all removed for the reason stated. In the first model we used the remaining variables to run our regression. 130 countries where analyzed, Table 2 displays the results of our model. The R^2 value is 0.990, for all countries in the data set 99% of the variation in PM2.5 can be described by the model specified. Out of the various model specifications attempted, model 1 listed below had the lowest AIC and BIC thus we went forward with the parameters in the following equation.

Model 1:

$$2014pm25 = \alpha + \beta_1 Solar + \beta_2 Coal + \beta_3 Gas + \beta_4 Hydro + \beta_5 Wind + \beta_6 Waste + \beta_7 Biomass$$
$$+\beta_8 Nuclear + \beta_9 2013pm25 + \beta_{10} 2014co2$$

In model 1 there were four statistically significant variables (p-value < 0.05) Gas, Hydro, 2013pm25 and 2014co2; their beta coefficients are 0.0290, 0.0237, 0.9557 and -0.0857 respectively. Out of the significant coefficients The variables of interest are Gas and Hydro. The model estimates that a 1 percent increase in gas power plants causes a countries mean annual PM2.5 exposure to increase by 0.029 micrograms per cubic meter. It also suggests that a 1 percent increase in hydro power plants causes a country's mean annual PM2.5 exposure to increase by 0.0237 micrograms per cubic meter. The residual plots in both Figure 2 and Figure 3 roughly suggest that our OLS assumptions have been held.

Model 2:

$$2014pm25 = \alpha + \beta_1 Solar + \beta_2 Coal + \beta_3 Gas + \beta_4 Hydro + \beta_5 Wind + \beta_6 Waste + \beta_7 Biomass$$
$$+\beta_8 Nuclear + \beta_9 2014co2$$

The second model analyzed countries that had at least 100 power plants listed in the data set. 26 countries meet that criteria [Table 1.] and where analyzed, Table 3. displays the results of our model. The R^2 value is 0.514, for countries in the data set 51% of the variation in PM2.5 can be described by the model specified. Out of the various model specifications attempted, model 2 had the lowest AIC and BIC, even lower than that of model 1. It used all of the same variables as model 1 except for 2013pm25 due to the multicolinearity issues that arouse when including it.

In model 2 There is one statistically significant variable (p-value < 0.05) Coal, its beta coefficients is 1.3667. The model estimates that a 1 percent increase in coal power plants causes a countries mean annual PM2.5 exposure to increase by 1.3667 micrograms per cubic meter. The residual plots in both Figure 4 and Figure 5 roughly suggest that our OLS assumptions have been held.

7. Conclusion

Our first model found statistical significance for gas and hydro power plants. Both are positively related to PM2.5 emissions, with gas having a marginally larger effect. The second model only used data from countries with 100 or more total power plants. This model found statistical significance for coal power plants, showing a much greater relationship with PM2.5 emissions than gas or hydro plants. There is also a notable negative relationship for nuclear power plants, which makes sense given their lack of emissions. Due to a lack of significance, it is difficult to compare and draw conclusions for some of our variables. A likely reason for this is that the emissions data is only categorized by country, rather than specific geographic location, which would allow us to more closely analyze the effects of each plant type. The significant results of model 2 show that a higher ratio of coal power plants in use relative to other types of plants causes a significant increase in PM2.5 emissions. Gas and hydro power plants also show this trend, but to a much lesser extent. While Coal plants are not the most common type of power plant worldwide [Table 1.], there are high concentrations of coal plants among east Asian nations, specifically China and Indonesia. This could offer an explanation for the estimated 1.6 million annual deaths attributed to PM2.5 emissions from China.[10] If we were to improve air quality worldwide, offering alternatives to existing coal plants in Asia would be a very effective start, since they can also serve to reduce the amount of premature deaths caused by excessive air pollution in areas such as China.

The results from model 2 also challenge the popular notion that solar power plants are the most environmentally friendly option for power generation. Table 3 shows that solar power plants actually generate more PM2.5 per 1 percent increase than the median, whereas nuclear energy has one of the lowest PM2.5 emissions. Despite the data, recent impressions surrounding nuclear energy are considerably worse than solar energy.[11] While there are certainly other factors to consider than air pollution when choosing what the ideal type of power plant is, the significant difference in particle emissions when comparing nuclear energy to solar energy is significant enough to give legitimate grounds for public opinions that favor nuclear energy over solar energy.

8. The Future

At the end of our project we realized a few things that could be improved upon. To improve the model, a more geographically specific emissions data set should be used. Categorizing emission sources solely by country is fine for small countries, but causes the impact of individual plants in large countries to be diminished. Ideally, we would have data for air quality at any given geographic location - which would be a significantly larger data set.

From our results we may direct more research into why natural gas, coal, and hydroelectric power plants increased PM2.5 emissions. From this information we may recommend actions to reduce gas, coal, and hydroelectric emissions through either more eco-friendly practices or abandoning the energy source entirely. Our results also showed that nuclear power plants have a negative relationship with PM2.5 levels. From this we may advise the use of Nuclear power generation as a way to reduce air pollution.

We may be able to factor in previous research on PM2.5 levels and their affects on public health. Such as the aforementioned paper Air Pollution in the previous research section. This would work to show some of the importance in our research and data.

Air pollution is just one of the pieces to the puzzle of a sustainable, energy sufficient, future. Our research found that coal power plants are bad for air quality and nuclear energy is good for air quality but this doesn't capture the whole picture. Coal is abundant and accessible. Humans reliance on coal energy is likely far from over as it is still the number one source of power in many countries. Coal mining also produces the risk of mining accidents which claim an average of 27 lives annually[12]. If we compare coal energy to nuclear energy just in terms of air pollution, nuclear energy is the better option but this leaves out factors such as the cost of creating a nuclear power plant. Not all countries are economically stable enough to afford a transition to cleaner more modern energy sources. Aside from the start up cost of getting a modern nuclear power plant operating, nuclear energy comes with the risk of a reactor meltdown and although nuclear energy might be better for the air, it creates lethal radioactive material that is incredibly hard to dispose of. Instead of pumping the pollution into the air nuclear pollution is barrelled up and put into caves where it sits decaying for thousands of years (and this was after dumping the barrels in the ocean was banned in 1991!). Another factor to consider is that nuclear energy goes hand in hand with nuclear weapons production which is a risk in a whole other ball park, which may reduce which countries have access to it. In order to identify the superior energy source other factors such as the cost of energy production, all the forms of pollution the energy source produces (not just air), and how they affect mortality rates, need be taken into account. As technology becomes more efficient, modern nuclear power plants hold a more promising future for energy production. Humans are creating reactors that can yield more energy from fewer inputs, be less prone to meltdown, and reuse spent fuel which reduces the radioactive output the energy source is associated with. Future research will be more valuable if other factors of power sources are taken into account.

Table 1. Percent of power plant types in each country (countries with at least 100 power plants)

	Solar	Coal	Gas	Hydro	Oil	Wind	Waste	Biomass	Geothermal	Nuclear	Other
Argentina	0.8	5.8	22.9	20.8	42.1	4.6	0.0	0.0	0.0	1.3	1.7
Australia	2.6	8.6	32.2	17.4	8.6	12.9	11.9	5.7	0.0	0.0	0.0
Austria	0.0	0.0	2.9	94.1	0.0	2.9	0.0	0.0	0.0	0.0	0.0
Brazil	0.2	0.9	5.7	32.5	28.4	10.1	0.5	21.5	0.0	0.1	0.1
Canada	12.0	1.3	6.5	48.2	0.8	20.9	0.0	9.6	0.0	0.5	0.2
Chile	6.3	5.5	4.0	39.1	29.2	7.1	0.0	8.7	0.0	0.0	0.0
China	4.4	26.1	6.0	33.3	0.2	29.5	0.0	0.0	0.1	0.4	0.0
Finland	0.0	2.2	9.2	51.6	6.0	6.5	0.0	21.2	0.0	1.1	2.2
France	33.7	0.2	0.4	21.3	0.2	35.7	0.0	7.3	0.0	0.9	0.0
Germany	42.1	9.6	18.5	11.6	2.5	1.5	6.8	5.5	0.0	0.7	1.1
India	28.7	16.2	2.8	12.5	2.1	25.4	0.0	11.8	0.0	0.5	0.0
Indonesia	0.0	31.6	25.9	25.9	10.1	0.0	0.0	0.0	6.3	0.0	0.0
Italy	30.0	3.6	23.1	23.5	4.5	0.4	0.0	0.0	13.4	0.0	1.6
Japan	40.4	13.2	9.1	17.2	8.5	1.9	0.3	0.0	4.4	5.0	0.0
Mexico	1.2	1.2	24.3	29.1	9.2	8.0	0.0	24.7	2.0	0.4	0.0
Norway	0.0	0.0	1.6	95.1	0.0	3.3	0.0	0.0	0.0	0.0	0.0
Portugal	13.1	0.4	0.9	26.3	0.0	49.6	5.1	4.2	0.4	0.0	0.0
Russia	0.0	24.0	54.1	14.4	0.0	0.0	0.0	0.0	0.0	7.5	0.0
South Korea	10.9	10.1	26.1	30.3	2.5	10.1	3.4	1.7	0.0	5.0	0.0
Spain	4.6	2.4	9.5	20.2	4.2	55.6	2.4	0.2	0.0	0.8	0.0
Sweden	0.0	0.0	1.8	85.5	0.6	5.4	0.0	4.8	0.0	1.8	0.0
Switzerland	0.0	0.0	0.0	97.6	0.0	0.0	0.0	0.0	0.0	2.4	0.0
Thailand	68.1	2.4	19.3	6.0	0.0	1.2	0.0	3.0	0.0	0.0	0.0
United Kingdom	43.4	0.2	1.7	4.3	0.4	29.2	12.6	7.6	0.0	0.3	0.0
United States	13.5	6.1	15.0	20.6	21.0	11.9	8.8	0.6	0.9	0.9	0.1
Vietnam	0.0	11.1	4.5	79.3	3.0	1.0	0.0	1.0	0.0	0.0	0.0

Figure 1. Correlation matrix of all variables

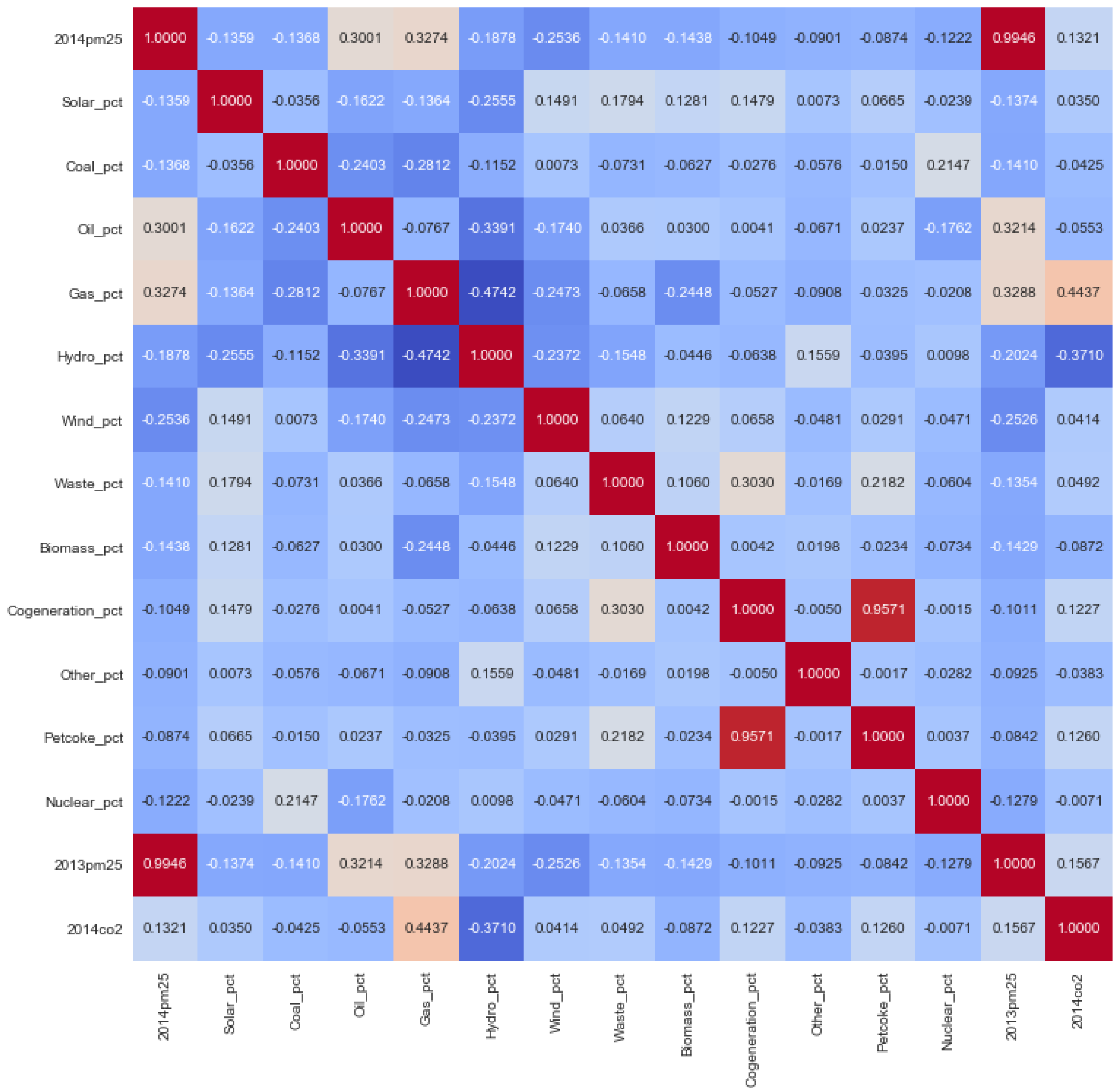


Table 2. OLS Regression Results for Model 1

OLS Regression Results

Dep. Variable:	2014pm25	R-squared:	0.990
Model:	OLS	Adj. R-squared:	0.990
Method:	Least Squares	F-statistic:	1233.
Date:	Tue, 23 Apr 2019	Prob (F-statistic):	4.11e-115
Time:	17:42:57	Log-Likelihood:	-279.28
No. Observations:	130	AIC:	580.6
Df Residuals:	119	BIC:	612.1
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.4854	0.940	-0.516	0.607	-2.347	1.376
Solar_pct	0.0253	0.018	1.384	0.169	-0.011	0.062
Coal_pct	0.0221	0.014	1.582	0.116	-0.006	0.050
Gas_pct	0.0290	0.012	2.523	0.013	0.006	0.052
Hydro_pct	0.0237	0.011	2.227	0.028	0.003	0.045
Wind_pct	0.0217	0.016	1.383	0.169	-0.009	0.053
Waste_pct	0.0113	0.063	0.180	0.858	-0.114	0.136
Biomass_pct	0.0210	0.039	0.543	0.588	-0.056	0.097
Nuclear_pct	0.0469	0.083	0.563	0.575	-0.118	0.212
2013pm25	0.9557	0.010	96.990	0.000	0.936	0.975
2014co2	-0.0857	0.030	-2.879	0.005	-0.145	-0.027

Omnibus:	21.443	Durbin-Watson:	1.762
Prob(Omnibus):	0.000	Jarque-Bera (JB):	122.655
Skew:	0.094	Prob(JB):	2.32e-27
Kurtosis:	7.755	Cond. No.	281.

Figure 2. Plot of residuals from model 1

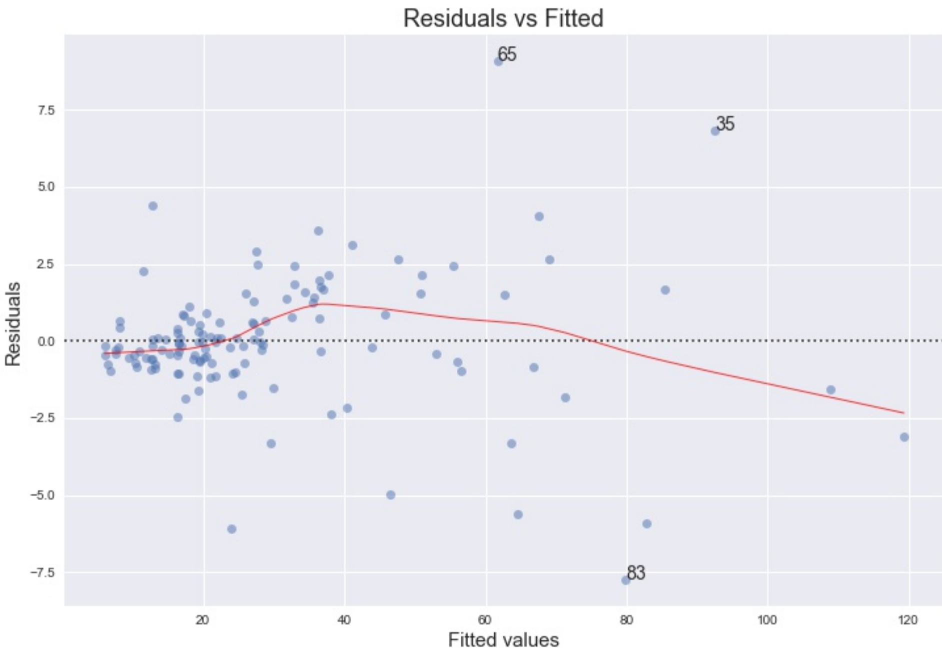


Figure 3. QQ Plot of from model 1

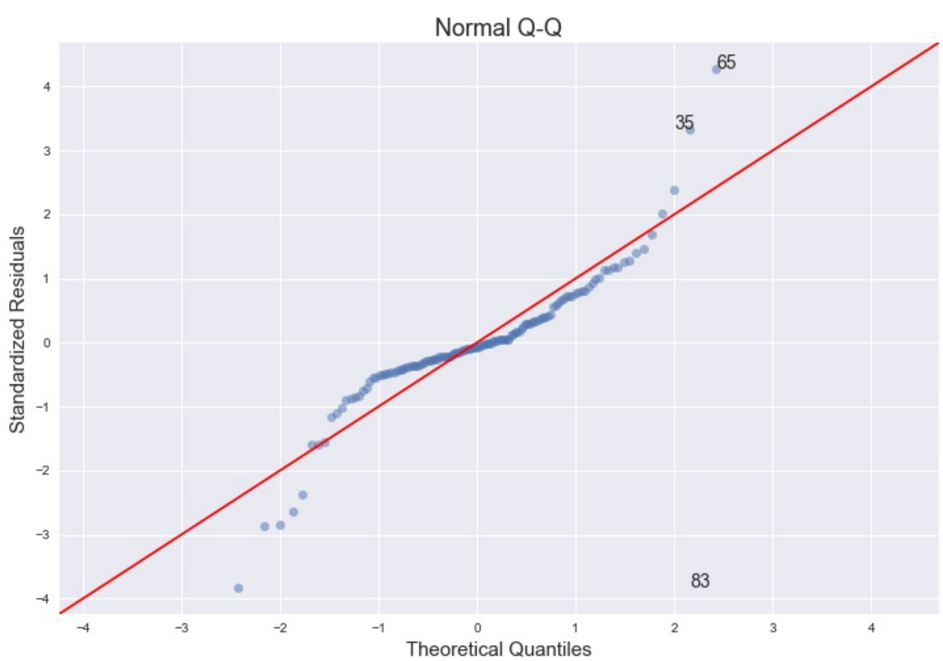


Table 3. OLS Regression Results for Model 2

OLS Regression Results

Dep. Variable:	2014pm25	R-squared:	0.514
Model:	OLS	Adj. R-squared:	0.240
Method:	Least Squares	F-statistic:	1.878
Date:	Tue, 23 Apr 2019	Prob (F-statistic):	0.130
Time:	17:43:21	Log-Likelihood:	-97.791
No. Observations:	26	AIC:	215.6
Df Residuals:	16	BIC:	228.2
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-2.1889	23.489	-0.093	0.927	-51.984	47.606
Solar_pct	0.3384	0.272	1.246	0.231	-0.237	0.914
Coal_pct	1.3667	0.440	3.105	0.007	0.433	2.300
Gas_pct	-0.1085	0.435	-0.250	0.806	-1.030	0.813
Hydro_pct	0.1484	0.255	0.581	0.569	-0.393	0.689
Wind_pct	0.2630	0.287	0.916	0.374	-0.346	0.872
Waste_pct	-0.6849	0.965	-0.710	0.488	-2.731	1.361
Biomass_pct	0.5017	0.489	1.026	0.320	-0.535	1.538
Nuclear_pct	-0.6686	1.803	-0.371	0.716	-4.491	3.154
2014co2	-0.2930	0.830	-0.353	0.729	-2.053	1.467

Omnibus:	3.543	Durbin-Watson:	2.815
Prob(Omnibus):	0.170	Jarque-Bera (JB):	2.161
Skew:	0.242	Prob(JB):	0.339
Kurtosis:	4.327	Cond. No.	443.

Figure 4. Plot of residuals from model 2

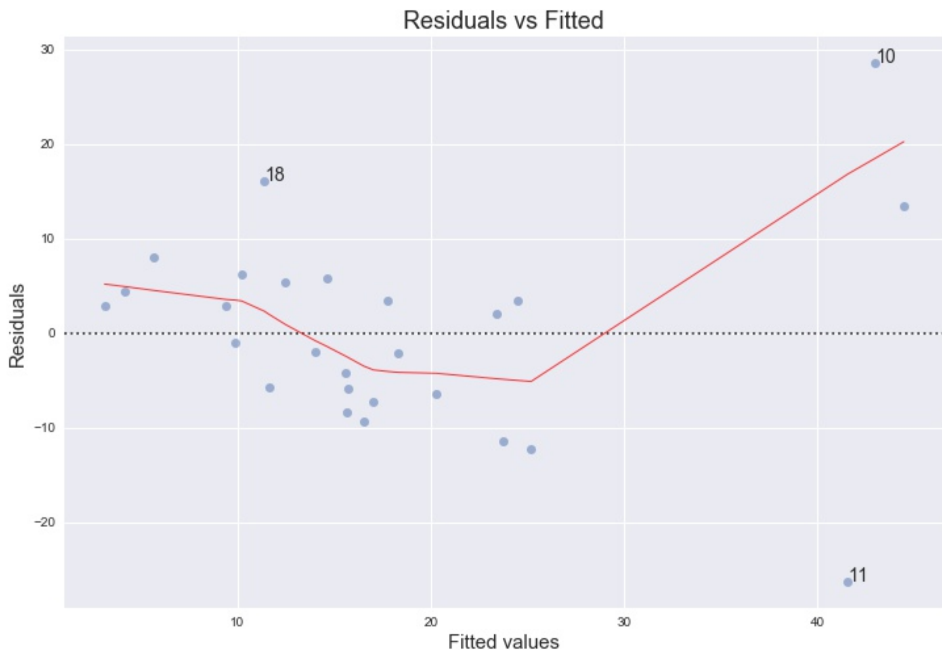
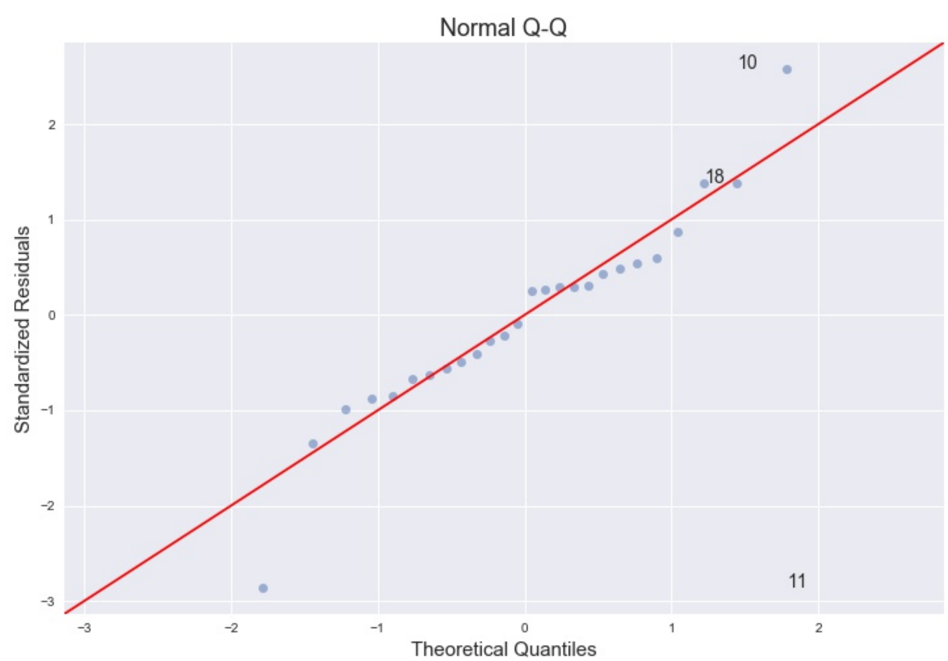


Figure 5. QQ Plot of from model 2



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