Effect of Particulate Matter Measures on Personal Income

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Background

- Fine particulate matter is one of the main pollutants that is monitored in the US, as it is an important component of air quality
- Particles come from a variety of sources of emissions, including various economic activities
- Exposure causes adverse health effects in both the short-term and long-term
- Short-term effects include throat irritation, coughing, sneezing, and shortness of breath
- Long-term effects can range from increased cardiovascular and respiratory hospital admissions to increased mortality from lung cancer or heart disease

Research Question

- Because exposure leads to adverse health effects, I aim to measure what the
 effect of particulate matter exposure is on personal income per capita levels
- While particulate matter is a byproduct of economic activity that can be seen as increasing income, the negative health effects caused by exposure will outweigh the positives of production
- Results of this study can hopefully help formulate a basis for policies that balance economic productivity and preserve human health

Data Sources

- Data from 3 different sources
- Quarterly particulate matter data extracted from the Air Quality System API provided by US Environmental Protection Agency
- Quarterly personal income per capita data sourced from the Bureau of Economic Analysis (BEA)
- Census data providing regional and divisional mappings for states sourced from Github repo

Variables

- Year
- Quarter
- State
- Period
- PM2.5 Measure
- Personal Income Per Capita Data
- Region
- Division

Air Quality System API

- Contains ambient air sample data collected by state, local, tribal, and federal air pollution control agencies from various monitors nationwide
- Provides access to daily summary, quarterly summary, annual summary, and quality assurance data
- Only 19 parameters to tweak in total, this number shrinks greatly depending on what kind of data you want
- Documentation provided step-by-step details on how to build out a URL for a specific data extract
- API is free to use, but a key is required

API Request

- Only 6 parameters needed to tweak for state quarterly data
- Documentation was easy to understand and provides a step-by-step on how to build out the URL

Quarterly Summary Data	By County	quarterlyData/byCounty	email, key, param, bdate, edate, state, county	cbdate, cedate	
		Example; returns quarterly summary FRM/FEM and non-FRM PM2.5 data for Wake County for 2016: https://aqs.epa.gov/data/api/quarterlyData/byCounty? email=test@aqs.api&key=test¶m=88101,88502&bdate=20160101&edate=20160228&state=37&county=183			
	By State	quarterlyData/byState	email, key, param, bdate, edate, state	cbdate, cedate	
		Example; returns all benzene quarterly summaries from North Carolina for 1995: https://aqs.epa.gov/data/api/quarterlyData/byState?email=test@aqs.api&key=test&param=45201&bdate=19950515&edate=19950515&state=37			

API Request (cont.)

- Needed quarterly state data for 4 different years, meaning over 200 API requests needed to be made
- Challenge was to figure out how to efficiently extract data from over 200 calls with minimal code
- Documentation also delineated a limitation on how many calls can be made within a minute
- Had to figure out how to build out a loop so that can extract data for each state in each period without overloading the server

API Request (cont.)

```
#First created the list of states the API needs to retrieve information from using the document
state = [num1call, num2call, num4call, num5call, num6call, num8call, num9call, 10, 11, 12, 13,
         23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40,
         41, 42, 44, 45, 46, 47, 48, 49, 50, 51, 53, 54, 55, 561
date = [2016, 2017, 2018, 2019] #Then created the list of the 4 years I needed as well
data = [] #Initialized an empty list to append the JSON output to
for year in date: #looping thru URL for different time periods,
    #delineating parameter (PM2.5) and that I want quarterly data
    for st in state: #nested for loop to also loop through states
        url = f"https://aqs.epa.gov/data/api/quarterlyData/byState?email=rshehata1000@qmail.com
        url += f"param=88101&bdate={year}0101&edate={year}0101&state={st}"
        response = requests.get(url) #Get request
        data.append(response.json()) #Appending each JSON output to the initialized list
        time.sleep(7) #Resting the loop every 7 seconds to avoid overloading the API server
```

API Output

```
"Header": [
   "status": "Success",
   "request_time": "2023-05-08T10:57:21-04:00",
   "url":
"https://aqs.epa.gov/data/api/quarterlyData/byCounty?email=test@aqs.api&key=test&param=88101,88502&bdate=201601
01&edate=20160228&state=37&county=183",
   "rows": 58
 "Data": [
   "state_code": "37",
   "county_code": "183",
   "site_number": "0014",
   "parameter_code": "88101",
   "poc": 3,
   "latitude": 35.856111,
   "longitude": -78.574167,
   "datum": "WGS84",
   "parameter": "PM2.5 - Local Conditions",
```

API Output (cont.)

- Had some issues figuring out how to convert the JSON output to a dataframe, used the JSON library and normalize function
- After conversion to a dataframe, over 140K rows and 42 columns of data were populated
- Row-level data is at the site-level within a specific state, each state and time period has hundreds of monitoring sites collecting data in different sample durations and pollutant standards
- Had to trim down by specific pollutant standard and sample duration, and also calculate a state average for each time period based on all site values

Data Cleaning

Dropping columns

• df = df.loc[:, df.columns.intersection(['site_number','datum', 'sample_duration', 'pollutant_standard','year', 'quarter', 'arithmetic_mean', 'local_site_name', 'state', 'county', 'city', 'cbsa'])]

Dropping sample duration duplicate rows

- sample_duration_list = ['1 HOUR', '24-HR BLK AVG']
- df = df[df.sample_duration.isin(sample_duration_list) == False]

Creating period value

df['period'] = df['year'].astype(str) + " Q" + df['quarter']

Calculate average PM2.5 for each state and period combination

df['pm2.5_measure'] = df.groupby(['period', 'state'])['arithmetic_mean'].transform('mean')

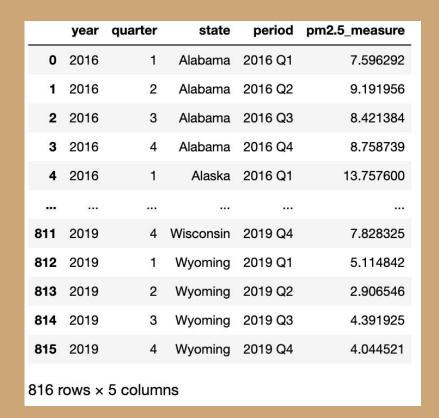
Data Cleaning (cont.)

Dropping duplicates to get to 816 rows

- df = df.drop_duplicates(subset=['state', 'period'])
- df = df.reset_index(drop=True)

Dropping final columns

df = df.loc[:, df.columns.intersection(['state', 'period', 'pm2.5_measure', 'year', 'quarter'])]



Bringing in External Data Sources

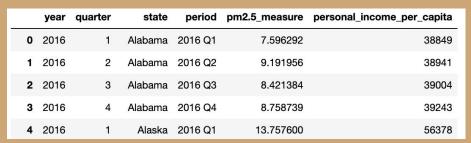
Merging the Income Data

merged_df = pd.merge(df, incomedf, on=['state', 'period'])



Bringing in Census Data

- region_map = dict(zip(census['State'], census['Region']))
- divisions_map = dict(zip(census['State'], census['Division']))
- merged_df['region'] = merged_df['state'].map(region_map)
- merged_df['division'] = merged_df['state'].map(divisions_map)



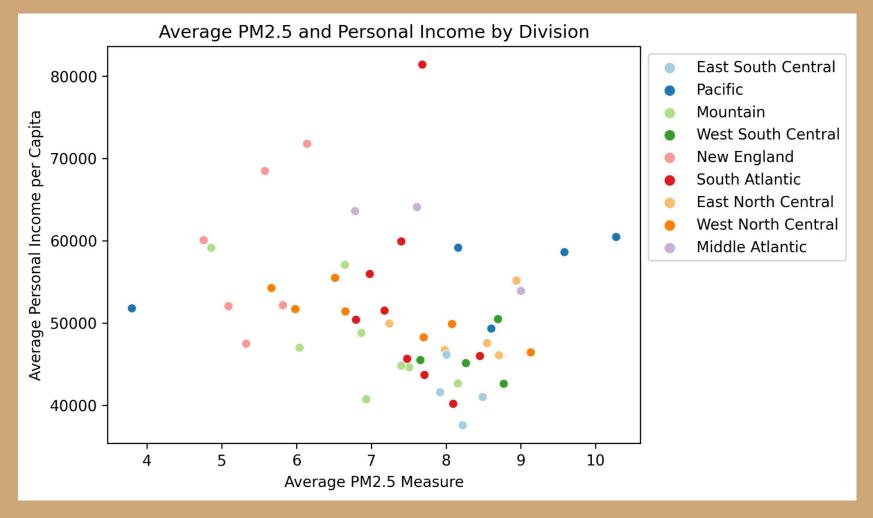
Г	year	quarter	state	period	pm2.5_measure	personal_income_per_capita	region	division
ď	2016	1	Alabama	2016 Q1	7.596292	38849	South	East South Central
1	2016	2	Alabama	2016 Q2	9.191956	38941	South	East South Central
2	2016	3	Alabama	2016 Q3	8.421384	39004	South	East South Central
3	2016	4	Alabama	2016 Q4	8.758739	39243	South	East South Central
4	2016	1	Alaska	2016 Q1	13.757600	56378	West	Pacific

Completed Dataset

816 rows × 8 columns

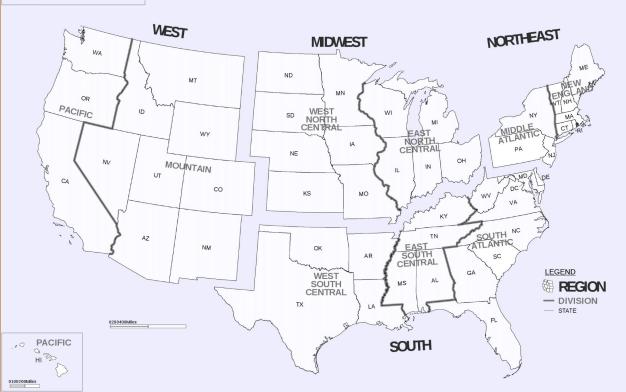
	year	quarter	state	period	pm2.5_measure	personal_income_per_capita	region	division
0	2016	1	Alabama	2016 Q1	7.596292	38849	South	East South Central
1	2016	2	Alabama	2016 Q2	9.191956	38941	South	East South Central
2	2016	3	Alabama	2016 Q3	8.421384	39004	South	East South Central
3	2016	4	Alabama	2016 Q4	8.758739	39243	South	East South Central
4	2016	1	Alaska	2016 Q1	13.757600	56378	West	Pacific
•••		•••		•••			•••	
811	2019	4	Wisconsin	2019 Q4	7.828325	53502	Midwest	East North Central
812	2019	1	Wyoming	2019 Q1	5.114842	63294	West	Mountain
813	2019	2	Wyoming	2019 Q2	2.906546	63786	West	Mountain
814	2019	3	Wyoming	2019 Q3	4.391925	64536	West	Mountain
815	2019	4	Wyoming	2019 Q4	4.044521	64732	West	Mountain

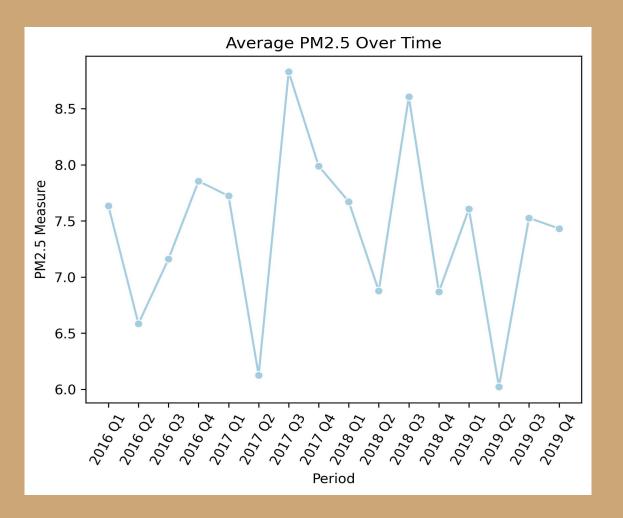
15

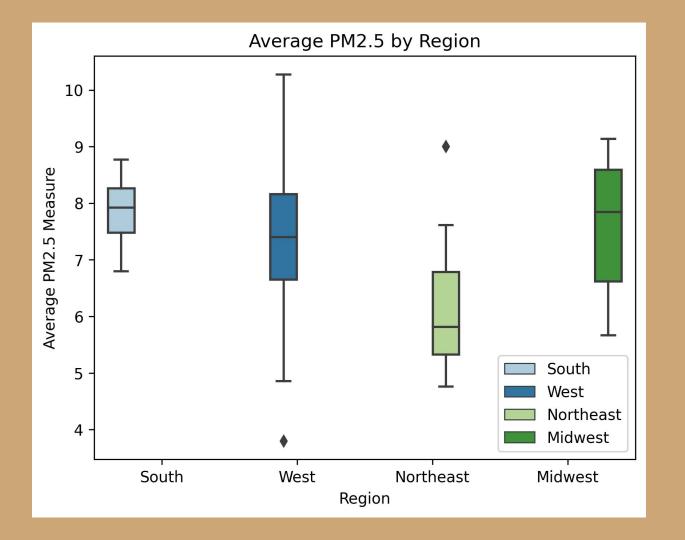




Census Regions and Divisions of the United States







Models

Model 1: $ln(personal_income_per_capita_{it}) = \beta_0 + \beta_1 pm2.5_measure_{it} + \lambda_t + \mu_{it}$

Model 2: $ln(personal_income_per_capita_{it}) = \beta_0 + \beta_1 pm2.5_measure_{it} + \lambda_t + \mu_{it} (excludes West states)$

Model 3: $ln(personal_income_per_capita_{it}) = \beta_0 + \beta_1 pm2.5_measure_{it} + \lambda_t + \alpha_i + \mu_{it}$

Ryan Shehata Regression Results							
-		Dependent variable:					
	Lo	Log of Personal Income per Capita					
	Time Controls Only Non-West States Only State FE Added						
	(1)	(2)	(3)				
PM2.5 Measure	-0.015***	-0.042***	-0.0002				
	(0.003)	(0.004)	(0.0003)				
2016 Q2	-0.012	-0.017	0.003				
	(0.031)	(0.035)	(0.002)				
2016 Q3	0.003	0.008	0.010***				
	(0.031)	(0.035)	(0.002)				
2016 Q4	0.019	0.024	0.016***				
	(0.031)	(0.035)	(0.002)				
2017 Q1	0.029	0.022	0.028***				
	(0.031)	(0.035)	(0.002)				
2017 Q2	0.014	-0.012	0.036***				
	(0.031)	(0.036)	(0.002)				
2017 Q3	0.062**	0.077**	0.044***				
20 - 12 to 1	(0.031)	(0.035)	(0.002)				
2017 Q4	0.058*	0.052	0.053***				
	(0.031)	(0.035)	(0.002)				

2018 Q1	0.066**	0.071**	0.065***
	(0.031)	(0.035)	(0.002)
2018 Q2	0.063**	0.063*	0.074***
	(0.031)	(0.035)	(0.002)
2018 Q3	0.101***	0.123***	0.087***
	(0.031)	(0.035)	(0.002)
2018 Q4	0.088***	0.049	0.099***
	(0.031)	(0.036)	(0.002)
2019 Q1	0.116***	0.114***	0.116***
	(0.031)	(0.035)	(0.002)
2019 Q2	0.098***	0.073**	0.121***
	(0.031)	(0.036)	(0.002)
2019 Q3	0.129***	0.146***	0.130***
	(0.031)	(0.035)	(0.002)
2019 Q4	0.134***	0.112***	0.137***
	(0.031)	(0.035)	(0.002)
Constant	10.885***	11.093***	10.559***
	(0.031)	(0.042)	(0.004)
State FE?	No	No	Yes
Observations	808	608	808
R^2	0.108	0.191	0.996
Adjusted R ²	0.090	0.169	0.996
Residual Std. Error	0.156 (df = 791)	0.154 (df = 591)	0.010 (df = 741)
F Statistic 5	$.993^{***}$ (df = 16; 791)	8.695*** (df = 16; 591	$3,193.266^{***}$ (df = 66; 741)
Note:			*p<0.1; **p<0.05; ***p<0.01

Regression Results

- PM2.5 is statistically significant at the 1% level in Model 1 where only time fixed effects are included
- A one microgram per cubic meter increase in the particulate matter measure leads to a -1.5 percent change in personal income per capita holding all else constant
- PM2.5 is again statistically significant at the 1% level in Model 2
 Census-designated Western states are excluded
- A one microgram per cubic meter increase in the particulate matter measure leads to a -4.2 percent change in personal income per capita holding all else constant

Regression Results (cont.)

- In Model 3 where time fixed effects and state fixed effects are included, particulate matter is no longer statistically significant
- A one microgram per cubic meter increase in the particulate matter measure leads to a -.02 percent change in personal income per capita holding all else constant

Discussion & Conclusion

- While the effect is small, the sheer presence of a pollutant in the air lowering income levels indicates that its effects on health in the long-term can't be ignored
- When health is negatively impacted, economic productivity at an individual level decreases in the long-run
- In the future, studies should try isolating other pollutants as well and see if the effect on income is also negative
- Some missing variables including state population and largest source of economic productivity within a state
- Interested in measuring the impact of particulate matter or other air quality indicators on personal consumption expenditures

Thank you!

Source

https://www.health.ny.gov/environmental/indoors/air/pmg_a.htm