Heart disease risk factors the Panda way

Spaar, Andrew, Ivan, Michel, Danielle

Motivation & Summary

Thesis:

Freely available county-level data will identify impact of different heart disease risk factors.

Why This Is Important:

- Heart disease results in 600,000 deaths in the US each year (#1 cause)
- The costs of heart disease exceed \$200 billion annually in the US
- The results of traditional medical studies have not yet led to hoped-for reductions in risk factors.

Data Collection Process

County Health Rankings & Roadmaps (Univ. Wisconsin), "county" and "state" in separate fields -- only available one state as a time

Merge 50 csv files into one big csv

CDC WONDER:
Mortality Data -csv files, no
breakdown by
year, "county and
state" names

Split "county and state" into separate "county" and "state" but retain both forms for merging National Survey on Drug Use and Health (Substance Abuse & Mental Health Services Admin) - US Dept of Health & Human Services, limited by privacy concerns, broken down by unique "regions", only way to mesh with county data is by grouping to state level and merging in on state (copy to counties)

Merged pandas data frame

Manually merge old and new county names by copying and delete entries in data frame Sunlight Data (North American Land Data Assimilation System) --30-year old county names in "county and state" format

Cleaned pandas data frame

Data Analysis Process

Cleaned pandas data frame

Transform variables to normal distribution

Food environment, exercise, physician density, smoking, and non-insurance transformed

Transform if > 50 samples AND abs(skew) OR abs(kurtosis) > 1

Data frame with normally-dis tributed variables

Drop counties with NaN for any variable (>2800 left)

Fit ensemble of 100 model (except PLS)

Translate coefficients into impacts (ElasticNet and OLS only)

Base predictor and measurement data

Choose regression model (drugs / no drugs, fit type (ElasticNet, OLS, PLS, Random Forest)

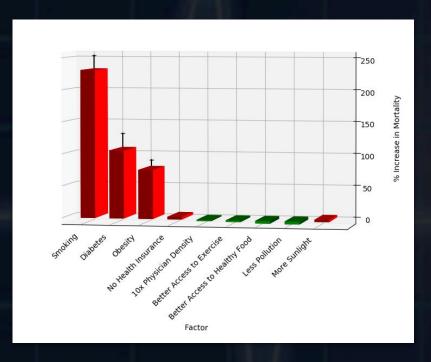
Compare scores, impacts, and robustness

Statistical Results

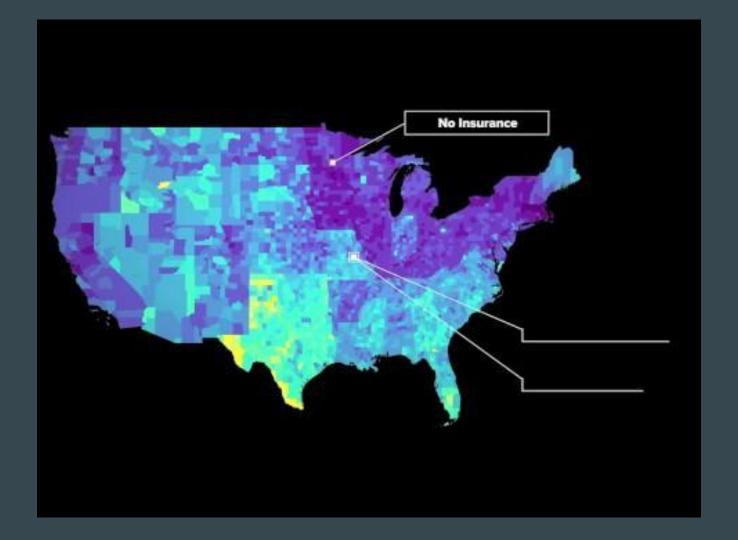
Factors	P-Values	Findings
Smoking	4 x 10 ^ -35	SIGNIFICANT
Diabetes	6 x 10 ^ -10	SIGNIFICANT
Obesity	3 x 10 ^ -17	SIGNIFICANT
Lack of Health Insurance	2 x 10 ^ -5	SIGNIFICANT
Access to Physicians	2 x 10 ^ -3	SIGNIFICANT
Sunlight Exposure	5 x 10 ^ -10	SIGNIFICANT
Pollution	2 x 10 ^ -20	SIGNIFICANT
Food Environment Index	5 x 10 ^ -13	SIGNIFICANT
Exercise	6 x 10 ^ -5	SIGNIFICANT

Assumes n > 2000 independent, random samples. Does not take systematic effects into account.

Impacts on Mortality



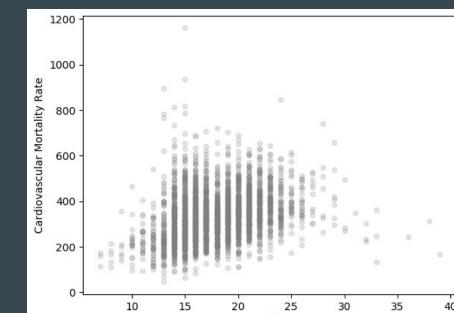
- Impacts generated from average coefficients in ensemble of linear regressions
- Order and magnitude of obesity, diabetes, and smoking impacts computed on county basis qualitatively similar to impacts for individuals reported in the literature..
- Factors such as "food environment" are likely not independent of obesity in a meaningful sense.



Smoking

- Smoking has the most impact out of any other factor
- Native American reservations have a disproportionate amount of smokers in them

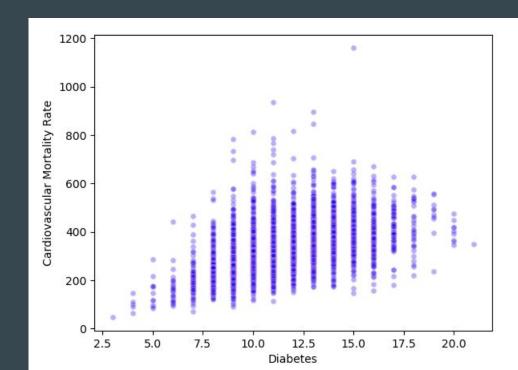




Diabetes

- South western Alabama and Mississippi have some of the highest diabetes counties in the USA.
- Mortality rate seems to peak at 12.5% of diabetic population.





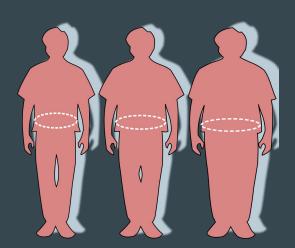
Obesity

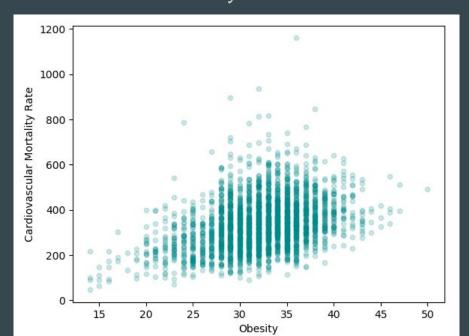
3rd factor with most impact on cardiovascular mortality rate

• The higher the percentage of obesity(in counties across the U.S.) is, the higher the cardiovascular mortality rate is

Therefore, there is a correlation between obesity and cardiovascular

mortality rate





Conclusions:

- Lifestyle factors have more apparent effects than environmental factors
- County data indicates smoking increases your risk of heart disease at least twice as much as the second leading cause -- similar to individual studies
- The southern and midwest counties tend to have a larger amount of heart disease-related deaths and also engage more in all risk factors

Project Post Mortem

- County-level data is very useful for illustrating the issues and might have value for capturing the effects of factors not otherwise considered
- Drug use data was grouped by regions, when we wanted our data to be grouped by county
 - Group by state for drug use dataset lost a lot of information
 - Most drug user populations too small to use for estimating impacts at county level
- Linear regression provided some useful analysis despite issues ...
 - Assumptions needed to relate county-level and individual impacts
 - Strong correlations and complex causal relationships among factors
 - Counties are not truly random, independent samples

