University of Michigan - Master of Applied Data Science: SIADS 591-592

Physician Payments Analysis

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Motivation

In 2013, the Sunshine Act was passed into law. The Act required the reporting and disclosure of payments made to physicians by pharmaceutical companies. The intent was to have transparency to physician payments by industry.

Many physicians maintain close relationships with pharmaceutical industries, routinely getting paid from industry representatives for travel, speaking, education, grants, and royalties. In our project, we are focused on what, if any, influence these payments have on physician behavior, as measured by (a) physician's performance scores and (b) drugs prescribed. Our investigation of physicians' performance scores will help shed insight into whether the close ties between industry and physicians ultimately leads to better patient outcomes. Similarly, our investigation of drug prescriptions will show whether pharmaceutical companies can effectively pay to have their medicines prescribed. We also explore geographical trends in physician payments.

Data Sources

The Physician Payments Sunshine Act was implemented as part of the Affordable Care Act of 2010. The Act stipulated that pharmaceutical and medical device companies must report payments made to physicians or hospitals. This data is posted publicly on a website maintained by federal Centers for Medicare and Medicaid Services (CMS). The intent was to bring transparency into physician/industry relationships. CMS also has performance scores at *organization* and *physician* levels as part of their "Care Compare" initiative program where patients can compare doctor and hospital ratings before seeking treatment. For our prescription drug analysis, we use CMS data on the drugs prescribed by physicians to Medicare beneficiaries enrolled in part D plan. Medicare Part D is an optional prescription drug program for people on Medicare. Our project analyzes CMS data for the year 2019, as 2020 onward have been atypical years for the medical industry due to the ongoing pandemic.

Click on the title of each dataset to download. Datasets #13 and #14 were built for this project.

(1) National Plan and Provider Enumeration System (NPPES)	8.5 GB	NPI (National Provider ID) for all practicing physicians
(2) 2019 Open Payments from Centers for	6.2 GB	Payment information for each physician or

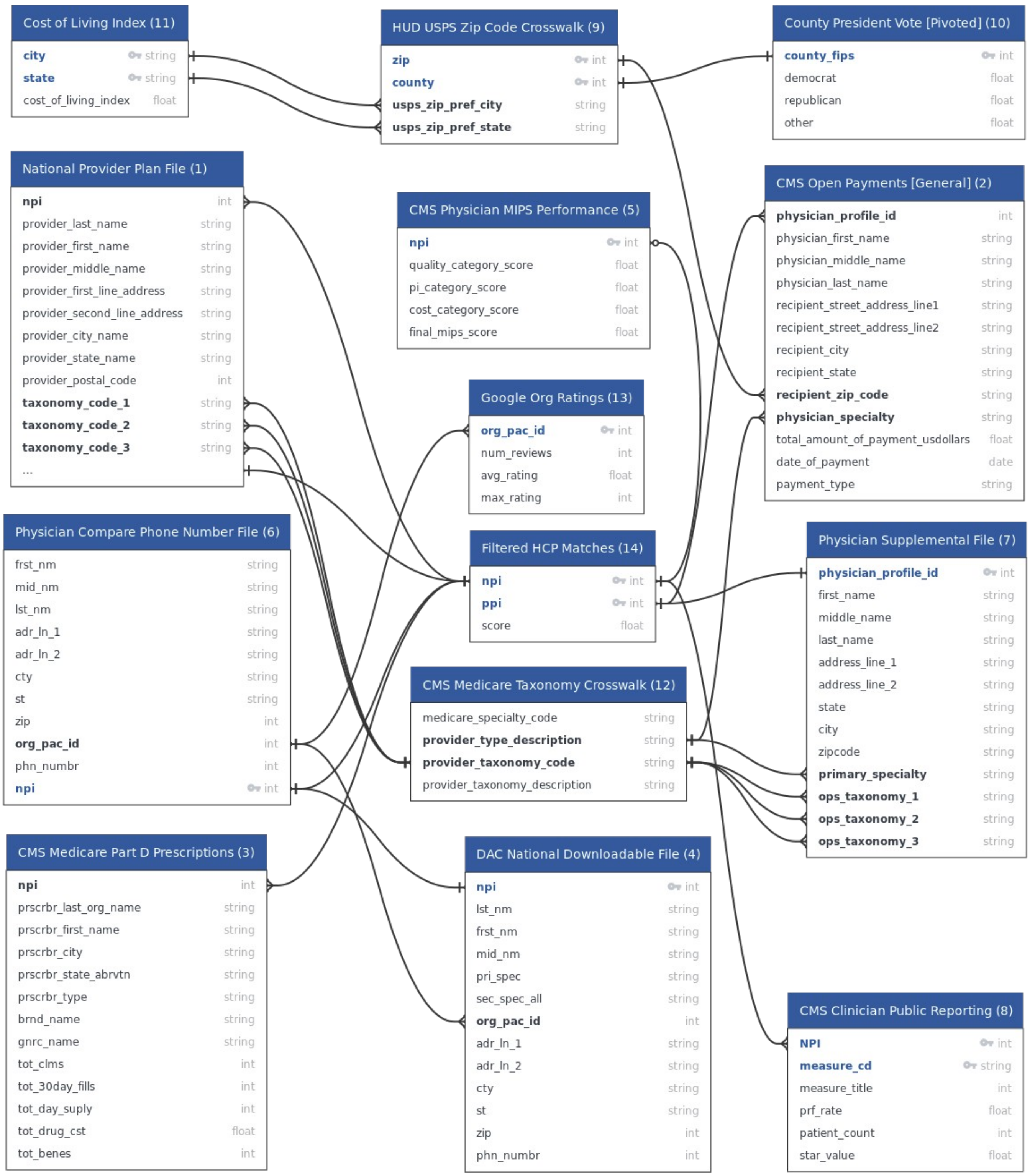
Medicare and Medicaid Services (CMS)		entity for 2019
(3) 2019 Medicare Part D Prescribers - by Provider and Drug (CMS)	3 GB	Drugs prescribed by physicians for Medicare Part D beneficiaries
(4) National Downloadable File (CMS)	738 MB	For each physician, phone number and organization
(5) Doctors and Clinicians Quality Payment Program PY 2019 Clinician Public Reporting: Overall MIPS Performance (CMS)	61 MB	Merit-Based Incentive Payment System (MIPS) final scores by performance category for individual physicians
(6) Physician Additional Phone Numbers (CMS)	426 MB	Organization, address, and phone number for each physician
(7) Physician Supplement File for all Program Years (CMS)	227 MB	Physician metadata such as name, address, and taxonomy
(8) Doctors and Clinicians Quality Payment Program PY 2019 Clinician Public Reporting: Measures and Activities (CMS)	124 MB	MIPS measures by physician
(9) HUD USPS ZIP Code Crosswalk Files	1.3 MB	Zip and FIPS county cross reference
(10) County Presidential Election Returns 2000-2020 (MIT Election Data Science Lab)	908.4 kB	Vote share by FIPS county code
(11) AdvisorSmith City Cost of Living Index	9.6 kB	Cost of living index for 500 cities
(12) Medicare Provider and Supplier Taxonomy Crosswalk Methodology	66 kB	Mapping of Medicare provider type to taxonomy
(13) Google Organization Ratings (scraped via SerpsBot)	705 kB	Average Google rating for each organization
(14) Filtered HCP Matches	187 MB	PPI NPI cross reference, generated from (1) and (7) as described below

Data Collection

Most datasets could be downloaded directly, but **organization reviews required scraping Google** search results. For each organization, the most common physician phone number was searched and the result scraped for reviews. This resulted in 50k queries with 34k returning at least one organization review. It was not practical to scrape Google reviews for all 600,000 physicians due to cost and time constraints.

Scraping Google search results is difficult, so we used a web API provided by SerpsBot. This API was slow, up to 30 seconds for each query. So we created scripts to run multiple scrapers in parallel by partitioning the organization IDs using modular arithmetic (e.g. last digit for mod 10). The simplified JSON API did not provide a parsed copy of the organization reviews, so we had to scrape the raw HTML with BeautifulSoup. Since each Google search result is typically 500kB, this would be over 25GB of data. To save bandwidth and ensure uninterrupted scraping, the entire process was run on AWS. The Google ratings were saved to CSV and downloaded for local analysis.

Entity Relationship Diagram

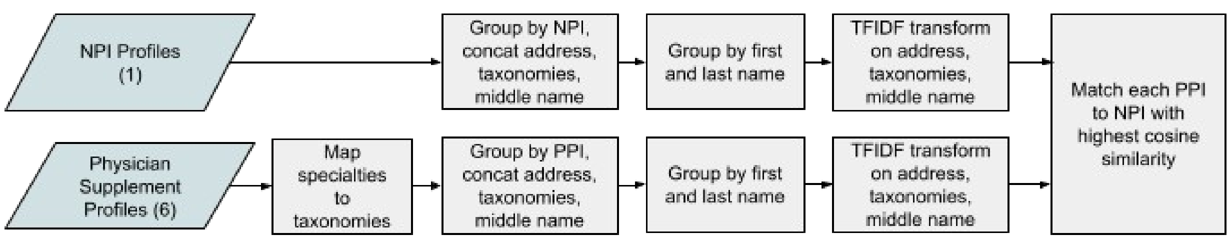


Dataset Manipulation

The greatest challenge was **joining physician payment (dataset 1) records to performance (dataset 2) and drug prescription (dataset 3) records**. Payment records are indexed by Physician Profile ID (PPI), but performance and drug prescriptions are indexed by National Provider ID (NPI). So we had to create a mapping between PPI and NPI records.

In both datasets, first and last names are almost always fully populated, so the mapping assumes that these fields are the same in both datasets. There is more variance in addresses, taxonomies (e.g. Endocrinology, Orthopedics), and middle name/initial. So for each first name/last name combination (e.g. "John Smith"), all the records with NPI are compared to all the records with PPI according to the following procedure:

1. Perform a term frequency/inverse document frequency (TFIDF) transformation on word count vectors for each field separately: addresses, taxonomies, and middle name. This ensures that more selective terms, such as a "123" in "123 River Rd", are given greater weight when comparing records. The TFIDF is done separately for each field due to their different term frequencies. For example, "Internal Medicine" is a common taxonomy but "Internal Road" is an uncommon address.
2. For each NPI/PPI record pair, compute the cosine similarity of the corresponding TFIDF vectors for each field separately.
3. Average the cosine similarity across all fields for these two records to compute how well they match.
4. For each PPI, record the highest scoring NPI match.
5. Filter out all matches with a score below a threshold (0.3).

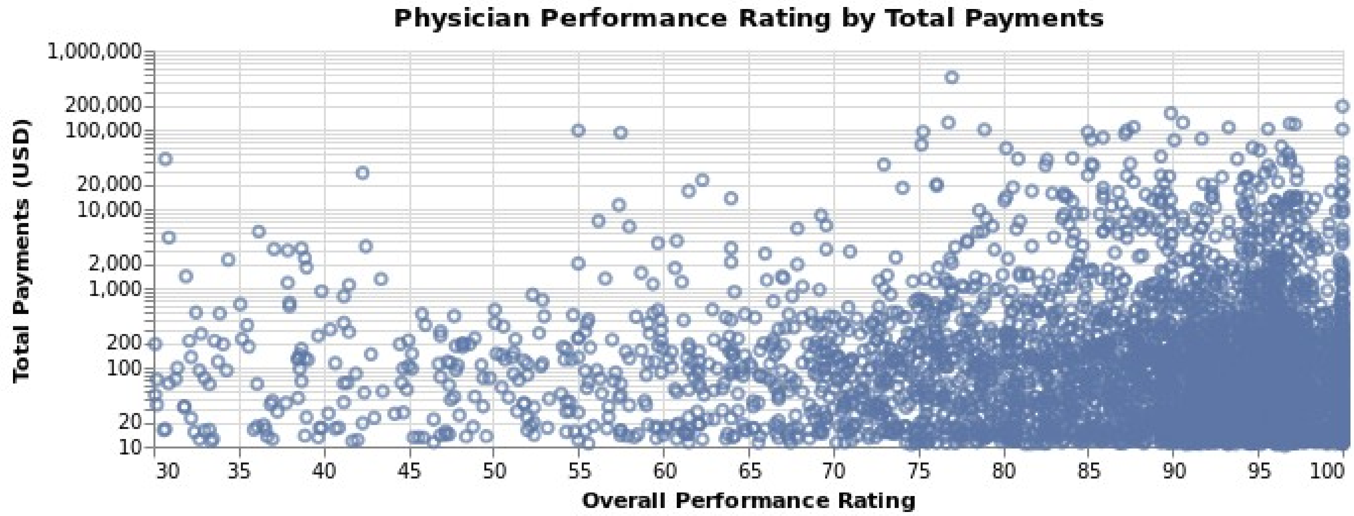


For Google **organization reviews**, star ratings were adjusted to avoid giving too much weight to organizations with few reviews. This was done using a Bayesian prior on the average of all reviews (3.928) with a confidence of 5. In other words, each rating has 5 ratings with 3.928 averaged in. The exact equation is (5*3.928 + N*rating) / (N + 5), where N is the number of reviews. So a single 5 star rating will be adjusted down to 4.1 and a single 1 star rating will be adjusted up to 3.44.

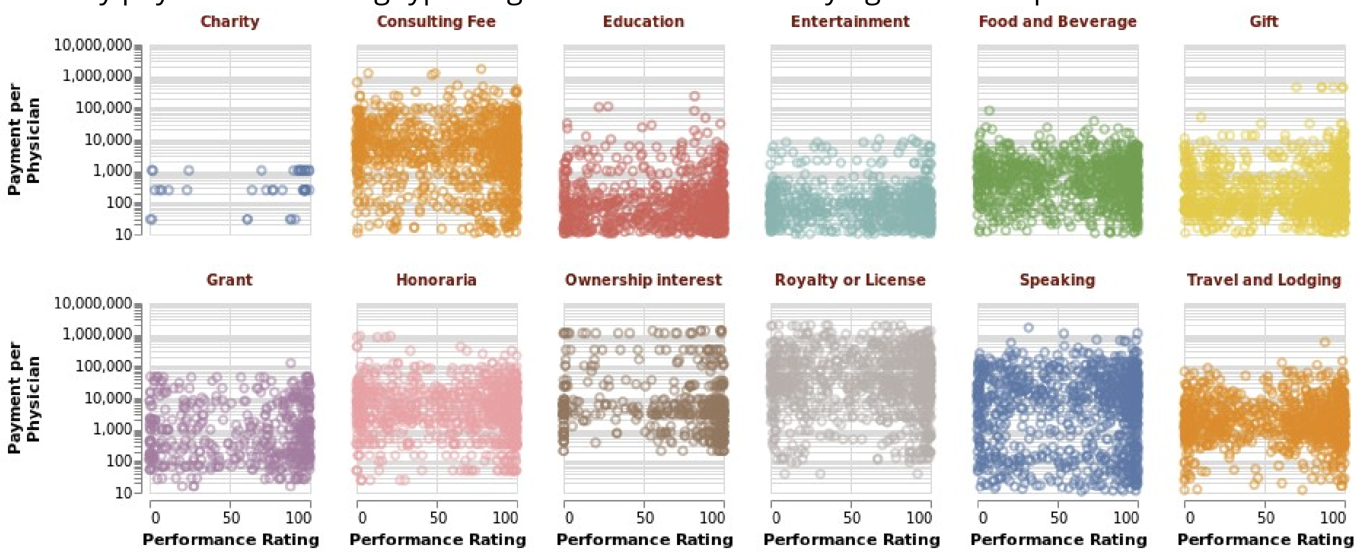
Physician Payments vs Performance

For physician payments, we examined the general payments recorded by CMS for the last full year on record (2019). This represents over 10 million payment records across 600 thousand physicians totalling 2.4 billion dollars.

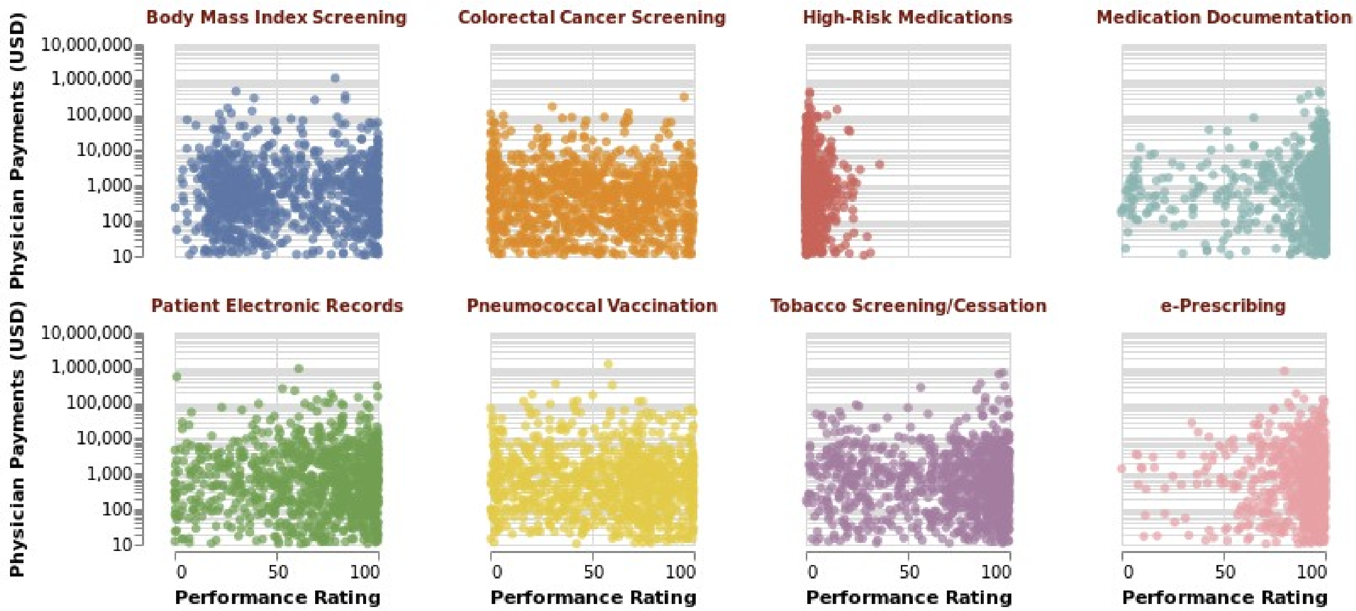
Surprisingly, we found that physician performance is independent of industry payments. We can see this with the scatterplot below which shows a negligible correlation of -0.0009.



But there are many types of payments, and many types of performance ratings. Perhaps grouping so many payment and rating types together obscures underlying relationships.

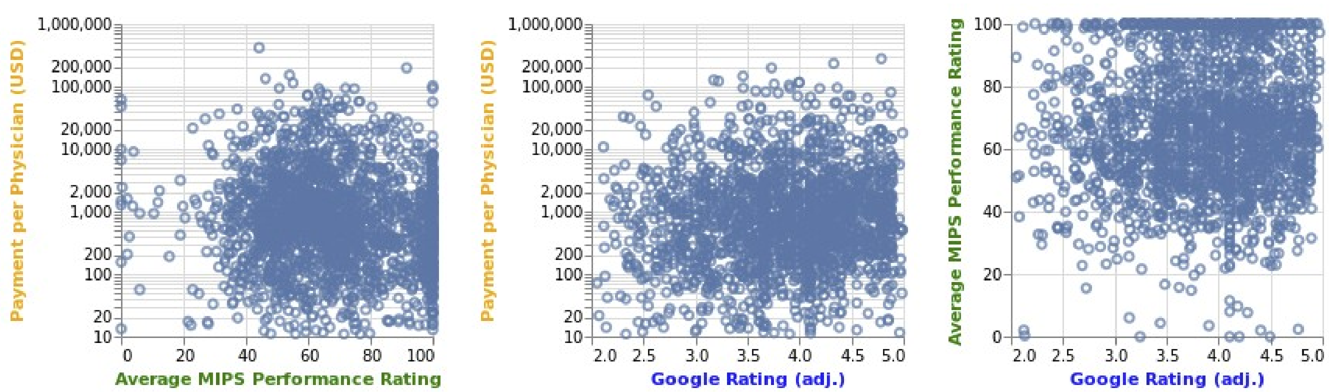


As we see above, there is still no clear correlation between the amount of any payment type and overall physician MIPS performance. We also examined all recorded performance measures, and similarly saw no significant correlation with payments. The eight most commonly recorded performance measures are plotted below.

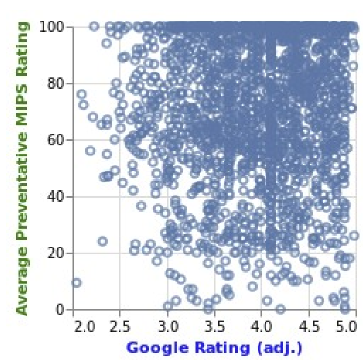


Organization Payments vs Performance vs Online Reviews

We see similar results when examining the relation between payments and MIPS ratings for organizations.

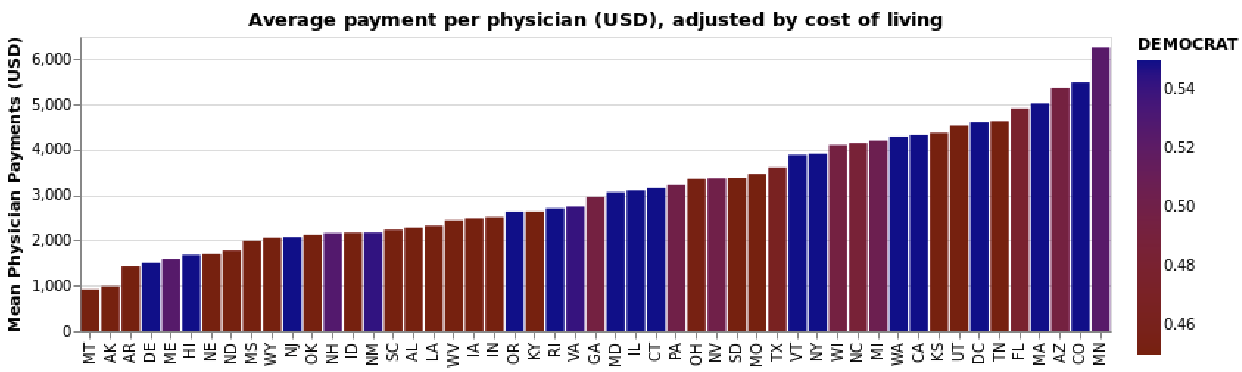


For organizations, we also have Google reviews. However, online user reviews are not correlated with payments or even MIPS performance ratings! Whatever MIPS is scoring, it seems to be independent of user reviews. This could be because of bias inherent in user reviews, or perhaps user reviews are more dependent on bedside manner than actual successful outcomes. Another potential explanation is that some performance ratings depend on delivering unpleasant news to the patient, such as screening for high BMI or tobacco use. However, we would expect to then see a *negative* correlation between preventative screening ratings and that's not what we see (right).

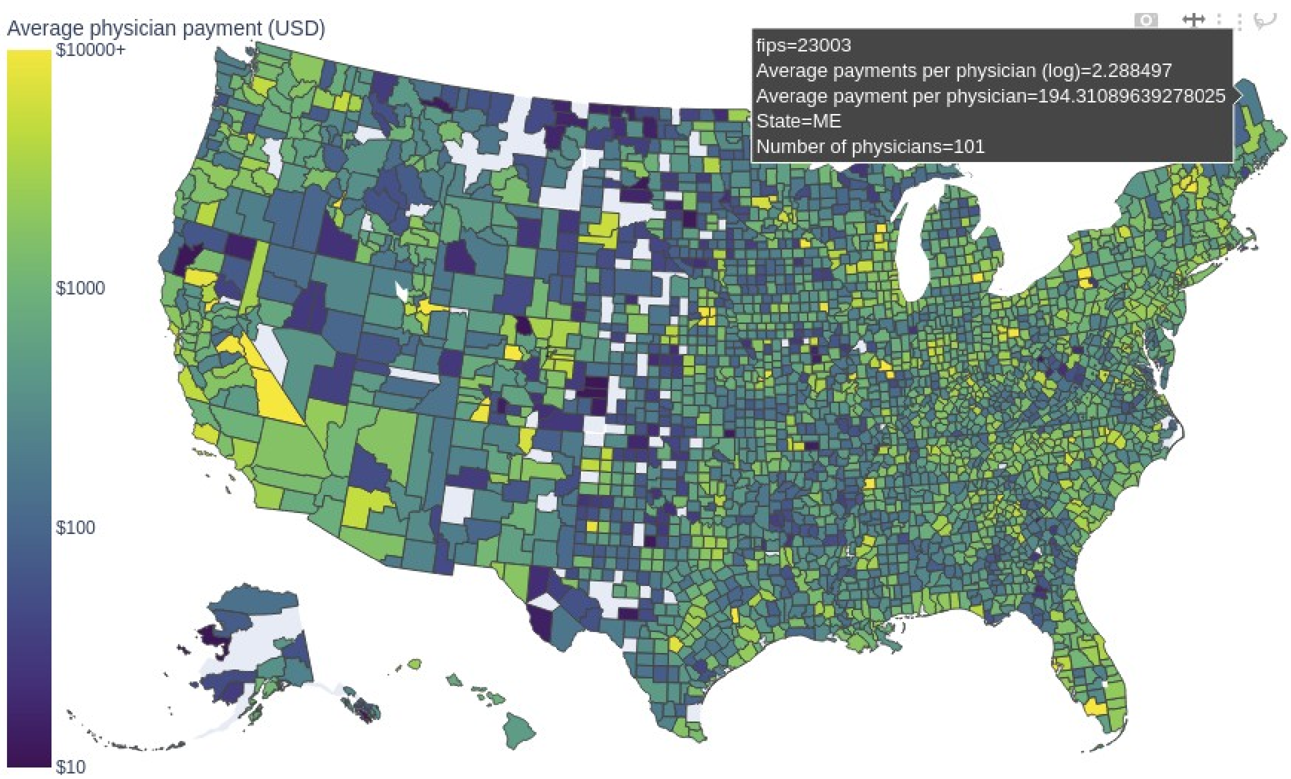


Geographic Trends

We do see variation in median physician payment at the state level, but it's not clear what causes this. It could be different state level regulations regarding industry payments to physicians. To test this, we examined the partisan lean of each state against the median physician payment, adjusted for cost of living. There does not seem to be a clear relation between partisan lean and median physician payment. So any regulation differences driving different levels of industry payments are likely idiosyncratic to each state.

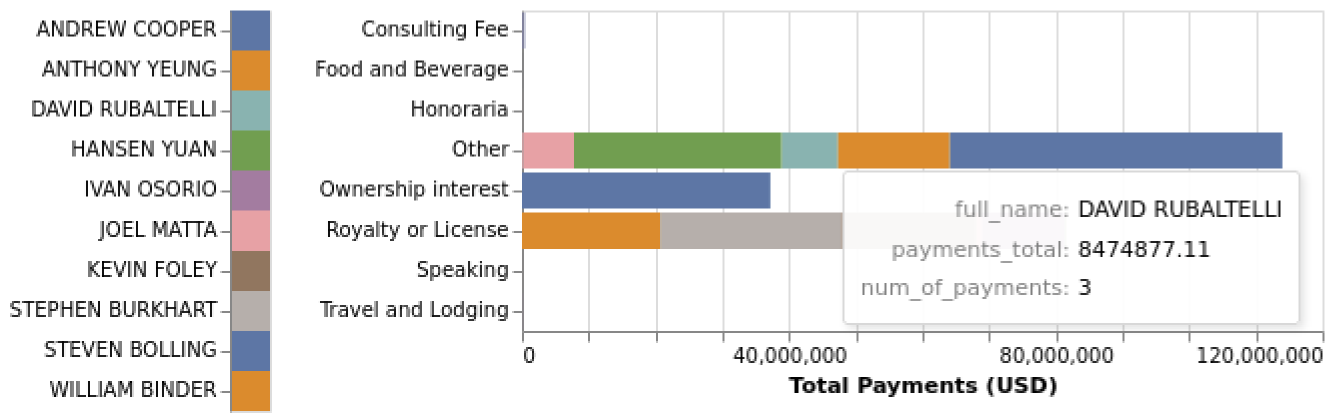


For each county, we also examined the average physician payment adjusted by cost of living. There are no clear geographic trends here, except a manual inspection shows that more extreme values (high and low) generally result from rural counties with few physicians, resulting in a higher variance of the average payment, as shown in the interactive choropleth below. Gray areas denote a lack of payment data.



Top Paid Physicians

The following interactive chart shows some clear patterns among the top paid physicians. It seems that the highest paid physicians have often developed devices or surgical techniques that the medical industry is willing to pay for. For example, [Dr. Anthony T. Yeung]() developed the “Yeung Endoscopic Spine System” which may be related to the $16 million USD he received in 2019. Another example Dr. Stephen Burkhart, who has developed ([and sued]()) over numerous patents.



While the success of these physicians is interesting, a single doctor is unlikely to prescribe millions of dollars worth of drugs or medical devices within a year, so it’d be wasteful even for a corrupt company to pay tens of millions to improperly influence a single physician. Improper industry influences, if they exist, are more likely to occur with smaller payments in the hundreds or thousands of dollars.

Medicare Prescribing Trends

Magnitude of Financial Ties to Industry and Prescribing Trends

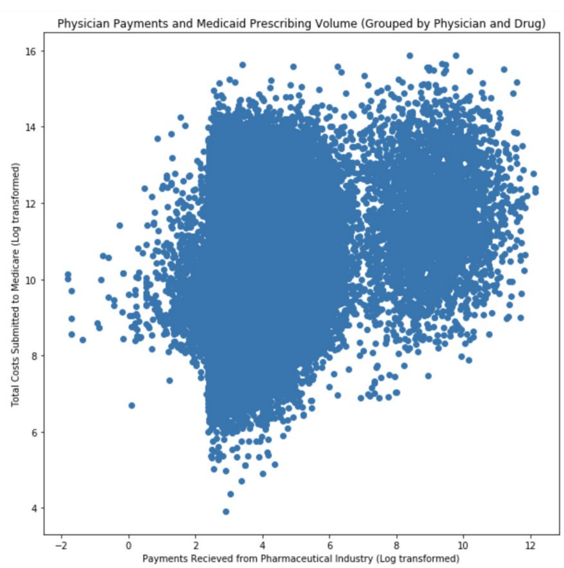
Our next topic of exploration was examining if there were correlations between various physician financial data and drug prescribing volume and costs.

We examined the following three financial relationships: Industry Payments to Physicians, Physician Ownership in Industry, and Research Payments to Physicians.

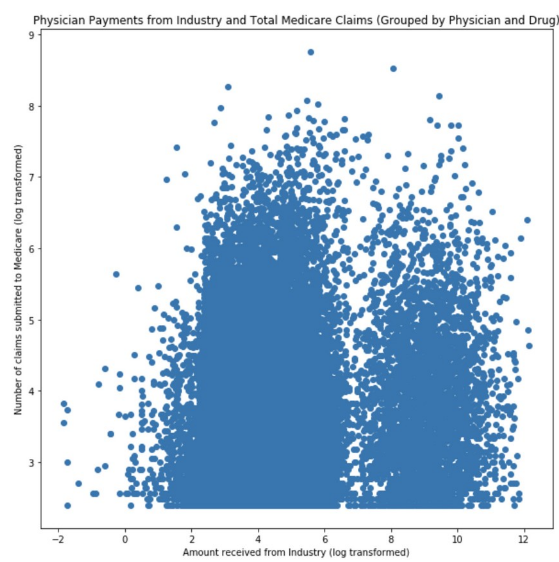
Industry Payments to Physicians

We analyzed whether there was a correlation between the amount of money a physician received for a drug, and A) the number of times that physician prescribed the drug and B) the total amount (US dollars) that physician submitted to Medicare for reimbursement. Each dot represents a unique physician and a specific drug.

A



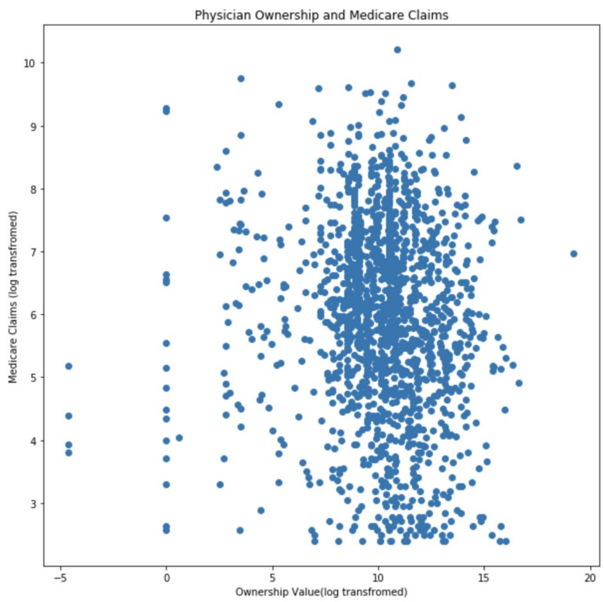
B



There appears to be clustering around the $1000 mark, meaning most physicians are receiving payments totaling less than $1000 or greater than $1000 for a given drug. Few physicians receive exactly $1000 for a drug. Beyond the clusters, we do not see any apparent correlation between the amount of money a physician received for a drug and the prescribing volume or prescribing cost of that drug.

Physician Ownership in Industry

A



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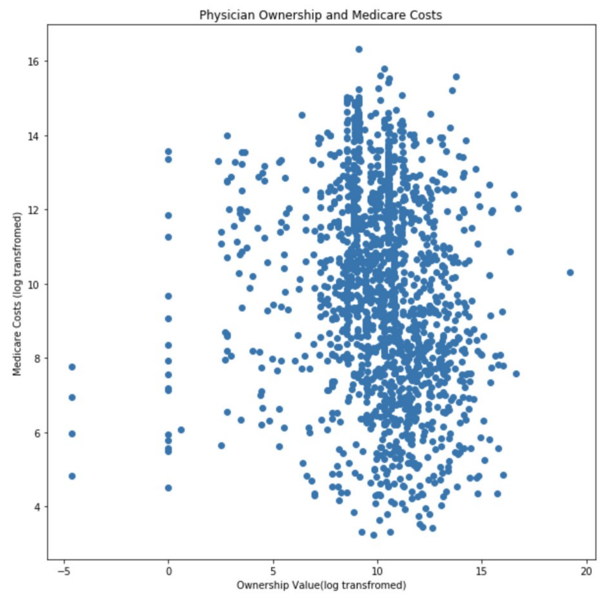
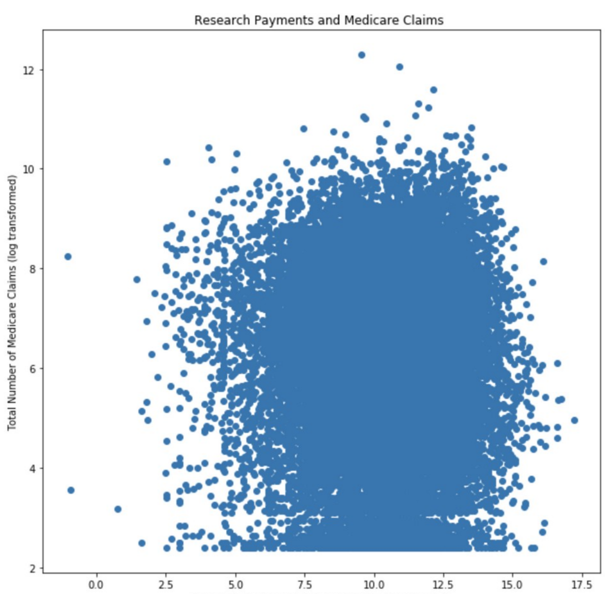
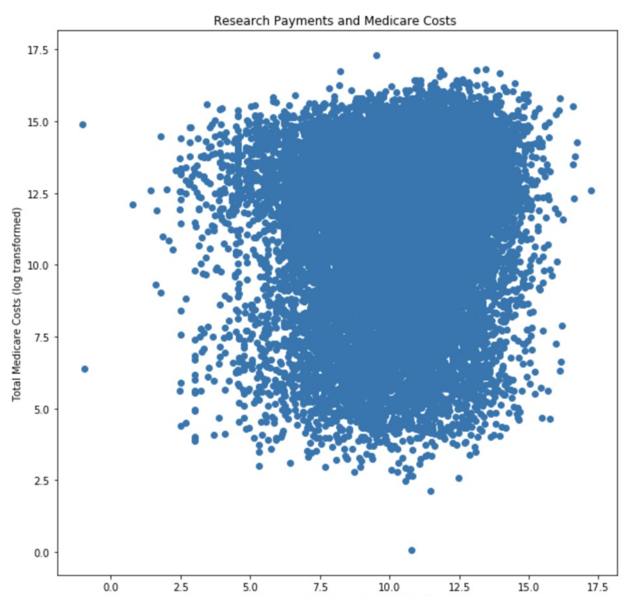


No correlation seen between a physician's ownership in pharmaceutical companies and drug prescribing volume and costs. The X axis represents a physician's total ownership value across pharmaceutical companies. The Y axis represents A) the total number of claims for that physician B) the total costs of claims for that physician.

Research Payments to Physicians.





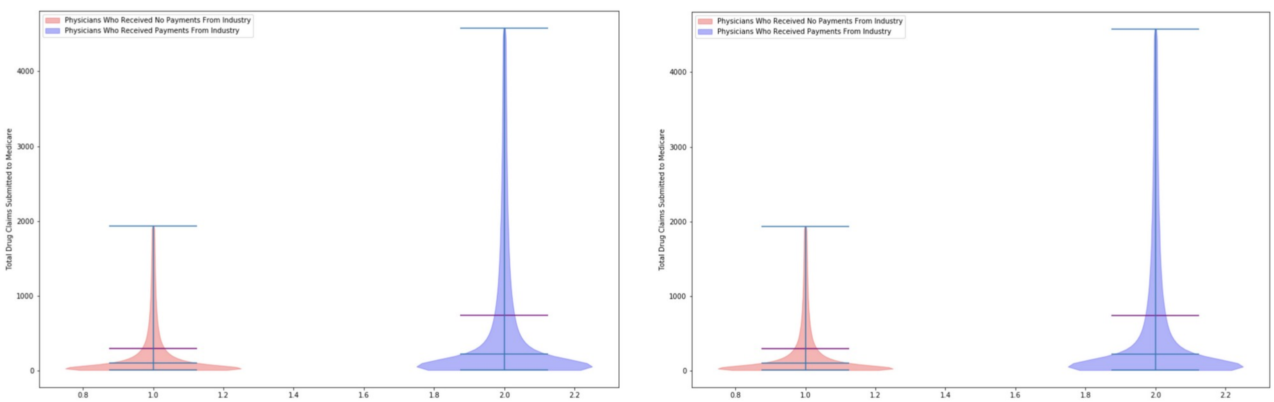
Similar to the two previous financial datasets, there appears to be no correlation between how much money a doctor receives for research (in total) and the volume or costs of the drugs the doctor prescribes.

Financial Ties to Industry Vs No Financial Ties to Industry

In the previous section we did not find any correlations in the amount of financial ties a physician had with industry and the prescribing volume and costs of that physician. There were no correlations seen within the financial datasets. Increasing payments, ownership, research, did not correlate to higher prescription claims and costs. We decided to see if there were differences between physicians with reported financial ties to the pharmaceutical industry and those physicians without any reported financial ties to the pharmaceutical industry.

Industry Payments to Physicians

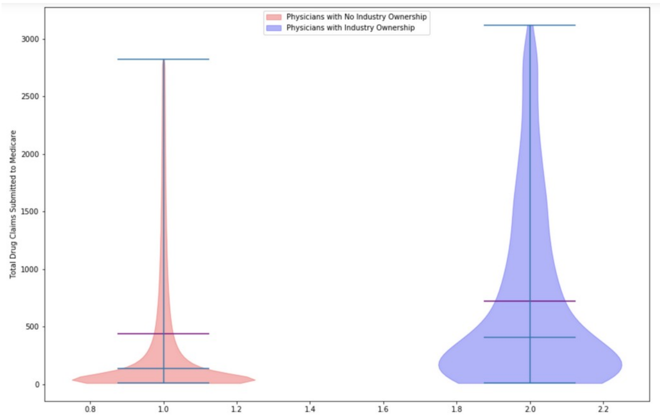
A B



We see on average, physicians who received at least one payment from industry had higher drug claims and drug costs compared to those physicians who have not received any payments from industry.

Physician Ownership in Industry

A



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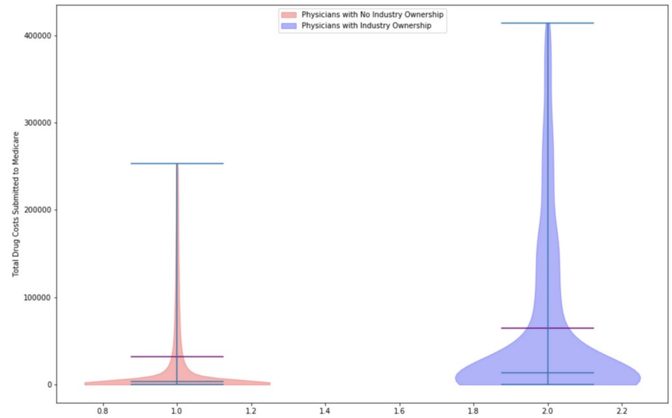
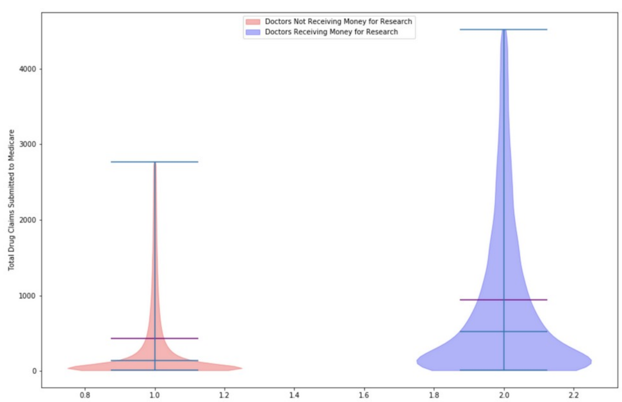


We see on average, physicians who have ownership in at least one pharmaceutical company had higher drug claims and drug costs compared to those physicians who do not have owernship in any pharmaceutical companies.

Research Payments to Physicians.

A



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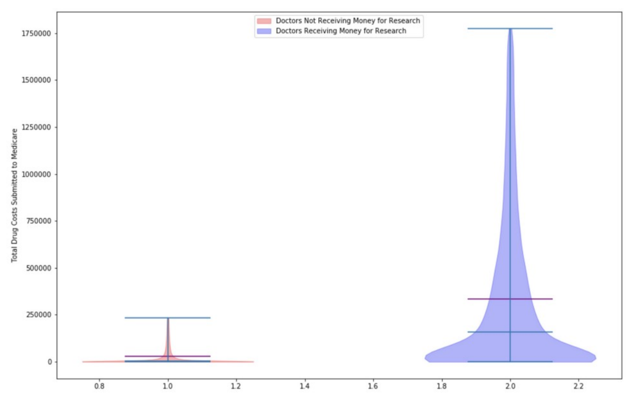

We see on average, physicians who have have received money as a research investigator had higher drug claims and drug costs compared to those physicians who did not receive money as a research investigator.

Conclusion

We did not find any correlation between the amount of money a physician received for a drug and how often that physician prescribed the drug or the total costs of the drugs prescribed. We did find that those physicians who had financial ties to the industry, whether in the form of payments received, ownership in stocks, or payments as a research investigator on average had higher drug claims and drug costs compared to physicians that did not have these financial ties to the pharmaceutical industry.

It is important to note that no conclusion can be made regarding whether physicians are prescribing drugs appropriately or not. The appropriateness of a prescribed drug is based on individual patient factors. Since we do not have patient data, any conclusions on the appropriateness of prescriptions are beyond the scope of this project.