An Initial Exploration of Patterns of Variation in Healthcare Provider Reimbursement Rates from a Massive New Dataset

Jim Dewey and Susan LeFrancois
Florida Polytechnic University
4700 Research Way
Lakeland, Florida 33805
jdewey@floridapoly.edu, slefrancois@floridapoly.edu

Abstract

Health Plan Price Transparency rules that became effective January 1, 2022 require most group health plan insurers to disclose reimbursement rates negotiated between insurers and providers. Using a small subset of this massive new data source, we characterize patterns of variation in rates negotiated between a large health insurance company and healthcare providers for office visits in Florida. Rates vary with location, specialty, and practice size and, importantly, with complex interactions among these factors. Rates are higher for larger providers, consistent with larger providers having more market power. Patterns of differences in rates across plans offered by the insurer with respect to moderating factors such as per capita income differ between larger and smaller providers, consistent with larger providers using their market power to engage in various forms of price discrimination. Considerable variation in rates remains after accounting for these factors in a highly parameterized model, some of which may be due to uncontrolled variation in provider quality. Our exploratory findings demonstrate the potential for this massive new dataset to facilitate a deeper understanding of the workings of healthcare markets, improving the knowledge base for policies aimed at controlling costs or improving quality or access.

Keywords
Healthcare spending, negotiated rates, market mechanisms, price transparency and health equity.

1. Introduction
The challenge of delivering quality healthcare at an affordable price is an ongoing problem in the United States and has been for decades. The United States spends nearly twice as much per person on healthcare as comparable OECD (Organization for Economic Co-operation and Development) countries, and much of this is driven by higher prices paid by commercial health insurers (Cooper, 2019). The high and rising cost of commercial health care has led to premiums and deductibles for employer-sponsored coverage growing faster than wages and inflation. Commercial insurance pays higher prices than Medicare pays for comparable services and that gap is growing (CMS, 2019). According to the Congressional Budget Office (CBO), and based on studies published between 2010 and 2020, on average commercial insurers paid 129 percent of Medicare Fee-For-Service (FFS) prices for physician services.

Solutions to problems that are not fully understood have little chance of success. The body of research that has been produced regarding details of the economic mechanism at work in determining how much commercial insurers pay providers for specific sorts of procedures is limited because this information has traditionally been considered trade secret. Such detailed data, on a large scale, is required to understand how healthcare markets function and how large any inefficiencies are that contribute to rising costs. Indeed, until we understand the market mechanisms, we can't really define the problems at all.

A massive new dataset that is just becoming available promises to allow new light to be shed in this area. Congress, the Department of Health and Human Services (HHS), the Centers for Medicare & Medicaid Services (CMS), and several states have implemented laws and regulations related to price transparency and surprise billing in healthcare. The Hospital Price Transparency rule (45 C.F.R. Part 180) which became effective in December of 2020, after the resolution of litigation, requires all U.S. hospitals "to establish, update, and make public a list of the hospital's standard charges for items and services provided by the hospital." (45 C.F.R. § 180.10). Where one parent company operates multiple hospitals that have disparate pricing, "[e]ach hospital location operating under a single hospital license (or approval) ... must separately make public the standard charges applicable to that location." (45 C.F.R. §

180.50). Each hospital must "make public" their pricing data in two ways: "(a) A machine-readable file containing a list of all standard charges for all items and services as provided in § 180.50"; and "(b) A consumer-friendly list of standard charges for a limited set of shoppable services as provided in § 180.60." (45 C.F.R. § 180.40).

The Hospital Price Transparency rule was followed by the Health Plan Price Transparency rule (HPPTR) which became effective January 1, 2022. It requires most group health plan insurers to disclose pricing information inclusive of contracted "in-network" pricing negotiated between insurers and providers. The idea is to prevent abuse with cost to patients, end surprise billing, and to provide for a good faith cost estimate for those who self-pay or are uninsured. Together these transparency rules constitute the largest government required disclosure of private company price data in US history. This data has the potential to change how insurers and providers negotiate prices and how consumers shop for healthcare or insurance (Kona and Corlette, 2022 and Appleby, 2022).

While the data is to be provided in machine readable files with a specific format (https://www.cms.gov/healthplan-pricetransparency/resources), the sheer amount of data and the inconsistency between insurers in how data is delivered has made acquiring and analyzing this data very difficult. Arguably, this difficulty is by design given the reluctance of those with the data to share it. However, with the assistance of an industry partner, D1 Data Solutions, LLC, we have extracted a subset of data which focuses on the negotiated reimbursement rates by a large insurer in the state of Florida for six types of office visits across numerous specialties. Our objective is to explore the quality of this massive new dataset and its ability to facilitate a deeper understanding of the workings of healthcare markets, improving the knowledge base for policies aimed at controlling costs or improving quality or access.

We characterize patterns of variation in rates negotiated between this large insurer and healthcare providers (ie. Hospitals, physician groups). Rates vary with location, specialty, and practice size and, importantly, with complex interactions among these factors. Rates are higher for larger providers, consistent with larger providers having more market power. Patterns of differences in rates across plans offered by the insurer with respect to moderating factors such as per capita income differ between larger and smaller providers, consistent with larger providers using their market power to engage in various forms of price discrimination. Considerable variation in rates remains after accounting for these factors in a highly parameterized model, some of which may be due to uncontrolled variation in provider quality.

2. Literature Review

Commercial insurer prices vary considerably depending upon whether the service is in-patient or out-patient, the state, as well as the service provided. Prices paid by commercial insurance are largely dictated by market conditions, with providers commanding higher prices when they have more leverage in negotiations with commercial insurers (Cohen and Maeda, 2022). Provider consolidation has increased the number of markets where providers have the upper hand in these negotiations (Cutler and Morton, 2013; Fulton, 2017).

As compared to other countries the United States spending cannot be explained by the idea that the U.S. uses more healthcare services than peer countries, as the U.S. has been found to have lower rates of physician visits and days spent in the hospital than other nations. In addition, the belief that the U.S. has too many specialists and not enough primary care physicians and provides too much inpatient hospital care have been found to not have merit (Kurani and Cox, 2020).

The ability of employers and insurers to negotiate lower prices is limited because providers' market power is much greater than employers' in many markets. In addition, enrollees in employment-based plans tend to value having access to broad networks, so if the insurer threated to exclude a provider in their network this could backfire since certain providers may be essential to a network in a given area and large insurers or employers may have enrollees in many locations with diverse medical needs. This all makes narrow-network plans hard to implement (Einsenberg et al., 2021).

A 2022 CBO analysis determined that the magnitude of the price variation was much larger for commercial insurers than for Medicare FFS. This price variation varied by state, by metropolitan statistical area in the state, and by provider in the same metropolitan statistical area (MSA). For example, in Massachusetts the average price paid by a commercial insurer was 294% higher than the national average Medicare FFS price while in Arkansas it was 54% higher. As an example of within MSA variability, the price paid by commercial insurers for a vaginal delivery in the city of San Francisco in 2016 ranged from $11,098 to $23,880 with a median of $13,363 (Cohen and Maeda, 2022).

According to a Kaiser Family Foundation study in 2021, health care spending would decline by more than $350 billion in 2021, if commercial insurance reimbursed health care providers using Medicare rates. An argument is sometimes made that higher prices paid by commercial insurers are necessary due to the share of providers' patients who are covered by Medicare and Medicaid. However, the CBO found that providers do not raise the prices they negotiate with commercial insurers to offset lower prices paid by government programs (Cohen and Maeda, 2022). Any proposals to limit commercial insurance reimbursement would undoubtedly be met with opposition from health care providers, since it would decrease their revenue, however legislation at the federal or state level could limit the prices health care providers charge commercial insurers (Schwartz et al, 2021).

3. Data

We extracted a subset of the data made publicly available under the HPTR for one large insurer across the state of Florida, with the help of RefMed (https://refmed.com/). RefMed is one of Florida Polytechnic University's industry partners. They provide consulting services related to medical rate determinations and so have developed an early expertise in dealing with this new, massive, and opaque dataset. We focus initially on one large insurer in one large and diverse state to simplify the data exploration while ensuring our data represents a significant component of relevant healthcare markets.

The subset of data we extracted includes the following variables: current procedural terminology (CPT) code, primary taxonomy code, employer identification number (EIN), national provider identifier (NPI), county, plan, and the negotiated rate. These are used in turn to construct the variables used in our study, as discussed below. For clarity, when referring to a variable used in one of our estimated models, we capitalize and italicize it. For example, when referring generally to negotiated rates we write rate, but when referring to the dependent variable in our models we write *Rate*.

CPT codes, developed by the American Medical Association, identify medical services and procedures for billing and record keeping. We focus on six CPT codes corresponding to office visits of varying length and complexity for new and returning patients, as described in Table 1. This set of codes is useful in an initial exploration of the data since nearly all specialties conduct office visits. The categorical variable *CPT* captures the type of visit.

Table 1: CPT Codes for Office Visits Selected

CPT Code	**Patient Type**	**Length** (Minutes)	**Decision Complexity**
99202	New	15-29	Straightforward
99203	New	30-45	Low Level
99204	New	45-59	Moderate
99212	Established	10-19	Straightforward
99213	Established	20-29	Low Level
99214	Established	30-39	Moderate

Primary taxonomy, developed and maintained by the National Uniform Claim Committee, provides codes that designate a healthcare providers' classification and specialization in the data set (e.g., 363LP0200X is the code for Pediatric Nurse Practitioner). Hereinafter specialty refers to this classification generally and *Specialty* refers to the resulting categorical variable used in our analysis.

We refer to a group of providers working under a given EIN as a practice. Our categorical variable *Practice Size* is constructed by counting unique NPIs associated with each EIN and grouping them into these bins: 1, 2-49, 50-199, 200 and above. These bins were chosen after inspecting histograms of the number of providers in a practice for several reasons. First, sole practices may be qualitatively different than any other type, so represent their own category. Second, to keep the number of categories down to promote interpretability while also respecting the fact that very large systems are likely quite different from modest sized groups of practitioners, which may in turn be different than smaller groups. Third, to ensure a reasonably large group of practices and providers in each bin. Modest variations in the bin cutoffs, or increasing the number of bins to five, does not qualitatively change our findings provided attention is paid to the three concerns above in choosing bins.

As is common, the insurer selected provides multiple plans. Each plan represents networks of practices with providers of varying specialties available to the groups insured under that plan at the specified negotiated rates. *Plan* is a categorical variable indicating the plan. The basic unit of observation thus is formed by all unique combinations of *Plan*, *CPT*, *Practice*, and *Specialty*. Our dependent variable is the negotiated rate for each such observational unit, *Rate*.

While the raw data extract contained eight distinct plans, we retained only two for analysis. The process and reasoning behind doing so was as follows. First, within a given plan a single rate should be associated with each combination of CPT code, practice, and specialty, or for any combination of CPT code and individual provider. However, in the raw data there were often many. These additional rates appear to represent discounted rates corresponding to participation by some sets of providers and insured groups in the insurer's value-based care model. However, as of the time of this writing we have been unable to find a completely correct identifier for rates associated with such alternative arrangements. While those arrangements merit further study on their own once fully identified, they are beyond the scope of our current work. Therefore, we retain only the maximum rate for each combination of provider, CPT code, and plan, making and maintaining the assumption that this is the relevant rate outside of value based care models, as seems reasonable.

Having eliminated additional rates associated with value based care, we found that two plans had exactly the same providers and exactly the same rates, and so eliminated one of them, since the other adds nothing to our analysis. We also found one plan had only three associated practices, and so we eliminated it as well. Finally, the set of providers in the other five plans was nearly identical, and the correlation of rates across plans withing these providers was over 0.98. Thus, for purposes of exploring patterns of rate variation, these five plans are all but duplicates, and we eliminate four of them. Thus, we are left substantively with two plans relevant to our purpose.

We also drop observations associated with specialties too rare to support comparison across plans, practices, or locations. Specifically, we drop specialties that occur less than 50 times in the data or that occur in less than 15 of the 61 Florida counties reflected in the data.

Table 2 below provides relevant descriptive statistics by plan membership and practice size. To illustrate how to read the table, consider the panel associated with practices of 2-49 providers. From the total column, we see that there are 3,133 practices in this size range present in the data. Of those, 2,556 participate in plan 1 only, 519 participate in plan 2 only, and 58 participate in both plans. There are 18,040 providers in those practices, and the average number of specialties present in a practice is 2.6. The practices that participate in both plans comprise 620 providers, and the average such practice comprises 3.91 different specialties. The average rate for this practice size category is \$100.09, with a standard deviation of \$35.75. By comparison, the average rate of those practices in this size category that participate in plan 2 only is \$143.17 with a standard deviation of \$58.19. Broadly, we see that rates are higher for larger practices and that rates are higher in plan 2 than plan 1.

To aid in the exploration of the potential relationship between specialization and rates, we construct a binary categorical variable that divides observations according to the prevalence of the specialty, *Specialty Prevalence*. To construct it we calculate the number of providers in each specialty, calculate the median of this measure over all providers, and classify observations according to whether they are above or below the median.

In addition to characteristics of practices, such as practice size, and characteristics of providers, such as specialization, characteristics of location may influence rates. The categorical variable *County*, indicating the county in which the practice is located, is used to capture potential effects associated with location. We further obtain county level measures of per capita personal income and population from the U.S. Bureau of Economic Analysis. The categorical variable *PCI* divides counties into higher income counties (per capita incomes \$55,000 and up) and lower income counties (under \$55,000). Similarly, the categorical variable *Population* divides counties into those that are more populous (150,000 or more residents) and those that are less populous (under 150,000).

Table 2. Descriptive Statistics

Practice Size (Number of Providers)	**Statistic**	**Plan Participation** 1 Only	2 Only	1 and 2	Total
1	Number of Practices in Category	4,745	532	21	5,298
	Number of Providers in Category	4,745	532	21	5,298
	Average Number of Specialties	1.00	1.00	1.00	1.00
	Average Rate	102.05	125.04	76.56	104.26
	Standard Deviation of Rate	15.78	62.07	24.36	25.73
2-49	Number of Practices in Category	2,556	519	58	3,133
	Number of Providers in Category	13,765	3,655	620	18,040
	Average Number of Specialties	2.40	3.45	3.91	2.60
	Average Rate	91.53	143.17	92.12	100.09
	Standard Deviation of Rate	20.29	58.19	27.07	35.75
50-199	Number of Practices in Category	75	14	14	103
	Number of Providers in Category	6,596	1,050	1,427	9,073
	Average Number of Specialties	13.92	14.43	19.64	14.77
	Average Rate	101.70	158.08	173.86	119.17
	Standard Deviation of Rate	21.40	67.46	120.13	59.95
200+	Number of Practices in Category	18	5	17	40
	Number of Providers in Category	10,903	2,676	11,811	25,390
	Average Number of Specialties	29.72	24.60	49.18	37.35
	Average Rate	137.67	155.70	144.72	142.92
	Standard Deviation of Rate	64.41	17.96	36.16	49.12
Total	Number of Practices in Category	7,394	1,070	110	8,574
	Number of Providers in Category	36,009	7,913	13,879	57,801
	Average Number of Specialties	1.68	2.48	12.35	1.92
	Average Rate	98.50	134.41	107.69	103.10
	Standard Deviation of Rate	18.57	60.84	59.14	30.73

4. Analytical Methods

We estimate and interpret the results of four regression models to explore patterns of rate variation. The first three employ ordinary least squares regression using the natural logarithm of *Rate* as the dependent variable. There are two main advantages to using the natural log of *Rate* in this context. First, it respects the strictly positive nature of *Rate*. Second, it allows for factors associated with higher costs to have a proportional effect on rates, rather than a constant absolute effect, which seems more reasonable in this situation than having an additive effect. Since rates are negotiated between practices and the insurer, rates across CPT codes and specialties within practices are not independent. There is also little reason to expect residual variance to be constant across specialties, CPT codes, practices, or counties. Therefore, we employ robust standard errors clustered by *Practice* in all models.

The first model uses the categorical variables *CPT*, *Practice Size*, *Specialty*, and *County* as predictors, with no interaction effects. This model establishes that these factors are indeed strongly related to variation in rates. It cannot, however, shed light on questions such as, for example, whether the differences in rates negotiated by larger practices in different locations or for different specialties are different from the differences in rates negotiated by smaller practices. To get at such issues, the second model includes all two-way interactions other than interactions between *County* and *Specialty* as well as three-way interactions between *Plan*, *Practice Size*, and *Specialty* and between *Plan*, *Practice Size*, and *County*. Any interactions between *County* and *Specialty* are excluded because, with 61 counties and 90 specialties, the number of interactions makes the model intractable. Additional interactions with *CPT* are also excluded to keep the number of effects tractable. This model establishes that the interactions are statistically significant, however the interactions introduce a great deal of collinearity, meaning that while the model as a whole captures much of the variation in rates, and while the groups of interactions are individually significant statistically, it is not possible to ascribe much of the variation predicted by the model to particular interactions.

To reduce, at least to some extent, the collinearity between sets of interaction terms, the third model averages the rate across the six CPT codes before taking the natural log. While this cuts the number of observations to one sixth that in models one and two, it facilitates removing the two-way interactions with *CPT*. While the model precludes examining variation within practice and specialty across types of office visits, it provides a potentially more precise way to examine other interactions.

While models two and three are capable of establishing whether or not interactions among the factors examined are related significantly to variations in rates, it is difficult to find and interpret specific patterns due to the sheer number of factor levels involved. Model four thus replaces specialty with *Specialty Prevalence* and replaces *County* with *PCI* and *Population*. While these variables cannot capture the richness of the relationships underlying those in models two and three, this approach facilitates interpretability by allowing us to prepare plots to examine interactions that may be of particular interest.

To further interpretability, model four is estimated using Poisson regression, where the log of the rate function is a linear function of the included categorical variables. This, in turn, facilitates generating predicted rates with appropriate confidence intervals in untransformed dollars, rather than log dollars, easing interpretation. While Poisson regression was originally developed for count data, it produces unbiased estimates of the conditional expectation of non-negative response variables and appropriate inference provided robust standard errors are employed to accommodate over or under dispersion relative to the exponential distribution.

5. Results and Discussion

Table 3 presents the results of interest from Models 1-3. The top panel provides summary information concerning the performance of each model. The bottom panel presents results for individual factors and their various interactions. Specifically, the bottom panel presents partial sums of squares (or type III sums of squares) relative to the total sum of squares for the model. Thus, the bottom panel closely resembles the ANOVA tables for the regression models, however the independent sums of squares attributable to each factor or set of interactions is expressed relative to the total sum of squared variation to facilitate interpretation. Thus, these contributions sum to the model's R-Squared value. The last row of the table shows how much of the R-Squared value cannot be attributed to any set of factors or interactions—that is how much is captured by the collinear portion of the predictors and thus cannot be attributed to any specific factor or interaction.

From the summary information in the top panel, two things are of immediate note. First, the factors jointly account for considerable variation. Second, even accounting for location at the county level and for specialty, a great deal of variation in rates remains unaccounted for. Model 2 produces the lowest RMSE at 0.22. Letting one standard deviation up or down represent typical variation in rates from the value expected given the predictive factors used, this means it is typical for rates to fall from $e^{-0.22} \approx 0.8$ to $e^{0.22} \approx 1.25$ times the expected value. Accounting for this variation would require more detailed information, such as provider level information beyond specialty, for example quality indicators such as patient ratings or outcomes, or additional sub-county level location information, for example localized wage or rent information or neighborhood density and demographics.

Considering the results for specific factors for Model 1, we see that the nature of the visit captures a great deal of the variation in *Rate*. We also see that rates vary notably with both *Practice Size* and with *Specialty*. While rates vary statistically with location, location alone explains only a tiny fraction of rate variation. This, however, does not mean location plays no role, for two reasons. First, *County* may be too coarse a measure to pick up some effects. Second, location may be important only through its interactions with other factors.

Turning to the results for Model 2, while the factors are highly significant statistically, almost none of the predictive content of the model can be attributed to any particular factor or interaction. Indeed, of the R-Squared value of 0.8155, 0.7434 may be only jointly attributed to the 1,816 predictors due to collinearity. Thus, while we can say that the model as a whole predicts most of the variation in rates, and that the individual factors and interactions tend to be statistically significant, we can say little about the magnitude of the relationship between specific factors or interactions and rates. That is, Model 2 says virtually nothing about the practical significance of any of the factors or interactions included.

Model 3 attempts to get at the magnitude of the relationship between *Rate* and *Plan*, *Practice Size*, *Specialty*, and *County* by using the log of the average of *Rate* across all types of office visits as the dependent variable, rather than the Rate for each type of office visit. Focusing on the average rate across visit types means terms involving *CPT* are not needed, reducing the model degrees of freedom from 1,816 to 1,036 and thereby reducing collinearity among the predictor variables in the model.

Table 3. Results from Models 1-3

Model		1	2	3
Rates Averaged Over CPTs		No	No	Yes
Number of Observations		106,920	106,920	17,820
Model Degrees of Freedom		160	1816	1036
R-Squared		0.7625	0.8155	0.5064
RMSE		0.2504	0.2224	0.2249
Independent Contributions to R-Squared				
Source	Model df	Contribution [a]		
CPT	5	0.6289	0.0198	
Plan [b]	1	0.0494	0.0013	0.0036
Practice Size [b]	3	0.0219	0.0029	0.0089
Specialty	90	0.0427	0.0065	0.0154
County	61	0.0048	0.0034	0.0095
CPT X Plan	5		0.0000	
CPT X Practice Size	15		0.0002	
CPT X Specialty	450		0.0001	
CPT X County	305		0.0001	
Plan X Practice Size [b]	3		0.0040	0.0023
Plan X Specialty	89		0.0033	0.0073
Plan X County	51		0.0054	0.0109
Practice Size X Specialty	262		0.0147	0.0281
Practice Size X County	141		0.0086	0.0210
Plan X Practice Size X Specialty	227		0.0045	0.0123
Plan X Practice Size X County	108		0.0084	0.0236
Jointly Attributed		0.0147	0.7434	0.3635

[a] In almost all cases, the p-values for the null hypothesis that all levels of a factor or interaction are jointly zero are less than 0.001. Thus, nearly all of the results reported above are statistically significant at any conventional level. The few exceptions are described in note b.

[b] Plan and Practice Size are so highly correlated with their interaction that neither factor is statistically significant individually in either model 2 or 3 at any conventional level, while the interaction is significant at the 0.005 level in both cases. However, the p-value for the joint hypothesis that all effects of both factors and their interaction are zero is essentially 0 in both models.

Model 3 accounts for just over half of the variation in the log of the average rate. Unfortunately, most of that accounted for variation cannot be apportioned to individual sets of factors or interactions, with 0.3635 of the R-Squared value of 0.5064 unattributable to any specific factor or included interaction. However, enough is attributable to specific factors or interactions to draw some interesting conclusions. First, interactions of *County* with *Plan* and *Practice Size* account for over 5% of the variation in average rates, in addition to making some unmeasurable contribution to the unattributable but explained variation. Second, interactions of *County* with *Plan* and *Practice Size* account for just under 5% of the variation in average rates, in addition to making some unmeasurable contribution to the unattributable but explained variation.

The results of Model 3 suggest specialty and location seem to play a role in moderating the impact of *Practice Size* on differences in rates both within and across plans. This would occur if, for example, larger practices hold more market and bargaining power, and use it to bundle different levels of service in different plans at different prices as a form of second degree price discrimination to extract higher compensation in response to variation in demand and willingness to pay across locations and specialties.

While Model 3 sheds more light on the magnitudes of underlying relationships than Model 2, the specific nature of those relationships remains uninterpretable because most accounted for variation is still unattributable to specific factors or interactions and, more fundamentally, because a model with 1,036 model degrees of freedom, including 90 coefficients for *Specialty* and 61 for *County*, is too opaque for clear and direct interpretation. Model 4 simplifies, as discussed in the Methods section, by focusing on binary indicators for high and low county per capita income (*PCI*) and population (*Population*) and of whether a specialty is more or less common (*Specialty Prevalence*). The results are depicted in an easy to interpret manner in Figures 1-3, which show how expected (predicted) rates and their 95% confidence intervals vary for different levels of *Plan*, *Practice Size*, and those three additional variables in turn.

Focusing on Figure 1, three patterns are apparent. First, and as we saw in Table 2, rates are higher for larger practices regardless of the other factors. This is consistent with consolidation increasing market and negotiating power, leading to higher rates at the expense of the insured. However, competing explanations are possible. For example, the greater scale and scope of larger practices may enable them to offer higher quality, which might cost more and might also result in higher willingness to pay.

Second, rates are higher for plan 2 than plan 1. Without knowing more about the exact structure of the plans, for example deductibles and copayments and any other associated requirements for participating practices, it is difficult to make much of this. It could be due, for example, to higher quality providers being present in plan 2 compared to plan 1 due to some mundane unknown but innocuous selection mechanism, or it could be due to bundling different levels of service across different plans to extract more value through price discrimination enabled by the increased market power of larger practices.

Third, and perhaps most interesting, the pattern of variation between the high and low plans with variation in per capita incomes differs between larger and smaller practices. Differences in rates across income levels are negligible for small practices regardless of the plan, and for larger practices in plan 1. However, the difference between rates in higher and lower income counties is sizeable for plan 2 for larger practices. This is consistent with larger practices being able to engage in second degree price discrimination through bundling, thus extracting more value. An alternative explanation for this pattern is not readily apparent, but it might relate to variation in demand across income levels interacting with higher quality in larger practices due to larger scale and wider scope.

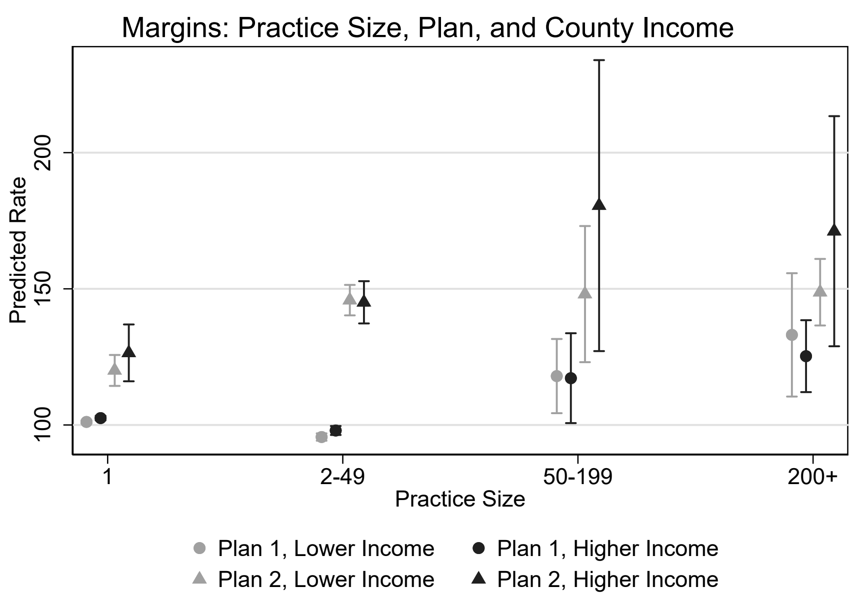

Figure 1. Expected Rates and the Interaction of Plan, Practice Size, and PCI.

Employing robust standard errors clustered by practice is crucial to getting the information conveyed in Figure 1 (and 2 and 3) right. Due to the large number of observations, owing to multiple specialties existing within practices, if standard errors are not clustered by practice the resulting confidence intervals are, incorrectly, very narrow, so that even tiny differences in expected rates appear to be estimated with extreme precision. Whereas, once the lack of independence of rates within a practice is accounted for, we see that while the differences in expected values are large enough to be of considerable practical importance, and while the patterns apparent in the interactions are of considerable interest, the differences are measured relatively imprecisely, and more work is needed to reach firmer conclusions and to confirm the findings herein.

Figure 2 is similar to Figure 1, the difference being that interactions with *Population*, rather than *PCI*, are depicted. Though somewhat less clear than in Figure 1, we can again see the tendency for rates to be higher in Plan 2 and for larger practices. We also see that differences in rates across plans associated with differences in county population tend to be larger for larger practices, suggesting there may be some subtle interaction at work. Beyond that, it is difficult to take any clear insight from the pattern of predicted rates. This binary variable may simply be too crude to capture much about underlying relationships, or to do so clearly. For example, population might reasonably be related to cost, in that very populous areas tend to have higher real estate and labor costs. However, very rural areas may have higher costs due to sparsity. On the other hand, more populous areas may have higher quality due to the density of services facilitated by higher population density, while more rural locations may result in lower quality due to sparsity. If all these factors are present, a single binary indictor will clearly be unable to capture all of them. By contrast, while they could have been captured by the full set of county indicators, clean and specific interpretation of those results along these lines is not possible.

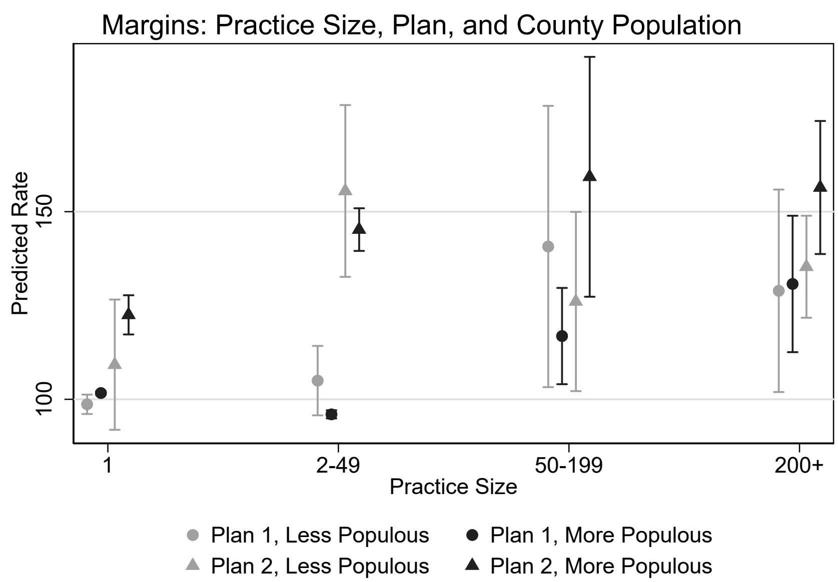

Figure 2. Expected Rates and the Interaction of Plan, Practice Size, and Population.

Finally, Figure 3 depicts interactions of *Practice Size*, *Plan*, and *Specialty Prevalence*. Again we see higher rates for larger practices and for plan 2. We also see that rates tend to be higher for less common specialties, which is not surprising. No notable interaction of *Specialty Prevalence* with the other factors is apparent.

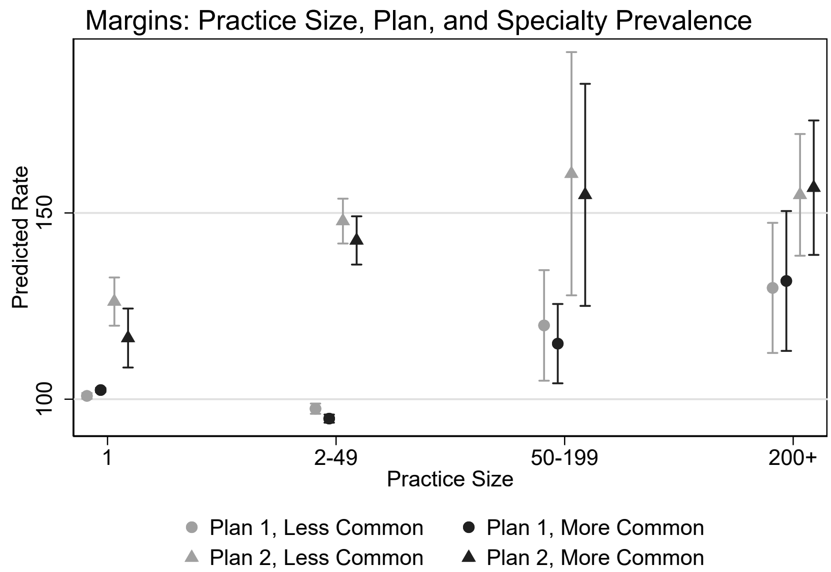

Figure 3: Expected Rates and the Interaction of Plan, Practice Size, and Specialty Prevalence

6. Conclusion

We utilized a limited extract of data from a rich and massive newly available dataset on rates negotiated between insurers and medical practices to explore patterns or variation in rates across counties, specialties, practice sizes, and different plans representing different insured groups and provider networks. We find larger practice sizes are associated with higher rates, at least for the insurer examined herein. Moreover, we find that both specialty and location moderate differences in rates associated with variation in practice size across plans. We also find that even after controlling for county, specialty, practice size, and plan, tremendous variation in rates around the conditional expectation remains.

There are many avenues for future work. We plan to pursue several of them in the future. First, we plan to expand the analysis to include more insurers and more states. Second, with the addition of extensive data from other insurers and other states, we should be able to conduct both analyses to confirm the patterns we found in this study and to further explore patterns of rate variations in response to other factors. Third, we plan to collect data on patient ratings of providers, provider outcomes, location specific measures of provider wages by specialty, and other such information in order to explain more of the variation in rates.

Fourth, additional work is needed to differentiate between different plausible explanations of the patterns found in this exploratory analysis. For example, are rates higher for larger practices because they are able to offer higher quality due to the scope and scale of their operations, and thus face higher demand, or because they have more bargaining power? Or, similarly, do differences between the ways rates in larger and smaller practices adjust with differences in per capita incomes across counties and across plans arise from using market power to engage in price discrimination to extract more value from patients, or from differences in demand across locations due in part to income?

The ability to exploit this new data source to provide rich characterizations of pricing patterns is promising. Moreover, this data may facilitate distinguishing between differing underlying causes of those patterns more rigorously, and with more generalizability, than has been possible in the past. Thus, continued analysis of this new dataset promises to greatly improve our understanding of healthcare markets and thereby our ability to design policies to control costs or improve outcomes, quality, and access.

References

Abelson, R. When Hospitals Merge to Save Money, Patients Often Pay More, New York Times, November 18, 2018, Sec. B. https://www.nytimes.com/2018/11/14/health/hospitalmergers-health-care-spending.html

Appleby, J. How much health insurers pay for almost everything is about to go public, Available: https://www.fiercehealthcare.com/payers/how-much-health-insurers-pay-almost-everything-about-go-public, July 1, 2022.

Beaulieu, N and Dafny, L. et al. Changes in Quality of Care after Hospital Mergers and Acquisitions. The New England Journal of Medicine. 382, no. 1, 51-59, 2020.

Centers for Medicare and Medicaid Services. 2019. National Health Expenditures 2018 Highlights. Washington, D.C.: Centers for Medicare and Medicaid Services. Available: https://www.cms.gov/files/document/highlights.pdf, Accessed on May 22, 2023.

Cohen, M. and Maeda, J. et al. Congressional Budget Office Report: The Prices That Commercial Health Insurers and Medicare Pay for Hospitals' and Physicians' Services, Available: https://www.cbo.gov/publication/57422, January 20, 2022.

Cooper, Z. High Prices Drive High Health Care Spending In The US, But So Too Do Other Factors: A Response To Anderson And Colleagues, Available: https://www.healthaffairs.org/content/forefront/high-prices-drive-high-health-care-spending-us-but-so-too-do-other-factors-response, January 14, 2019.

Cutler, D and Morton, F. Hospitals, Market Share, and Consolidation., JAMA, vol. 310, no. 18, 2013.

Einsenberg, M. and Meiselbach, M. Large Self-insured Employers Lack Power to Effectively Negotiate Hospital Prices. Am J Manag Care., 27, no. 7, 290-296, 2021.

Fulton, B. Health Care Market Concentration Trends in The United States: Evidence and Policy Responses, Health Affairs, 36, no. 9 ,1530–38, 2017.

Hospital Price Transparency, 45, C.F.R § 180 (2023).

Hospital Price Transparency, 45, C.F.R § 180.10 (2023).

Hospital Price Transparency, 45, C.F.R § 180.50 (2023).

Hospital Price Transparency,45, C.F.R § 180.40 (2023).

Hospital Price Transparency, 45, C.F.R § 180.60 (2023).

Kona, M. and Corlette, S. Hospital and Insurer Price Transparency Rules Now In Effect But Compliance Is Still Far Away. Available: https://www.healthaffairs.org/content/forefront/hospital-and-insurer-price-transparency-rules-now-effect-but-compliance-still-far-away , September, 2022.

Kurani, N. and Cox, C. What drives health spending in the U.S. compared to other countries. Available: https://www.healthsystemtracker.org/brief/what-drives-health-spending-in-the-u-s-compared-to-other-countries/#Healthcare%20spending%20per%20capita,%20by%20spending%20category,%202018, September 25, 2020.

Schwartz, K. and Biniek, J. et. al. Limiting Private Insurance Reimbursement to Medicare Rates Would Reduce Health Spending by About $350 Billion in 2021.Available: https://www.kff.org/medicare/issue-brief/limiting-private-insurance-reimbursement-to-medicare-rates-would-reduce-health-spending-by-about-350-billion-in-2021/, March 2021.

Transparency in Coverage. A Rule by the Internal Revenue Service, the Employee Benefits Security Administration, and the Health and Human Services Department on 11/12/2020. https://www.cms.gov/healthplan-price-transparency/resources

Acknowledgements

We acknowledge and thank Ahna Cecil and Isabel Morales for their contributions to this line of research through their senior capstone project. We also acknowledge and thank Todd McDaniel of RefMed for providing data and insights for this work and for supporting related student capstone projects.

Biographies

Jim Dewey is an assistant professor in the Department of Data Science and Business Analytics and Director of Economic Analysis at Florida Polytechnic University. He has a Ph.D. in Economics from the University of Florida. His Master's Degree is in Economics from the University of South Florida, where he also received his Bachelor's Degree with a double major in Economics and Political Science. His research interests are in the areas of applied microeconomics, policy analysis, education finance, labor economics, and urban and regional economics. He is a member of Regional Science Association International, the National Education Finance Academy, and Industrial Engineering and Operations Management Society International.

Susan LeFrancois is an assistant professor in the Department of Data Science and Business Analytics. She has a Ph.D. in Pharmacology and Physiology from the University of Florida. She also received her bachelor's degree in chemistry. Her research interests are in the areas of applied health equity, health policy, and maternal health. She is a member of the American Public Health Association.