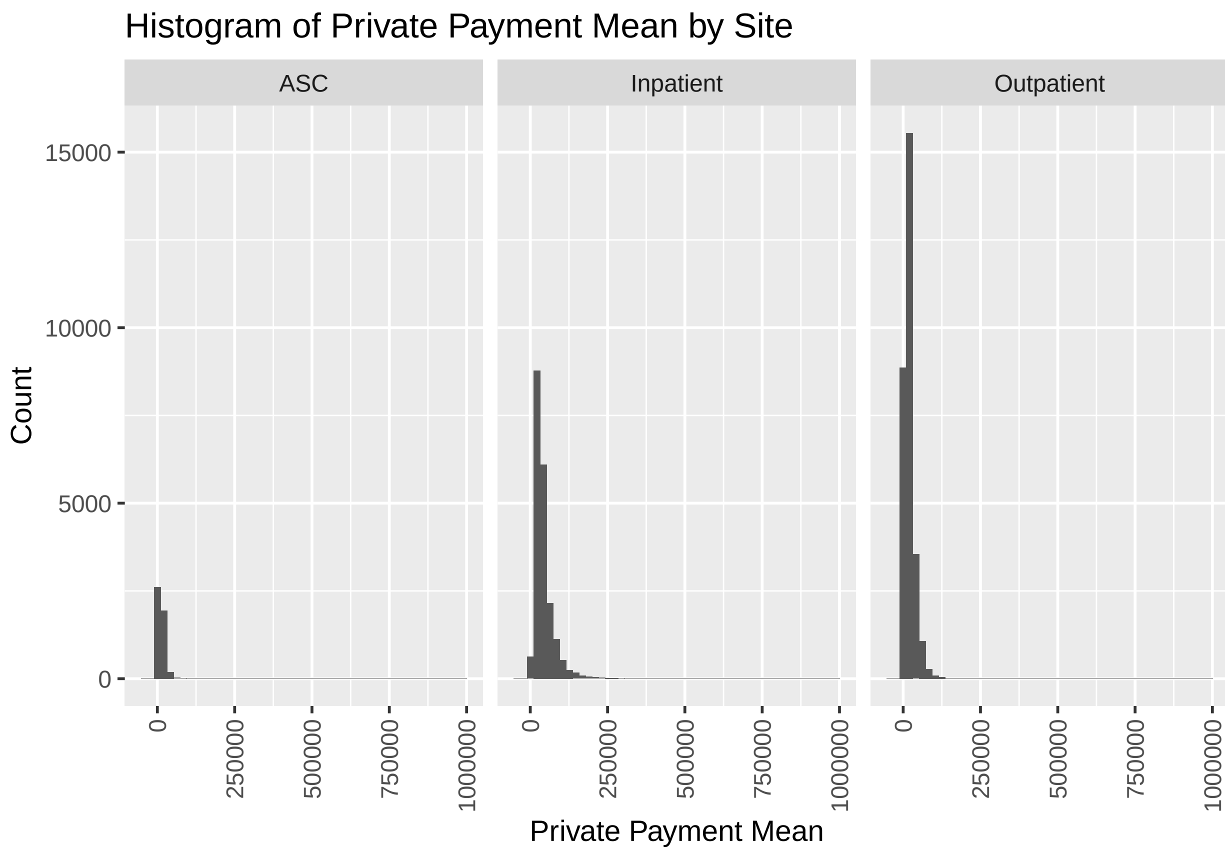
Capstone EDA

Exploratory Data Analysis

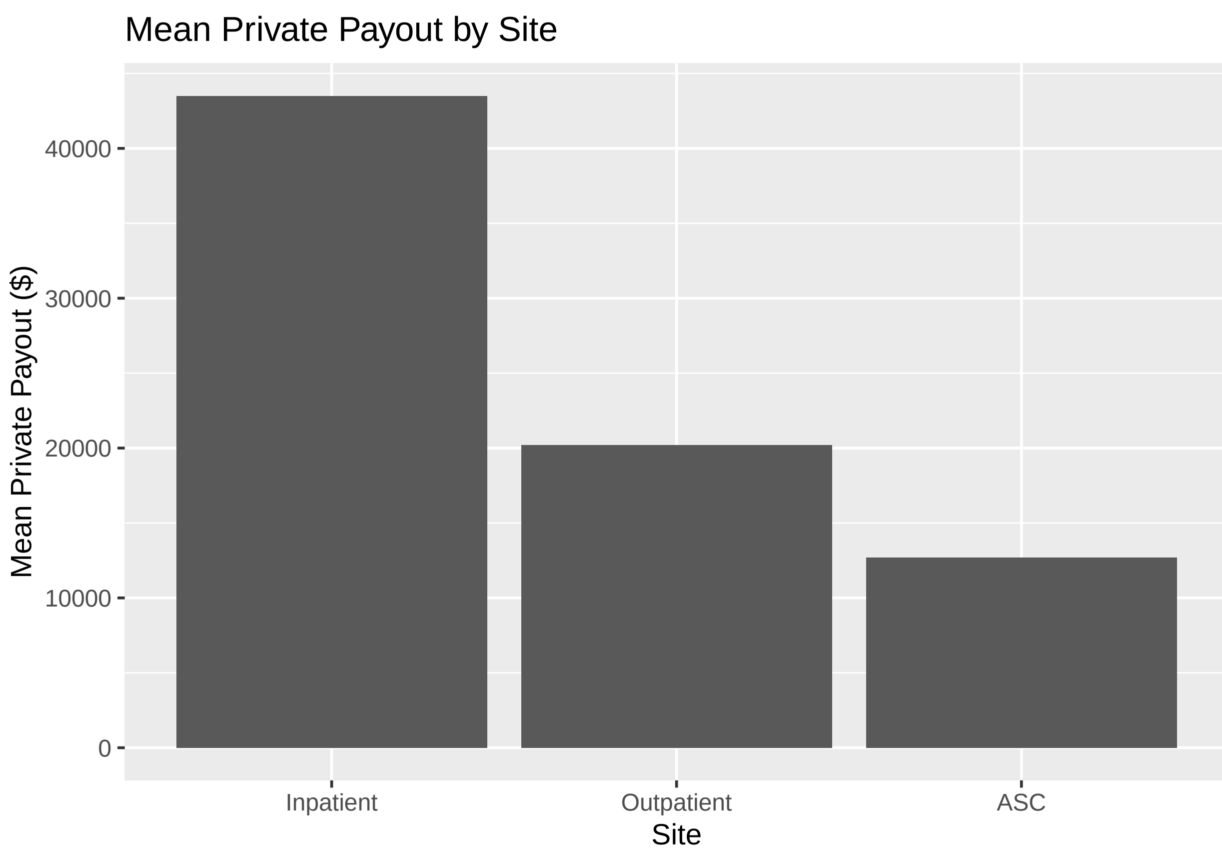
To start, we wanted to look at some of the features that were helpful in predicting `priv_pay_mean` in the original model done by JnJ. First, we wanted to see how `priv_pay_mean` varied by `site`. To do this, we created a histogram faceted by site as well as a table with summary statistics by site.



From the histogram, we can see that there is clearly a right-skew in the data regardless of site. This is unsurprising since some procedures can be very expensive which would result in higher `priv_pay_mean`, but there isn't going to be symmetry since there is not any procedure where `priv_pay_mean` will be very negative. These histograms also show us that ASC is the least common site used for surgery, and outpatient surgeries are more common than inpatient in our data. From the distribution of the three histograms, it looks like inpatient surgeries typically have the highest `priv_pay_mean`, followed by outpatient, then ASC being the cheapest. This is what we expected since inpatient surgeries involve the patient staying overnight which leads to `priv_pay_mean` being higher typically. It also makes sense that outpatient `priv_pay_mean` would be higher than ASC `priv_pay_mean` since outpatient surgeries happen at the hospital whereas ASC procedures are at a surgery center that is not a hospital. Outpatient surgery being part of a hospital-run facility leads to higher `priv_pay_mean` usually which is what we see in the data provided by Johnson and Johnson. The table reiterates some of the points mentioned above, and also looks at medicare payments by site. The same trends we saw with `priv_pay_mean` also exist with medicare payments in our data.

Table 1: Summary Statistics by Site

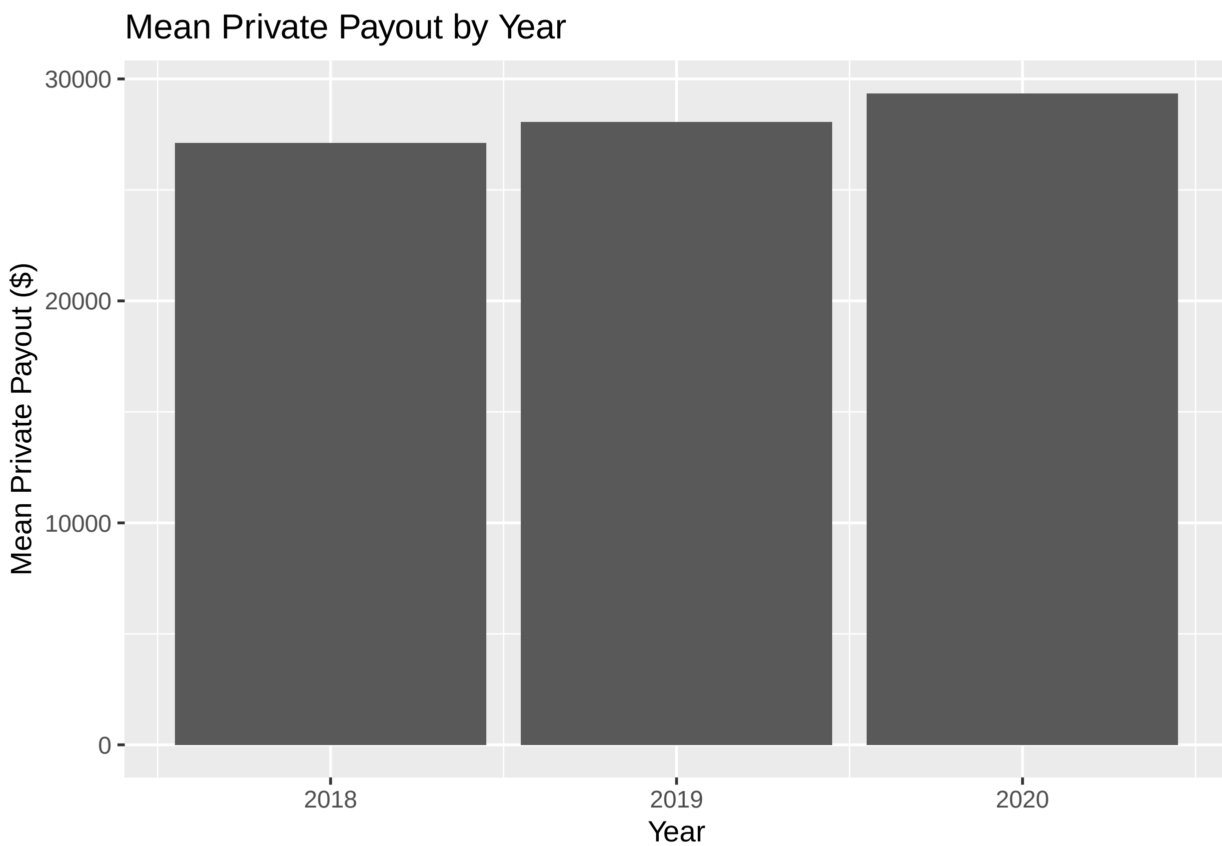
site	site_mean_priv_pay	site_median_priv_pay	site_mean_mcare_pay	site_median_mcare_pay	total_priv_count
Inpatient	43509.48	32910.476	20594.748	19342.245	212180
Outpatient	20213.08	15244.762	8124.497	8196.171	600142
ASC	12693.11	8920.038	5943.262	5678.334	113085



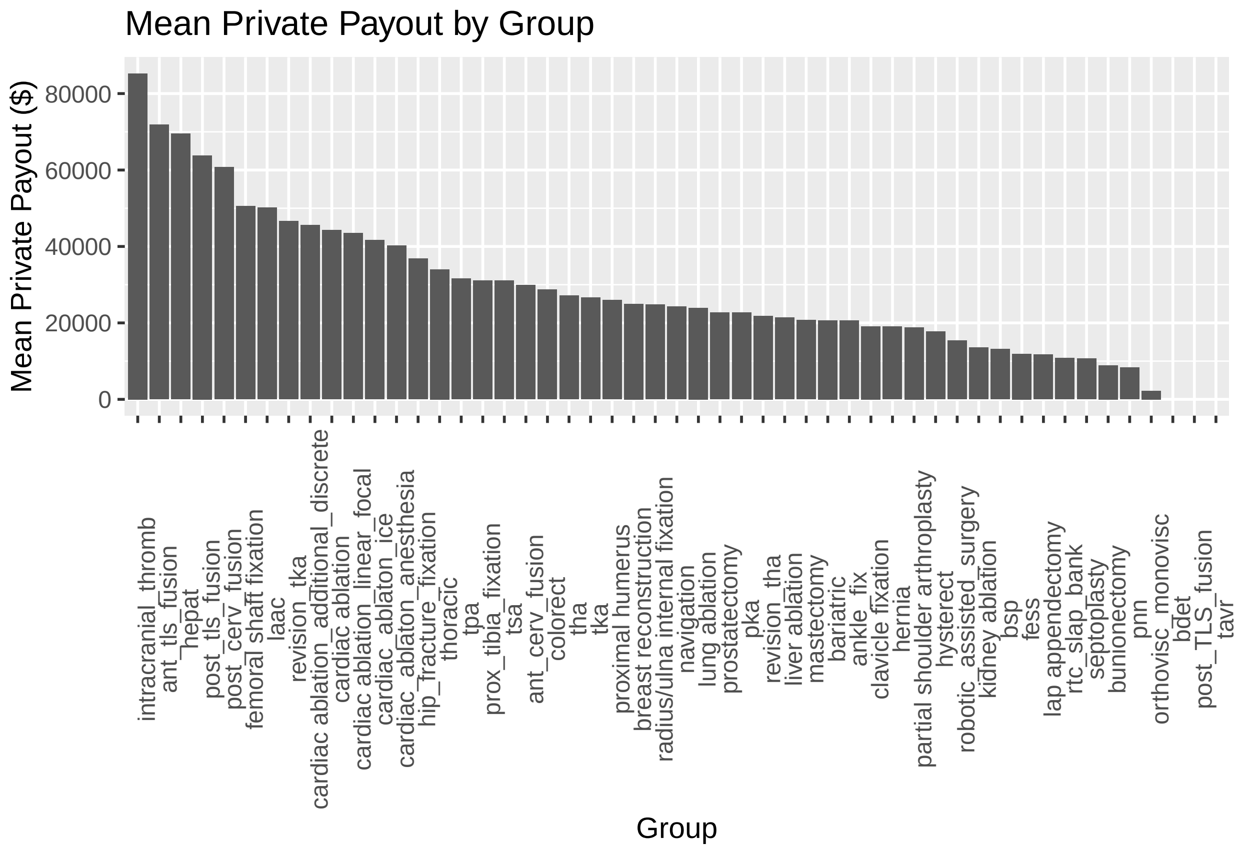
Next, we looked at variation in payment by year since the data included 2018-2020. We did not expect much to change from year-to-year, but did expect payments to increase slightly due to inflation. From the table, both private and medicare payments have increased slightly each year from 2018 to 2020. Another interesting thing to note is that `priv_count` decreased each year in the data. It seems logical that the number of procedures would have decreased in 2020 due to COVID, but it is not as clear why there was also a decrease from 2018 to 2019.

Table 2: Summary Statistics by Year

year	year_mean_priv_pay	year_median_priv_pay	year_mean_mcare_pay	year_median_mcare_pay	total_priv_count
2018	27121.98	20108.73	7422.005	7124.566	372001
2019	28065.65	20778.76	8034.075	7624.272	303315
2020	29353.92	21597.70	9009.511	8662.794	250091



We also wanted to look at how payment varied by group since different surgeries vary in cost, and thus also vary in payment. Looking at the table below, there are 51 different types of surgery in the data with `rtc_slap_bank` being the most common based on `priv_count`. There is large variation in average private payment by group with the lowest averaging just over $2200 and the highest averaging just over $85000.



Potential Dataset Expansion - Age and Sex Demographics Data

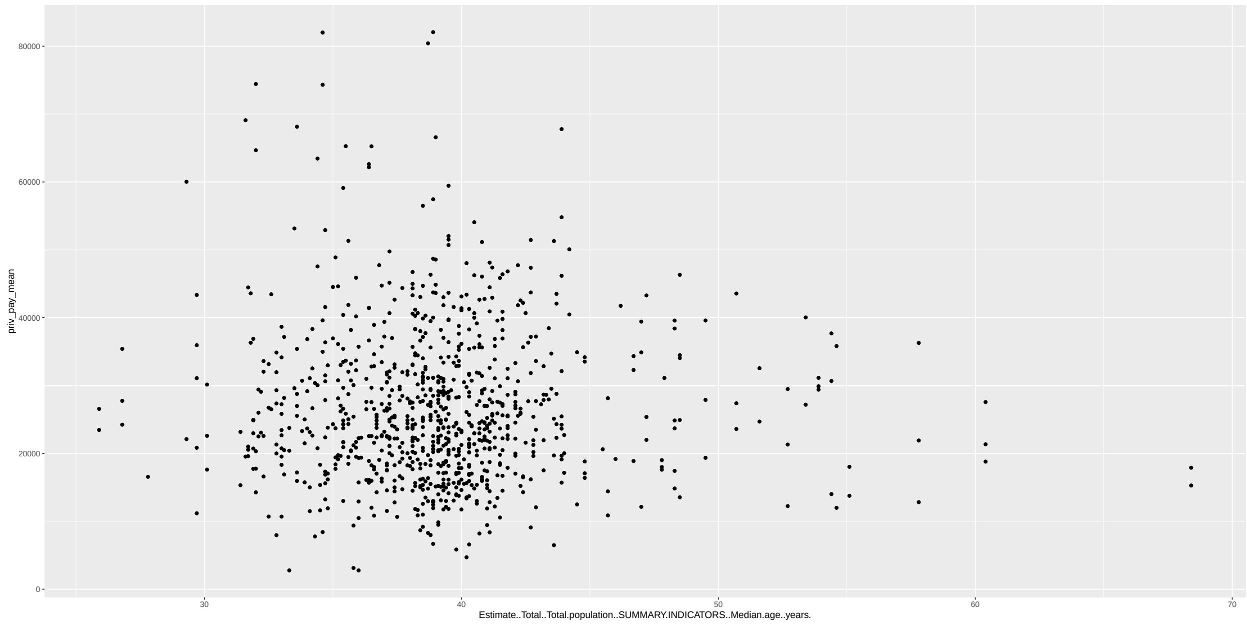
One area of interest to our analysis is how we can best leverage our data. Two facets of this are population age and sex demographic information, also obtained from the Census Bureau. We will look at the average private payment for tka in 2020, a group and year that is quite well-represented.

```
tka_2020_data <- data %>% filter(group == "tka" & year == 2020)
tka_2020_data <- inner_join(tka_2020_data, age_sex_data, by=c("CBSA_NAME" = "NAME"))
ggplot(data=tka_2020_data) +
  geom_point(aes(x=Estimate..Total..Total.population..SUMMARY.INDICATORS..Median.age..years., y=priv_pa
```

```
## Warning: Removed 238 rows containing missing values (geom_point).
```

Table 3: Summary Statistics by Group

group	group_mean_priv_pay	group_median_priv_pay	group_mean_mcare_pay	group_median_mcare_pay	total_priv_count
intracranial_thromb	85256.312	72161.250	28498.726	29088.644	796
ant_tls_fusion	71864.892	64185.967	33526.048	31884.588	3909
hepat	69549.109	48815.951	19438.154	13807.790	6410
post_tls_fusion	63839.024	62752.949	28729.442	27507.392	20888
post_cerv_fusion	60761.972	50711.060	25513.193	22493.884	2730
femoral shaft fixation	50588.634	37022.795	17719.976	16675.590	1567
laac	50207.853	44782.530	16317.891	16650.441	146
revision_tka	46656.752	40946.265	22408.088	21669.410	98
cardiac ablation_additional_discrete	45574.914	41532.000	21163.217	21450.404	5333
cardiac ablation	44266.388	40399.310	23746.398	23782.747	23744
cardiac ablation_linear_focal	43500.701	40288.448	21607.005	22109.825	3728
cardiac_ablaton_ice	41646.821	39375.380	21547.004	21933.067	14038
cardiac_ablaton_anesthesia	40226.110	37768.905	NaN	NaN	15332
hip_fracture_fixation	36859.235	30885.920	14561.084	13380.670	2445
thoracic	34022.736	30932.121	16826.731	15821.986	2320
tpa	31594.245	28119.810	15532.311	15108.532	2935
prox_tibia_fixation	31096.575	23470.170	13691.182	13046.771	4535
tsa	31091.793	29814.190	13306.561	13410.252	4826
ant_cerv_fusion	29904.385	26432.139	8480.087	8406.347	20451
colorect	28721.916	26574.884	17147.491	13830.769	21918
tha	27134.456	25793.878	14221.365	13652.864	39153
tka	26614.780	24857.907	9446.357	9504.127	55269
proximal humerus	25954.878	20024.944	14294.652	14186.412	3685
breast reconstruction	25001.692	20152.958	9293.869	9088.802	44591
radius/ulna internal fixation	24837.718	15228.101	10828.827	10351.535	15199
navigation	24247.969	22244.785	12400.528	12507.221	2334
lung ablation	23964.086	12037.610	10337.743	10351.706	92
prostatectomy	22747.804	21186.280	10027.186	10165.426	6343
pka	22674.411	20295.217	7941.219	7925.798	4896
revision_tha	21874.463	14179.720	14275.400	14193.668	964
liver ablation	21409.303	13505.900	11073.294	10855.424	597
mastectomy	20712.359	16999.277	6491.671	6674.743	37944
bariatric	20662.184	20422.877	16733.906	15336.532	41239
ankle_fix	20643.949	13717.686	5297.749	4001.100	26522
clavicle fixation	19100.965	13152.759	8634.423	8531.798	3352
hernia	19041.905	13463.575	10425.533	9139.392	24508
partial shoulder arthroplasty	18856.347	13005.200	12063.691	12391.246	1535
hysterect	17714.882	15970.557	9144.329	9294.473	90028
robotic_assisted_surgery	15385.740	13266.420	5304.823	5211.536	21961
kidney ablation	13575.053	11565.220	7563.422	7323.914	241
bsp	13202.974	11962.593	4886.031	4844.942	2399
fess	11938.086	10989.062	4223.115	4372.276	84719
lap appendectomy	11710.227	10834.927	4454.832	4459.976	34408
rtc_slap_bank	10788.735	9346.225	5568.469	5606.205	173520
septoplasty	10659.454	9721.611	3716.994	3829.554	24149
bunionectomy	8894.394	7057.646	2405.460	2362.119	25376
pnn	8340.173	6239.980	2481.660	2481.660	946
orthovisc_monovisc	2235.463	1391.926	732.236	858.645	1288
bdet	NaN	NA	NaN	NaN	0
post_TLS_fusion	NaN	NA	6283.426	6277.896	0
tavr	NaN	NA	1724.636	1674.128	0

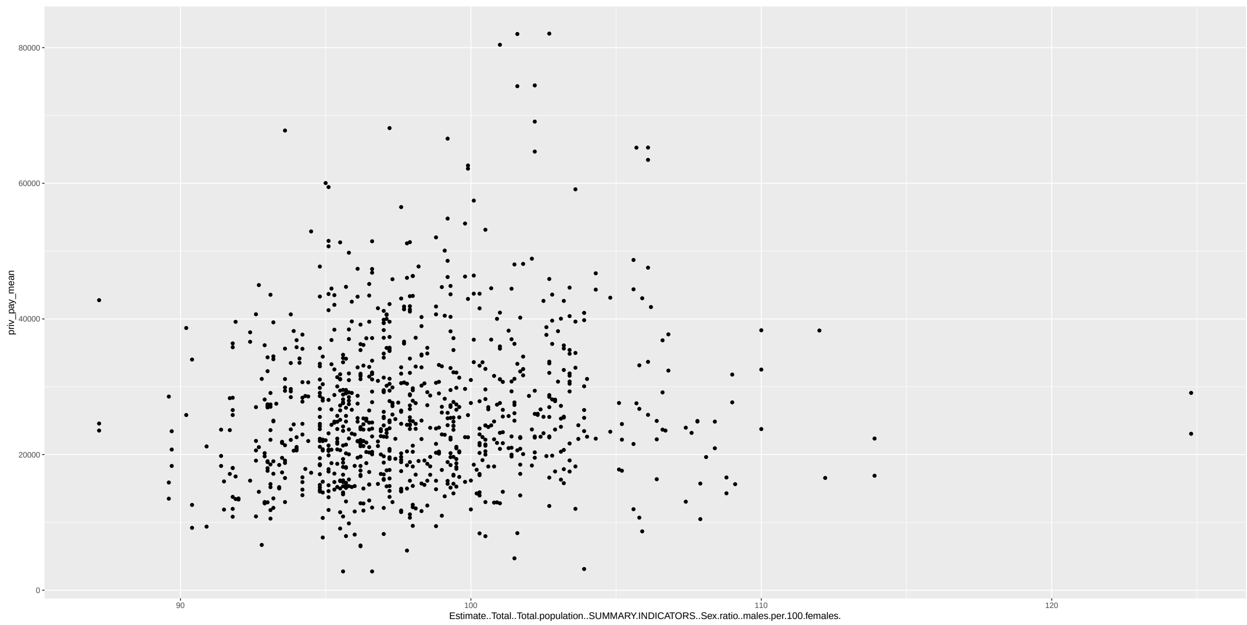



```
cor(x=tka_2020_data$Estimate..Total..Total.population..SUMMARY.INDICATORS..Median.age..years., y=tka_202
```

```
## [1] -0.03859502
```

```
ggplot(data=tka_2020_data) +
  geom_point(aes(x=Estimate..Total..Total.population..SUMMARY.INDICATORS..Sex.ratio..males.per.100.femal
```

```
## Warning: Removed 238 rows containing missing values (geom_point).
```



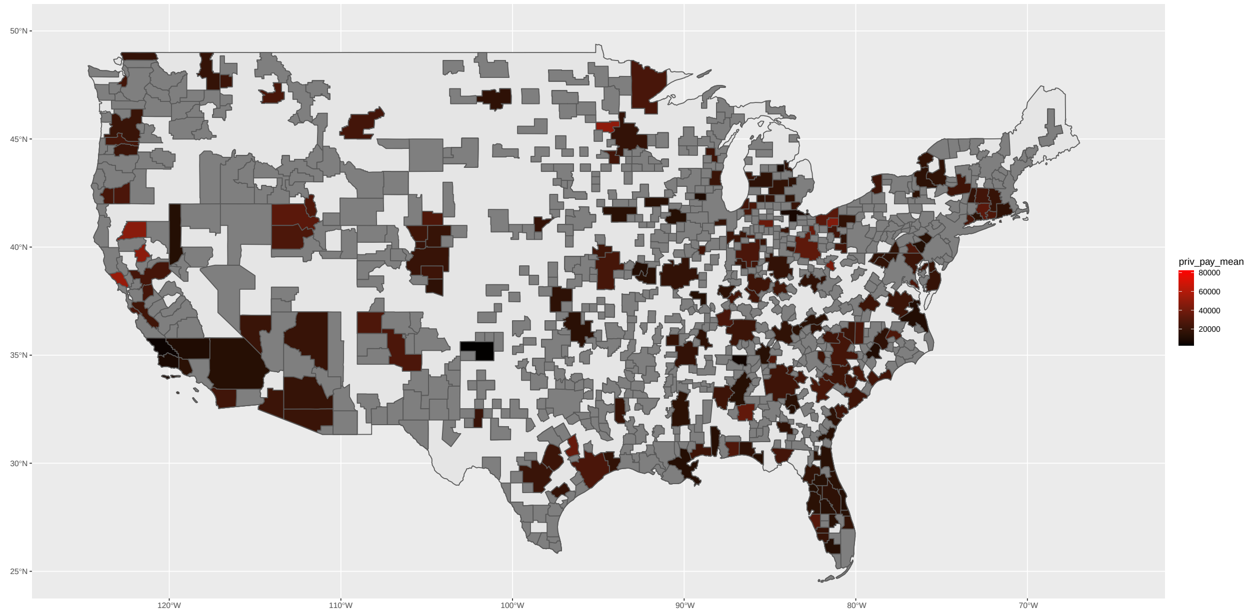

```
cor(x=tka_2020_data$Estimate..Total..Total.population..SUMMARY.INDICATORS..Sex.ratio..males.per.100.fema
```

```
## [1] 0.133202
```

Looking at geographic regions

Does geography seem to have an impact on insurance payouts? Let's take a look. First, we will look at the average private payment for tka in 2020, a group and year that is quite well-represented.

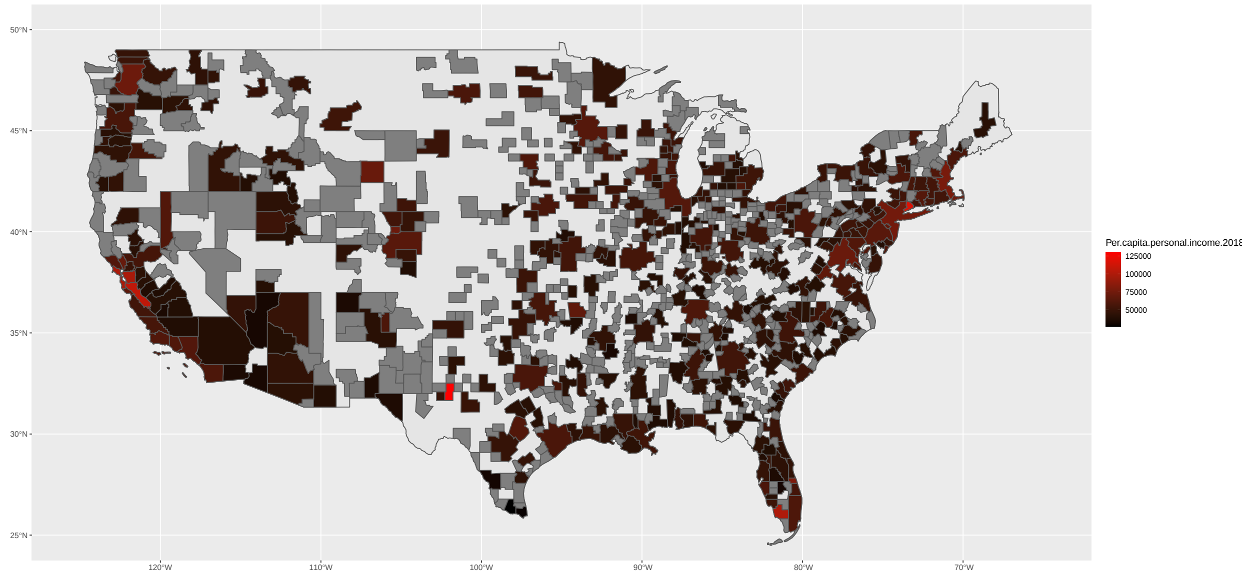
```
msa_geo <- read_sf("./shapefiles_cbsa", "cb_2021_us_cbsa_20m")
us_geo <- read_sf("./shapefiles_nation", "cb_2021_us_nation_20m")
msa_geo$GEOID = as.integer(msa_geo$GEOID)
tka_2020_data <- data %>% filter(group == "tka" & year == 2020)
tka_2020_data <- full_join(tka_2020_data, msa_geo, by=c("msa" = "GEOID"))
ggplot(data=tka_2020_data) +
  geom_sf(data=us_geo,aes(geometry=geometry)) +
  geom_sf(aes(fill=priv_pay_mean,geometry=geometry)) +
  scale_fill_gradient(low="black", high="red") +
  coord_sf(xlim=c(-125,-65),ylim = c(25,50))
```



There does not appear to be any immediately obvious geographical trend, though it should be noted that certain geographical areas (such as Florida and Southern California) tend to have somewhat lower payments. Some large metropolitan areas on the West Coast appear to show evidence of higher insurance payouts, but gaps in data make interpretation difficult.

Let us try visualizing per capita income across CBSAs:

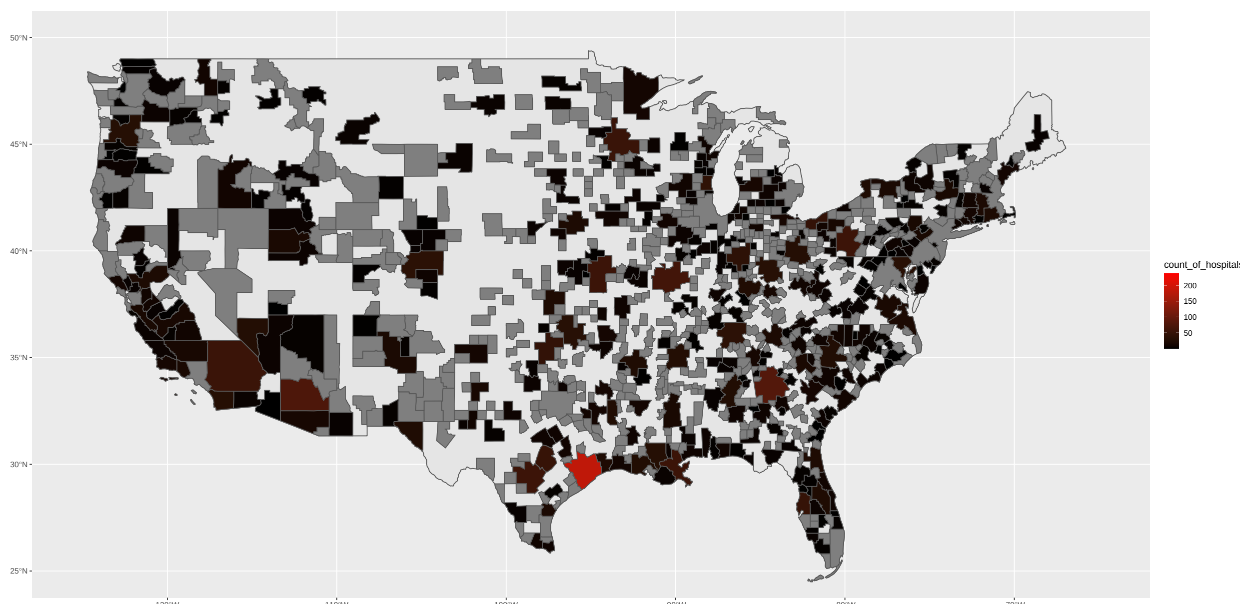
```
per_capita_income_data <- read.csv("MSAs income per capita (csv).csv")
per_capita_income_data$Per.capita.personal.income.2018 = as.integer(per_capita_income_data$Per.capita.pe
per_capita_income_data <- full_join(per_capita_income_data, msa_geo, by=c("ï..Metropolitan.Statistical.A
ggplot(data=per_capita_income_data) +
  geom_sf(data=us_geo,aes(geometry=geometry)) +
  geom_sf(aes(fill=Per.capita.personal.income.2018,geometry=geometry)) +
  scale_fill_gradient(low="black", high="red") +
  coord_sf(xlim=c(-125,-65),ylim = c(25,50))
```



This map is more complete, showing all CBSAs. One key observation that can be made is that many of the CBSAs with low private insurance payouts (focus on Florida and Southern California) also appear to be associated with lower per capita income levels. Interestingly, those CBSAs with exceptionally higher than average income levels (Ex: Midland, TX in bright red) do not have corresponding higher insurance payouts.

Lastly, we will take a look at the number of hospitals present in each CBSA.

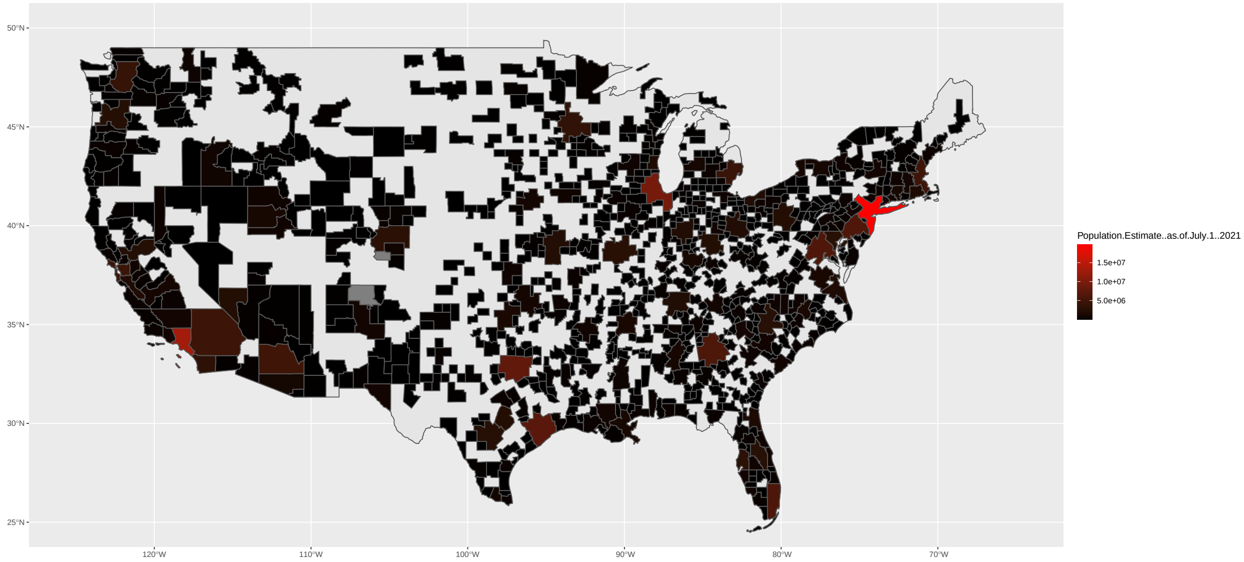
```
hospital_w_geo <- hospital_data %>% group_by(CBSA_CD) %>% count(name="count_of_hospitals")
hospital_w_geo <- full_join(hospital_w_geo, msa_geo, by=c("CBSA_CD" = "GEOID"))
ggplot(data=hospital_w_geo) +
  geom_sf(data=us_geo,aes(geometry=geometry)) +
  geom_sf(aes(fill=count_of_hospitals,geometry=geometry)) +
  scale_fill_gradient(low="black", high="red") +
  coord_sf(xlim=c(-125,-65),ylim = c(25,50))
```



In this map, we see an issue. CBSAs are not necessarily uniform in size, either in terms of population or area. We observe that many of the CBSAs with larger numbers of hospitals are the CBSAs which are largest geographically.

Let's look at a 2021 population view before updating this visual to reflect per capita hospital numbers.

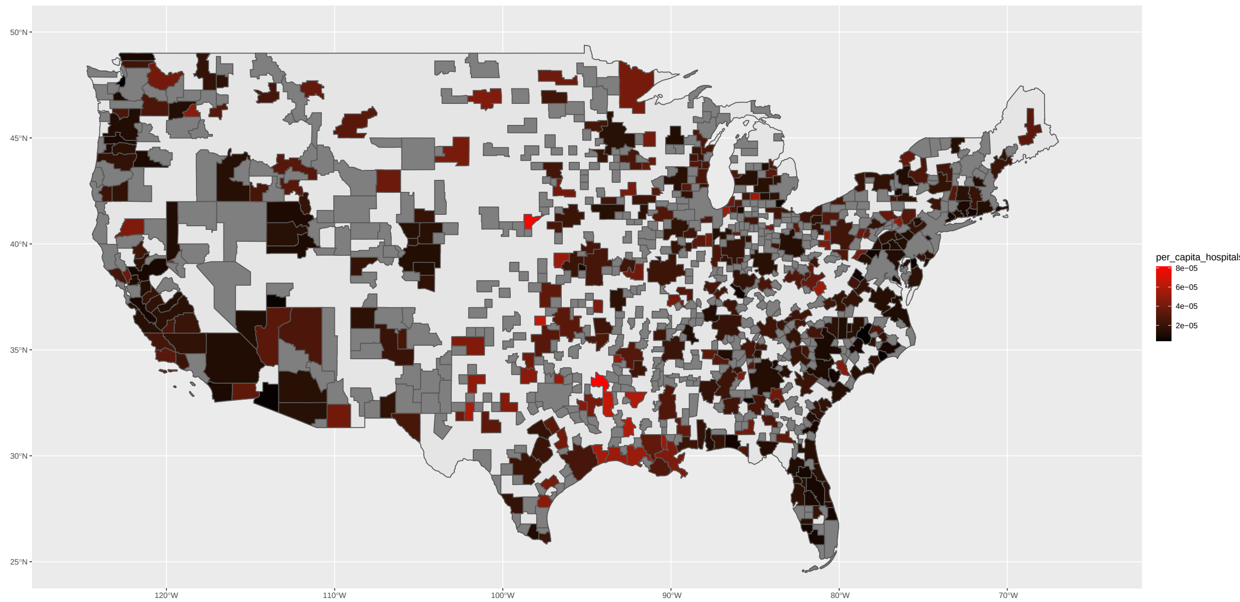
```
population_data$Population.Estimate..as.of.July.1..2021 = as.integer(population_data$Population.Estimate
pop_w_geo <- full_join(population_data, hospital_w_geo, by=c("ï..Geographic.Area" = "NAME"))
ggplot(data=pop_w_geo) +
  geom_sf(data=us_geo,aes(geometry=geometry)) +
  geom_sf(aes(fill=Population.Estimate..as.of.July.1..2021,geometry=geometry)) +
  scale_fill_gradient(low="black", high="red") +
  coord_sf(xlim=c(-125,-65),ylim = c(25,50))
```



With this view, we can also see that the larger MSAs observed before tend also to have larger populations, though there are some smaller MSAs where this does not hold (Ex: NYC area).

We now look at hospitals per capita:

```
pop_w_geo <- full_join(population_data, hospital_w_geo, by=c("ï..Geographic.Area" = "NAME"))
pop_w_geo$per_capita_hospitals = pop_w_geo$count_of_hospitals / pop_w_geo$Population.Estimate..as.of.Jul
ggplot(data=pop_w_geo) +
  geom_sf(data=us_geo,aes(geometry=geometry)) +
  geom_sf(aes(fill=per_capita_hospitals,geometry=geometry)) +
  scale_fill_gradient(low="black", high="red") +
  coord_sf(xlim=c(-125,-65),ylim = c(25,50))
```



We observe some previously unobserved patterns in the Midwest, which exhibits some elevated hospital counts, per capita. Notably, the some areas of Southern California and Florida show low numbers of hospitals per capita. Whether or not this is related to our observed insurance payment patterns remains to be seen.