## novis-i-hwk2-2

February 18, 2025

ECON 470 Hwk2-2

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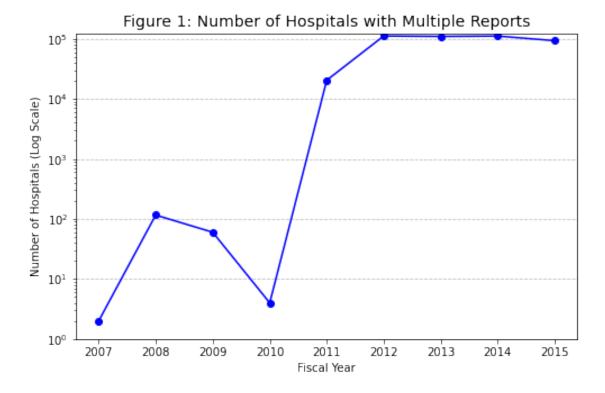
**Date:** 2/19/2025

GitHub Repository

#### Question 1:

How many hospitals filed more than one report in the same year? Show your answer as a line graph of the number of hospitals over time.

Number of distinct providers: 6731

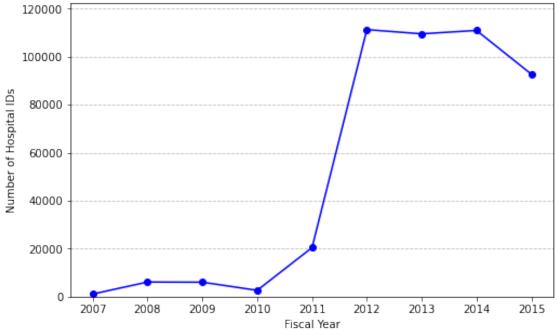


### Question 2:

After removing/combining multiple reports, how many unique hospital IDs (Medicare provider numbers) exist in the data?

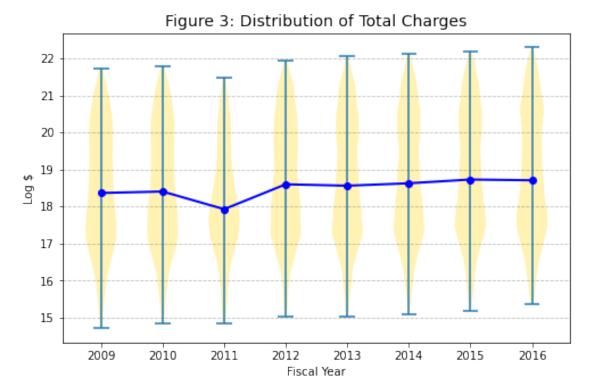
	fy_year	hosp_count
0	2007	1116
1	2008	6116
2	2009	6041
3	2010	2656
4	2011	20459
5	2012	111296
6	2013	109552
7	2014	110966
8	2015	92751



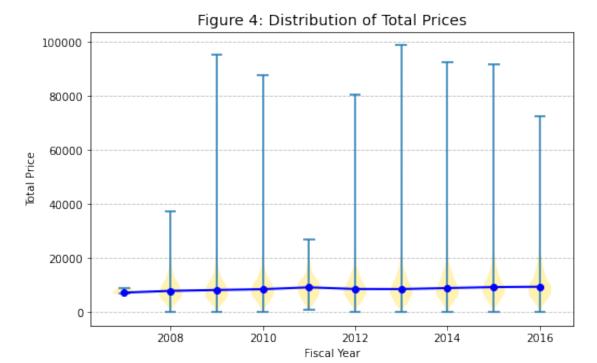


### Question 3:

What is the distribution of total charges (tot\_charges in the data) in each year? Show your results with a "violin" plot, with charges on the y-axis and years on the x-axis.



# Question 4: What is the distribution of estimated prices in each year?



### Question 5:

Calculate the average price among penalized versus non-penalized hospitals.

penalty

False 10200.321640 True 9748.015414

Name: price, dtype: float64

### Question 6:

Split hospitals into quartiles based on bed size. Provide a table of the average price among treated/control groups for each quartile.

Table: Average Price by Treatment Status for Each Bed Size Quartile

	Control	(No Penalty)	Treated	(Penalty)
Bed Quartile				
1		15254.11		26868.59
2		9263.94		9223.96
3		9019.22		8423.95
4		11414.75		10904.63

## Question 7:

Use different estimators to calculate ATE.

Q7.A: Nearest Neighbor Matching (Inverse Variance)

Nearest Neighbor Matching ATE: 28791.02

## Q7.B: Nearest Neighbor Matching using Mahalanobis Distance

Nearest Neighbor Matching (Mahalanobis) ATE: 24298.26

## Q7.C: Propesntiy Score Matching and Weighting

Mean Price (Treated): 23033.46 Mean Price (Control): 9989.76

ATE (IPW): 13043.69

#### Q7.D: Simple Regression for ATE Estimation

provider_number	int64
fy_start	datetime64[ns]
fy_end	datetime64[ns]
date_processed	object
date_created	object
beds	float64
tot_charges	float64
tot_discounts	float64
tot_operating_exp	float64
ip_charges	float64
icu_charges	float64
ancillary_charges	float64
tot_discharges	float64
mcare_discharges	float64
mcaid_discharges	float64
tot_mcare_payment	float64
secondary_mcare_payment	float64
street	object
city	object
state	object
zip	object
county	object
hvbp_payment	float64
hrrp_payment	float64
year	int64
source	object
fy_year	int64
discount_factor	float64
<pre>price_num</pre>	float64
<pre>price_denom</pre>	float64
price	float64
penalty	bool
bed_quart	int64
dtype: object	

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#### ValueError

Traceback (most recent call last)

/Users/ilsenovis/Documents/GitHub/ECON470HW2/submission2/results/novis-i-hwk2-2 ipynb Cell 36 line <cell line: 54>()

<a href='vscode-notebook-cell:/Users/ilsenovis/Documents/GitHub/ECON470HW2
submission2/results/novis-i-hwk2-2.ipynb#X56sZmlsZQ%3D%3D?line=50'>51</a> X =
sm.add\_constant(X)

```
---> <a href='vscode-notebook-cell:/Users/ilsenovis/Documents/GitHub/ECON470HW2
  →submission2/results/novis-i-hwk2-2.ipynb#X56sZmlsZQ%3D%3D?line=53'>54</a>
  →reg_model = sm.OLS(y, X).fit()
      <a href='vscode-notebook-cell:/Users/ilsenovis/Documents/GitHub/ECON470HW2</pre>
  osubmission2/results/novis-i-hwk2-2.ipynb#X56sZmlsZQ%3D%3D?line=55'>56</a> #∪
  →Display results
      <a href='vscode-notebook-cell:/Users/ilsenovis/Documents/GitHub/ECON470HW2</pre>
  →submission2/results/novis-i-hwk2-2.ipynb#X56sZmlsZQ%3D%3D?line=56'>57</a>
  →print(reg_model.summary())
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/regression/
  olinear model.py:890, in OLS. init (self, endog, exog, missing, hasconst,
  →**kwargs)
             msg = ("Weights are not supported in OLS and will be ignored"
     887
     888
                    "An exception will be raised in the next version.")
     889
             warnings.warn(msg, ValueWarning)
 --> 890 super(OLS, self).__init__(endog, exog, missing=missing,
                                   hasconst=hasconst, **kwargs)
     892 if "weights" in self. init keys:
             self._init_keys.remove("weights")
     893
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/regression/
  ⇔linear model.py:717, in WLS. __init__(self, endog, exog, weights, missing, __
  ⇔hasconst, **kwargs)
     715 else:
             weights = weights.squeeze()
 --> 717 super(WLS, self).__init__(endog, exog, missing=missing,
                                   weights=weights, hasconst=hasconst, **kwargs)
     719 nobs = self.exog.shape[0]
     720 weights = self.weights
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/regression/
  →linear_model.py:191, in RegressionModel.__init__(self, endog, exog, **kwargs)
     190 def __init__(self, endog, exog, **kwargs):
             super(RegressionModel, self).__init__(endog, exog, **kwargs)
 --> 191
             self._data_attr.extend(['pinv_wexog', 'wendog', 'wexog', 'weights']
     192
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/base/model.py:267,
  →in LikelihoodModel.__init__(self, endog, exog, **kwargs)
     266 def __init__(self, endog, exog=None, **kwargs):
 --> 267
             super().__init__(endog, exog, **kwargs)
             self.initialize()
     268
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/base/model.py:92,
  →in Model.__init__(self, endog, exog, **kwargs)
     90 missing = kwargs.pop('missing', 'none')
     91 hasconst = kwargs.pop('hasconst', None)
 ---> 92 self.data = self._handle_data(endog, exog, missing, hasconst,
     93
                                       **kwargs)
```

```
94 self.k_constant = self.data.k_constant
    95 self.exog = self.data.exog
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/base/model.py:132,
 →in Model. handle data(self, endog, exog, missing, hasconst, **kwargs)
   131 def _handle_data(self, endog, exog, missing, hasconst, **kwargs):
--> 132
           data = handle data(endog, exog, missing, hasconst, **kwargs)
           # kwargs arrays could have changed, easier to just attach here
   133
   134
           for key in kwargs:
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/base/data.py:673,u
 exog = np.asarray(exog)
   672 klass = handle_data_class_factory(endog, exog)
--> 673 return klass(endog, exog=exog, missing=missing, hasconst=hasconst,
   674
                   **kwargs)
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/base/data.py:82, i:
 →ModelData.__init__(self, endog, exog, missing, hasconst, **kwargs)
           self.orig endog = endog
    80
           self.orig exog = exog
    81
           self.endog, self.exog = self. convert endog exog(endog, exog)
---> 82
    84 self.const_idx = None
    85 self.k_constant = 0
File ~/opt/anaconda3/lib/python3.9/site-packages/statsmodels/base/data.py:507,u
 505 exog = exog if exog is None else np.asarray(exog)
   506 if endog.dtype == object or exog is not None and exog.dtype == object:
--> 507
           raise ValueError("Pandas data cast to numpy dtype of object. "
                           "Check input data with np.asarray(data).")
   508
   509 return super(PandasData, self)._convert_endog_exog(endog, exog)
ValueError: Pandas data cast to numpy dtype of object. Check input data with np
 ⇔asarray(data).
```

## ${\it Question~7:}$ Final Summary Table

	Estimator	ATE Estimator
0	Nearest Neighbor Matching	28791.021695
1	Mahalanobis Distance Matching	24298.260886
2	Inverse Propensity Weighting	13043.694639

#### Question 8:

With these different treatment effect estimators, are the results similar, identical, very different?

The results from the different treatment effect estimators vary significantly. Nearest Neighbor Matching produced the highest estimate at 28,791, while Mahalanobis Distance Matching yielded a slightly lower estimate of 24,298. Inverse Propensity Weighting, however, resulted in a much lower estimate of 13,043.

These differences arise because each estimator makes different assumptions and applies different methodologies:

- Nearest Neighbor Matching: pairs treated and control units based on similarity in key covariates, which can reduce bias but is sensitive to how matches are selected.
- *Mahalanobis Distance Matching*: accounts for *correlations* between covariates, potentially making it more robust, which could explain why its estimate is lower than simple nearest neighbor matching.
- Inverse Propensity Weighting (IPW): adjusts for differences in the probability of treatment, effectively reweighting observations to approximate a randomized experiment. The lower estimate suggests that after adjusting for observed covariates, the estimated treatment effect is smaller.

The fact that IPW produced a much lower estimate indicates that selection into treatment might be influenced by observable factors, and adjusting for those reduces the estimated effect.

#### Question 9:

Do you think you've estimated a causal effect of the penalty? Why or why not? (just a couple of sentences)

While techniques like propensity score weighting and matching help reduce selection bias, they only account for observed confounders. If there are unobserved factors influencing both the penalty and hospital prices (e.g., hospital quality, patient mix), the estimates may still be biased. Without a truly randomized experiment or strong instrumental variable, we cannot definitively claim a causal relationship.

#### Question 10:

Briefly describe your experience working with these data (just a few sentences). Tell me one thing you learned and one thing that really aggravated or surprised you.

One thing that really aggravated me was that the datasets didn't download correctly so it took a while to actually clean/fix the data before I could merge it into the final dataset. One thing that suprised me was the large difference in the charges from the hospitals versus the actual prices