Hospital Readmissions Data Analysis and Recommendations for Reduction

Background

In October 2012, the US government's Center for Medicare and Medicaid Services (CMS) began reducing Medicare payments for Inpatient Prospective Payment System hospitals with excess readmissions. Excess readmissions are measured by a ratio, by dividing a hospital's number of "predicted" 30-day readmissions for heart attack, heart failure, and pneumonia by the number that would be "expected," based on an average hospital with similar patients. A ratio greater than 1 indicates excess readmissions.

Exercise Directions

In this exercise, you will:

- critique a preliminary analysis of readmissions data and recommendations (provided below) for reducing the readmissions rate
- construct a statistically sound analysis and make recommendations of your own

More instructions provided below. Include your work **in this notebook and submit to your Github account**.

Resources

- Data source: https://data.medicare.gov/Hospital-Compare/Hospital-Readmission-Reduction/9n3s-kdb3 (https://data.medicare.gov/Hospital-Compare/Hospital-Readmission-Reduction/9n3s-kdb3)
- More information: http://www.cms.gov/Medicare/medicare-fee-for-service-payment/acuteinpatientPPS/readmissions-reduction-program.html (http://www.cms.gov/Medicare/medicare-fee-for-service-payment/acuteinpatientPPS/readmissions-reduction-program.html)
- Markdown syntax: http://nestacms.com/docs/creating-content/markdown-cheat-sheet (http://nestacms.com/docs/creating-content/markdown-cheat-sheet)

In [199]:

```
%matplotlib inline

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import bokeh.plotting as bkp
from mpl_toolkits.axes_grid1 import make_axes_locatable
from scipy import stats
%matplotlib inline
```

In [200]:
```
# read in readmissions data provided
hospital_read_df = pd.read_csv('data/cms_hospital_readmissions.csv')
```

Preliminary Analysis

In [61]:
```
# deal with missing and inconvenient portions of data
clean_hospital_read_df = hospital_read_df[hospital_read_df['Number of D
clean_hospital_read_df.loc[:, 'Number of Discharges'] = clean_hospital_r
clean_hospital_read_df = clean_hospital_read_df.sort_values('Number of I
```

```
/anaconda/lib/python3.6/site-packages/pandas/core/indexing.py:517: Settin
gWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-doc
s/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.or
g/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
  self.obj[item] = s
```

In [290]:
```
clean_hospital_read_df.head(5)
```

Out[290]:

	Hospital Name	Provider Number	State	Measure Name	Number of Discharges	Footnote	Excess Readmission Ratio	Predicted Readmission Rate	Rea
16857	THREE RIVERS MEDICAL CENTER	180128	KY	READM-30-HIP-KNEE-HRRP	0	7.0	NaN	NaN	
14582	SELLS INDIAN HEALTH SERVICE HOSPITAL	30074	AZ	READM-30-COPD-HRRP	0	7.0	NaN	NaN	
15606	PHS INDIAN HOSPITAL AT PINE RIDGE	430081	SD	READM-30-AMI-HRRP	0	7.0	NaN	NaN	
15615	FLORIDA STATE HOSPITAL UNIT 31 MED	100298	FL	READM-30-COPD-HRRP	0	7.0	NaN	NaN	
14551	GREENE COUNTY HOSPITAL	10051	AL	READM-30-AMI-HRRP	0	7.0	NaN	NaN	

In [278]:

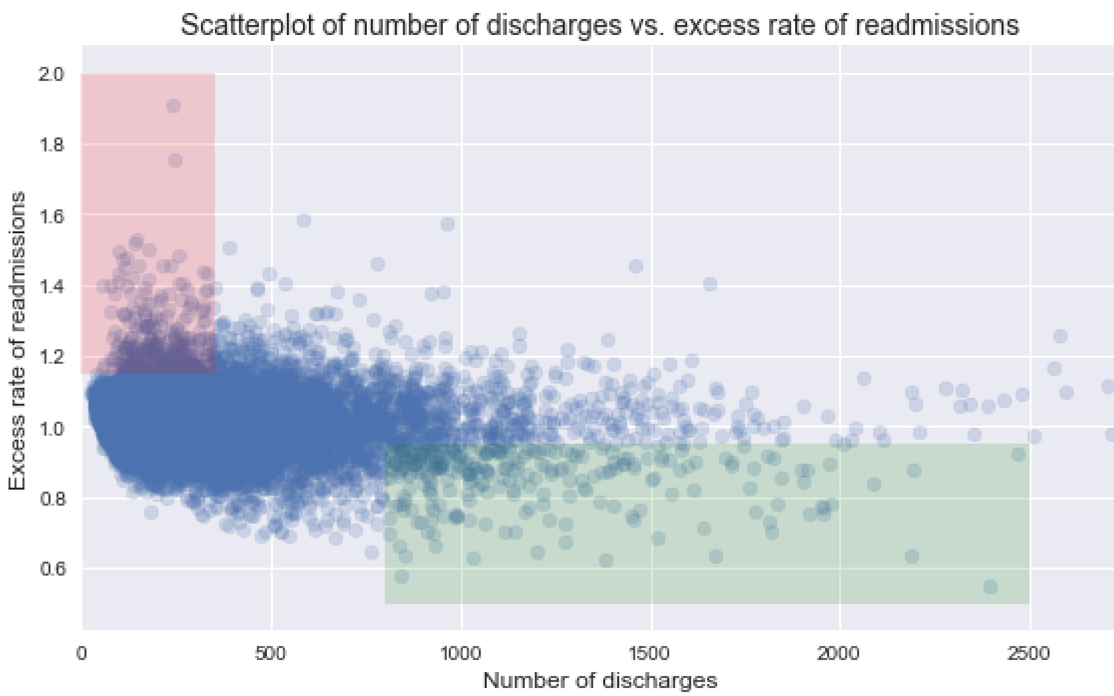
```
# generate a scatterplot for number of discharges vs. excess rate of rea
# lists work better with matplotlib scatterplot function
x = [a for a in clean_hospital_read_df['Number of Discharges'][81:-3]]
y = list(clean_hospital_read_df['Excess Readmission Ratio'][81:-3])

# Scatterplot: # Discharges vs Excess Readmission Ratio
fig, ax = plt.subplots(figsize=(8,5))
ax.scatter(x, y,alpha=0.2)

# POINTOUT areas
ax.fill_between([0,350], 1.15, 2, facecolor='red', alpha = .15, interpol
ax.fill_between([800,2500], .5, .95, facecolor='green', alpha = .15, int

# MINOR labels
ax.set_xlim([0, max(x)])
ax.set_xlabel('Number of discharges', fontsize=12)
ax.set_ylabel('Excess rate of readmissions', fontsize=12)
ax.set_title('Scatterplot of number of discharges vs. excess rate of rea

# MINOR extras
ax.grid(True)
fig.tight_layout()
```



Preliminary Report

Read the following results/report. While you are reading it, think about if the conclusions are correct, incorrect, misleading or unfounded. Think about what you would change or what additional analyses you would perform.

A. Initial observations based on the plot above

- Overall, rate of readmissions is trending down with increasing number of discharges (*hard to say, need to look into this and move forward with this issue. It is remaining constant.*)
- With lower number of discharges, there is a greater incidence of excess rate of readmissions (area shaded red) - small
- With higher number of discharges, there is a greater incidence of lower rates of readmissions (area shaded green) - small

B. Statistics

- In hospitals/facilities with number of discharges < 100, mean excess readmission rate is 1.023 and 63% have excess readmission rate greater than 1
- In hospitals/facilities with number of discharges > 1000, mean excess readmission rate is 0.978 and 44% have excess readmission rate greater than 1

C. Conclusions

- There is a significant correlation between hospital capacity (number of discharges) and readmission rates.
- Smaller hospitals/facilities may be lacking necessary resources to ensure quality care and prevent complications that lead to readmissions.

D. Regulatory policy recommendations

- Hospitals/facilties with small capacity (< 300) should be required to demonstrate upgraded resource allocation for quality care to continue operation.
- Directives and incentives should be provided for consolidation of hospitals and facilities to have a smaller number of them with higher capacity and number of discharges.

Exercise

Include your work on the following **in this notebook and submit to your Github account**.

A. Do you agree with the above analysis and recommendations? Why or why not?

B. Provide support for your arguments and your own recommendations with a statistically sound analysis:

1. Setup an appropriate hypothesis test.
2. Compute and report the observed significance value (or p-value).
3. Report statistical significance for α = .01.
4. Discuss statistical significance and practical significance. Do they differ here? How does this change your recommendation to the client?
5. Look at the scatterplot above.
   - What are the advantages and disadvantages of using this plot to convey information?
   - Construct another plot that conveys the same information in a more direct manner.

You can compose in notebook cells using Markdown:

- In the control panel at the top, choose Cell > Cell Type > Markdown

- Markdown syntax: http://nestacms.com/docs/creating-content/markdown-cheat-sheet (http://nestacms.com/docs/creating-content/markdown-cheat-sheet)

Thoughts and Reflections

Overall, the preliminary analysis looks weak.

1. Vague about downward trend.
2. Visualization problems are frustrating (they don't communicate the trends).
3. More statistics would be needed including correlations coefficient and linear regression!
4. No significant correlation highlighted in the graph!
5. All the following stats don't support the following conclusions and recommendations. It is a red flag!
6. No indication between small and large hospitals.
7. No consistency in terminology (i.e. hospital capacity = # discharges)

In short, this was a 'BS' graph, designed to fit the person's recommendations (common). With **11,578** observations, a bulk lies around an excess readmissions rate of **0.75 - 1.35** within 1,250 discharges. It is worth exploring this. And notice that the graph does have a couple of outliers.

So, this exercise has our work cut off for us.

Strategy

This will focus on creating a hypothesis test for (a) linear regression and (b) correlation.

- H_0: Significant correlation between # discharges and excess re-admission rate.
- H_a: No significant correlation between # discharges and excess re-admission rate.

To do this, let's clean the data removing any null readmission rates. Afterwards, let's modify the graph to show its better significance followed by a story of what occurred and whether this recommendation is acceptable.

Setup

In [134]:
```
# set a new data frame that has # readmissions as a value
clean_hos_df=clean_hospital_read_df[clean_hospital_read_df['Excess Readr
clean_hos_df_low = clean_hos_df[clean_hos_df['Number of Discharges'] <=
clean_hos_df_high = clean_hos_df[clean_hos_df['Number of Discharges'] >=
clean_hos_df.shape
```

Out[134]:
```
(11497, 12)
```

In [135]:

```
clean_hos_df_mid = clean_hos_df[(clean_hos_df['Number of Discharges'] >
clean_hos_df_mid
```

Out[135]:

	Hospital Name	Provider Number	State	Measure Name	Number of Discharges	Footnote	Excess Readmission Ratio	Predicted Readmission Rate
5092	ENNIS REGIONAL MEDICAL CENTER	450833	TX	READM-30-COPD-HRRP	101	NaN	1.0232	22.0
6788	SCOTTSDALE HEALTHCARE-THOMPSON PEAK HOSPITAL	30123	AZ	READM-30-COPD-HRRP	101	NaN	0.9982	19.9
4351	BROOKDALE HOSPITAL MEDICAL CENTER	330233	NY	READM-30-PN-HRRP	101	NaN	1.0354	20.6
2837	BROOKS MEMORIAL HOSPITAL	330229	NY	READM-30-HF-HRRP	101	NaN	1.0649	24.0

Simple Data Analysis

In [136]:

```
clean_hos_df.describe()
```

Out[136]:

	Provider Number	Number of Discharges	Footnote	Excess Readmission Ratio	Predicted Readmission Rate	Expected Readmission Rate	Numb Readmiss
count	11497.000000	11497.000000	0.0	11497.000000	11497.000000	11497.000000	11497.00
mean	257571.540141	365.466209	NaN	1.007504	17.984292	17.865695	63.63
std	154274.374018	308.754590	NaN	0.091964	5.487651	5.240749	59.54
min	10001.000000	25.000000	NaN	0.549500	2.700000	3.900000	11.00
25%	110129.000000	160.000000	NaN	0.952600	16.300000	16.600000	24.00
50%	250042.000000	282.000000	NaN	1.003500	19.000000	19.000000	45.00
75%	390039.000000	474.000000	NaN	1.058100	21.500000	21.400000	82.00
max	670082.000000	6793.000000	NaN	1.909500	32.800000	28.000000	879.00

In [137]:
```
clean_hos_df[clean_hos_df['Excess Readmission Ratio'] >= 1.0].describe()
```

Out[137]:

	Provider Number	Number of Discharges	Footnote	Excess Readmission Ratio	Predicted Readmission Rate	Expected Readmission Rate	Number Readmissio
count	5950.000000	5950.000000	0.0	5950.000000	5950.000000	5950.000000	5950.0000
mean	254612.042689	350.481681	NaN	1.072958	19.134437	17.954017	70.5099
std	149330.070483	294.146368	NaN	0.068870	5.684807	5.377508	65.3345
min	10001.000000	25.000000	NaN	1.000000	4.400000	4.000000	11.0000
25%	110186.000000	151.000000	NaN	1.025600	17.600000	16.800000	27.0000
50%	250034.000000	269.000000	NaN	1.056000	20.300000	19.100000	51.0000
75%	370056.750000	460.000000	NaN	1.097700	22.800000	21.500000	92.0000
max	670082.000000	3570.000000	NaN	1.909500	32.800000	28.000000	879.0000

In [154]:
```
clean_hos_df_mid['Excess Readmission Ratio'].describe()
```

Out[154]:
```
count    9810.000000
mean        1.007065
std         0.093517
min         0.574800
25%         0.948900
50%         1.001400
75%         1.059675
max         1.909500
Name: Excess Readmission Ratio, dtype: float64
```

In [139]:
```
len(clean_hos_df_mid[clean_hos_df_mid['Excess Readmission Ratio'] >= 1.0])
```

Out[139]: 0.50723751274209994

In [140]:
```
clean_hos_df_low['Excess Readmission Ratio'].describe()
```

Out[140]:
```
count    1223.000000
mean        1.022088
std         0.058154
min         0.893500
25%         0.983800
50%         1.016700
75%         1.052750
max         1.495300
Name: Excess Readmission Ratio, dtype: float64
```

In [203]:
```
len(clean_hos_df_low[clean_hos_df_low['Excess Readmission Ratio'] >= 1.(
```

Out[203]: 0.62796402289452169

In [204]:
```
clean_hos_df_low['Excess Readmission Ratio'].count()/clean_hos_df['Exces
```

Out[204]: 0.10637557623727929

In [205]:
```
clean_hos_df_high['Excess Readmission Ratio'].describe()
```

Out[205]:
```
count    464.000000
mean       0.978334
std        0.119878
min        0.549500
25%        0.908050
50%        0.986000
75%        1.057100
max        1.454300
Name: Excess Readmission Ratio, dtype: float64
```

In [144]:
```
len(clean_hos_df_high[clean_hos_df_high['Excess Readmission Ratio'] >= 1
```

Out[144]:
```
0.44396551724137934
```

In [145]:
```
clean_hos_df_high['Excess Readmission Ratio'].count()/clean_hos_df['Exce
```

Out[145]:
```
0.040358354353309561
```

The statistics reported are right. However, the size is what's important too!

Discharges	n	mean	ERAR > 1.0
All	11,497	1.056	52%
100 and few	1,223	1.023	63%
100 - 1000	9,810	1.007	51%
1000 and more	464	0.978	44%

The numbers do make a projection validating the case. When looking at 100 and fewer discharges, the excess re-admission is high but not by a lot. But we need to look further.

Hypothesis Test & Statistical Significance (α = 0.05)

In [146]:
```
# correlation coefficient
from scipy.stats.stats import pearsonr
pearsonr(x,y)
```

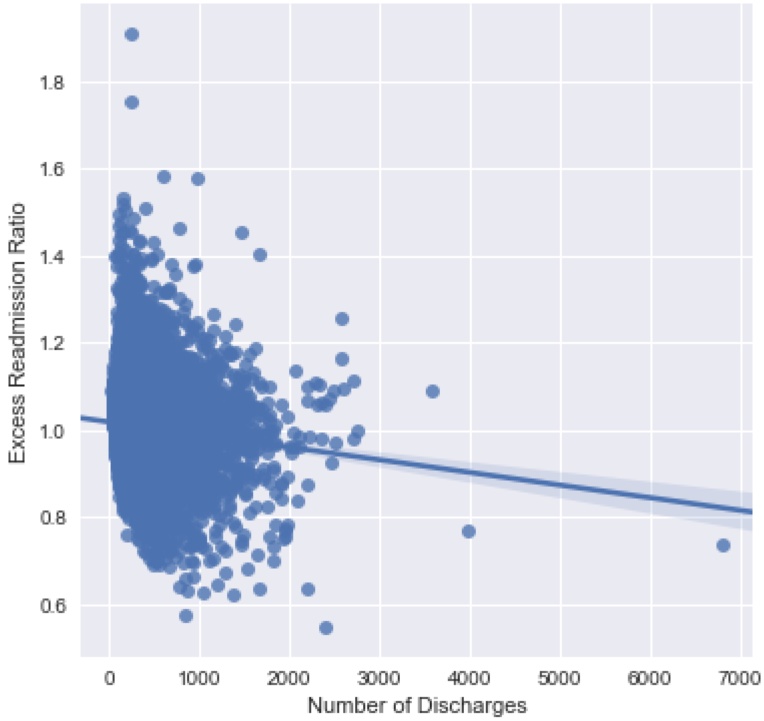
Out[146]:
```
(-0.093095542875904408, 1.5022756426464526e-23)
```

```
It is showing a downward trend; however, it is a very weak.  The correlation between the \# discharges and the excess re-admission ratio is -0.093, with a p-value of 1.502e-23.  This is very small, especially for a statistical significance of 0.05.  Therefore, just from this alone, we may **reject the null hypothesis**. There is no significant correlation between the excess re-admission rate and the number of discharges.  As a back-up, let's do a linear regression to see if it qualifies with a statistical significance of $\alpha = 0.01$.
```

Report Statistical Significance (α = 0.01)

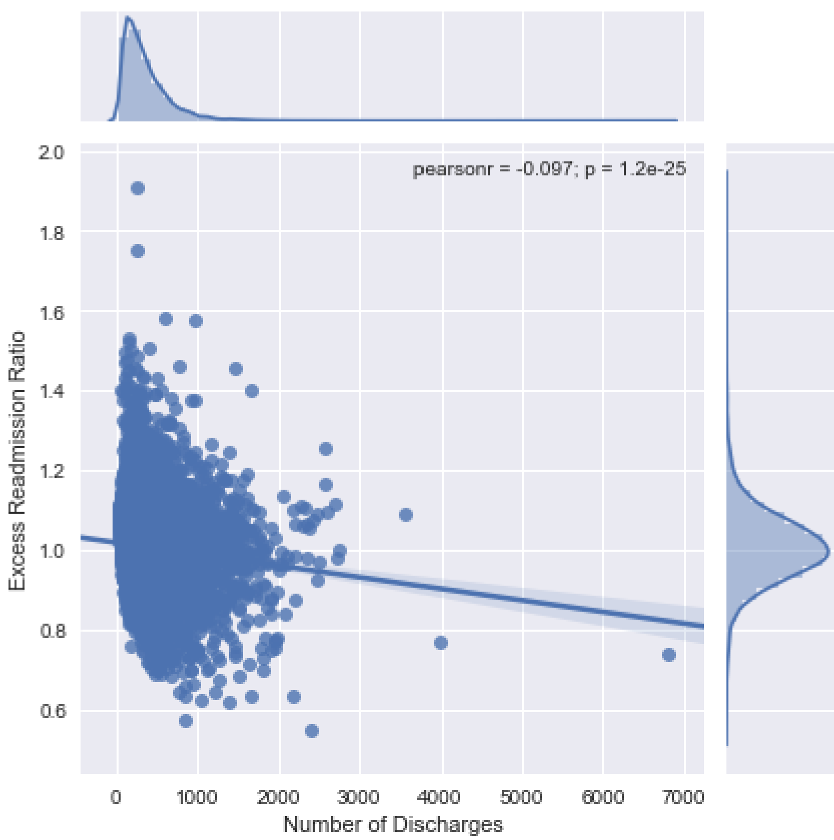
In [147]:

```
f, ax = plt.subplots(figsize=(6, 6))
sns.regplot(x="Number of Discharges", y="Excess Readmission Ratio", data
```



In [148]:

```
sns.jointplot(x="Number of Discharges", y="Excess Readmission Ratio", da
```



In [175]:

```
def simple_linear_regression(X, y): #ack http://charlesfranzen.com/posts
    '''
    Returns slope and intercept for a simple regression line

    inputs- Works best with numpy arrays, though other similar data stru
        X - input data
        y - output data

    outputs - floats
    '''
    # initial sums
    n = float(len(X))
    sum_x = X.sum()
    sum_y = y.sum()
    sum_xy = (X*y).sum()
    sum_xx = (X**2).sum()

    # formula for w0
    slope = (sum_xy - (sum_x*sum_y)/n)/(sum_xx - (sum_x*sum_x)/n)

    # formula for w1
    intercept = sum_y/n - slope*(sum_x/n)

    return (slope, intercept)
```

In [176]:

```
a, b = simple_linear_regression(clean_hos_df["Number of Discharges"], cl
print("[ERAR] = %.5f * [# discharges] + %.5f" % (a, b))
```

```
[ERAR] = -0.00003 * [# discharges] + 1.01811
```

Even with a statistical significance of $\alpha = 0.01$, the p-value remains unchanged. So the null hypothesis is rejected until α has a tiny significance. A significance of zero is not ideal; this would imply complete acceptance regardless of the test. Therefore, there is no significant correlation between the two variables.

Discuss statistical significance & practical significance

The statistical significance is telling:

- 0.09% (~ 1%) variability of the excess re-admission rate is coming from the hospital capacity
- the slope is trending downward, although by -0.00003 (a weak or non-existent) slope

The practical significance is telling what consequences would derive from this. A statistically significant finding may not be practically significant. Here, even if the correlation between hospital capacity and excess re-admission rates is small, doesn't mean that it doesn't have an impact at all.

To question whether there is practical significance, we may preform another hypothesis test.

$H_0 : \mu_{ERAR \geq 1.0} = \mu_{ERAR < 1.0}$

$H_a : \mu_{ERAR \geq 1.0} \neq \mu_{ERAR < 1.0}$

The null hypothesis states whether the mean for higher ERAR is the same as those for lower ERAR. The alternate hypothesis disputes that!

In [229]:
```
mul, sigl, nl = clean_hos_df[clean_hos_df['Excess Readmission Ratio']< 1
muh, sigh, nh = clean_hos_df[clean_hos_df['Excess Readmission Ratio'] >=

clean_hos_df[clean_hos_df['Excess Readmission Ratio'] >= 1.0]['Excess Re
# unequal variance, equal size
```

Out[229]: False

In [230]:
```
# degrees of freedom
v = np.square((np.square(sigl)/nl)+(np.square(sigh)/nh))/(np.square(np.s
nl, nh, v
```

Out[230]: (5547, 5547, 10495.262789379665)

In [231]:
```
# z-score for 95% percentile, using T-table calculator (http://stattrek.
zs = 1.96
```

In [235]:
```
# 2-sample t-test (unequal variance)
s_q = np.sqrt((np.square(sigl)/nl)+(np.square(sigh)/nh))
t_stat_2 = diff_mu / s_q
s_q, t_stat_2
```

Out[235]: (0.0011751012171167074, 37.234343159686617)

In [255]:
```
# Margin of error = critical value * standard error, @ 95%, 1.980
pval = stats.t.sf(np.abs(t_stat),v) # p-value
ME = 1.980 * s_q
CI = [mu - ME , mu + ME]
ME, CI, '{:5f}'.format(pval)
```

Out[255]: (0.0023267004098910808, [1.0051770831858235, 1.0098304840056056], '0.000000')

Here, the T-statistic is abnormally high to create a p-value very small (it's brief value is 0.00). However this complies with a small p-value recorded above. The p-value provided above shows it is statistically significant; $p < 0.01 < 0.05$. However, does it have practical significance? Possibly not. The hypothesis test depends on the sample size. Here, the sample size was larger than 1,000. The dataset is over 10,000.

Practical Significance: Because of a large sample set, notice that the graphs have two outliers near 2.0. These are unusual versus the remaining of the dataset. While the correlation was 1%, implying that 1% of the excess readmission rate's cause comes from the number of discharges, it still addresses the impact on individual hospitals nevertheless. And these are occurring with 1,000 discharges or less. Therefore, it is practically significant because as the discharges increases, the larger the hospital and the more resources these places do have. The recommendations and the explanation for some indications (like the outliers above) comply!

Scatterplot

Advantage: The scatterplot above conveys the information better than other graph forms. It is a scatterplot, showing the connection between the excess readmission rate and the number of discharges. The plot does show a side-triangle curve, where it has a elongated base at the beginning and then shrinks further to the point as the number of discharges increases.

Disadvantage: However, the scatterplot doesn't clarify how significant is the correlation, it highlights areas that don't really mean much, and doesn't convince the point of having these changes. As mentioned before, a linear regression line and a correlation coefficient would help clarify the information. These graphs are highlighted above.

In [289]:

```
# Scatterplot: # Discharges vs Excess Readmission Ratio
plt.figure(figsize=(15,5))
case1 = clean_hos_df[clean_hos_df['Excess Readmission Ratio'] < 1.0]
case2 = clean_hos_df[clean_hos_df['Excess Readmission Ratio'] >= 1.0]
plt.scatter(case1['Number of Discharges'],case1['Excess Readmission Rat
plt.scatter(case2['Number of Discharges'],case2['Excess Readmission Rat

# MAJOR correlation line
axes = plt.gca()
m, b = np.polyfit(x, y, 1)
X_plot = np.linspace(axes.get_xlim()[0],axes.get_xlim()[1],100)
plt.plot(X_plot, m*X_plot + b, '-')

# MINOR labels
plt.text(5000, 1.0, r'$y = x*(-2.8565052943822905e-05) + 1.018$')
plt.xlim([0, max(max(case1['Number of Discharges']),max(case2['Number o
plt.xlabel('Number of discharges', fontsize=12)
plt.ylabel('Excess rate of readmissions', fontsize=12)
plt.title('Scatterplot of number of discharges vs. excess rate of readm
plt.legend()

# MINOR extras
plt.grid(True)
plt.tight_layout()
```