Exploratory Data Analysis

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Course: DSC530 - Term Project

Source Link: [https://www.kaggle.com/noriuk/us-education-datasets-unification-project/version/4 (https://www.kaggle.com/noriuk/us-education-datasets-unification-project/version/4)](https://www.kaggle.com/noriuk/us-education-datasets-unification-project/version/4)

Data set: finance_districts.csv

Statistical/Hypothetical Question: By exploring this data set regarding financial school districts and their enrollment numbers, I want to find out whether there is a any statistical correlation between total revenues of the state and number of enrollment numbers for the school districts. If there is correlation, how much have an impact Total Revenues have on enrollment.

Import libraries and data set

In [11]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from math import sqrt
import scipy.stats as stats
import seaborn as sns

%matplotlib inline

plt.style.use('bmh')
```

In [12]:
```
# Importing data set
findistdf = pd.read_csv('src/finance_districts.csv')
findistdf.head()
```

Out[12]:

	STATE	ENROLL	NAME	YRDATA	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP	TCURINST	TCURSSVC	TCURONON
0	ALABAMA	9609.0	AUTAUGA COUNTY SCHOOL DISTRICT	2016	80867	7447	53842	19578	76672	43843	23941	6401.0
1	ALABAMA	30931.0	BALDWIN COUNTY SCHOOL DISTRICT	2016	338236	23710	145180	169346	299880	164977	97231	19439.0
2	ALABAMA	912.0	BARBOUR COUNTY SCHOOL DISTRICT	2016	10116	2342	5434	2340	10070	4907	3896	975.0
3	ALABAMA	2842.0	EUFAULA CITY SCHOOL DISTRICT	2016	26182	3558	15900	6724	29843	15302	7901	2274.0
4	ALABAMA	3322.0	BIBB COUNTY SCHOOL DISTRICT	2016	32486	3664	21846	6976	31662	16407	11087	3122.0

Variables

In [13]:
```
findistdf.columns
```

Out[13]:
```
Index(['STATE', 'ENROLL', 'NAME', 'YRDATA', 'TOTALREV', 'TFEDREV', 'TSTREV',
       'TLOCREV', 'TOTALEXP', 'TCURINST', 'TCURSSVC', 'TCURONON', 'TCAPOUT'],
      dtype='object')
```

Description of the data set

```
The data set consists of financials of each school district in each state for different years. It has the
following variables:

STATE - State of Financial School district
ENROLL - The U.S. Census Bureau's count for students in the state. Should be comparable to GRADES_ALL
NAME - Name of the school district
YRDATA  - Year that the record pertains to
TOTALREV: The total amount of revenue for the state.
            TFEDREV - Federal Revenue
            TSTREV  - State Revenue
            TLOCREV  - Local Revenue
TOTALEXP: The total expenditure for the state.
            TCURINST - Instruction Expenditure
            TCURSSVC - Supportive Services Expenditure
            TCURONON - Other Expenditure
            TCAPOUT - Capital Outlay Expenditure

Note: link for data set (finance_districts.csv)- https://www.kaggle.com/adrian1acoran/starter-u-s-
education-datasets-4a0c2b4b-7/data
```

Data Cleansing

In [14]:
```
# Let us ignore the variables that are not part of this analysis
findistdf_orig = findistdf # taking backup of the original dataset

findistdf  = findistdf[['STATE', 'ENROLL', 'NAME', 'YRDATA', 'TOTALREV', 'TFEDREV', 'TSTREV', 'TLOCREV', 'TOTAI
```

In [15]:
```
# Lets look at the basic information of the data set
findistdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 374161 entries, 0 to 374160
Data columns (total 9 columns):
STATE        374161 non-null object
ENROLL       358293 non-null float64
NAME         374161 non-null object
YRDATA       374161 non-null int64
TOTALREV     374161 non-null int64
TFEDREV      374161 non-null int64
TSTREV       374161 non-null int64
TLOCREV      374161 non-null int64
TOTALEXP     374161 non-null int64
dtypes: float64(1), int64(6), object(2)
memory usage: 25.7+ MB
```

Looks like ENROLL variable data is not available for the rows. For this analysis, discard the rows that have null or nan values in the 2 important variables - ENROLL and TOTALREV

In [16]:
```
findistdf = findistdf.dropna(subset = ['ENROLL',  'TOTALREV'])
findistdf_orig2 = findistdf
findistdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 358293 entries, 0 to 358292
Data columns (total 9 columns):
STATE       358293 non-null object
ENROLL      358293 non-null float64
NAME        358293 non-null object
YRDATA      358293 non-null int64
TOTALREV    358293 non-null int64
TFEDREV     358293 non-null int64
TSTREV      358293 non-null int64
TLOCREV     358293 non-null int64
TOTALEXP    358293 non-null int64
dtypes: float64(1), int64(6), object(2)
memory usage: 27.3+ MB
```

Distributions - Histograms, Outliers

In [17]:
```
# Getting basic stats
findistdf.describe()
```

Out[17]:

	ENROLL	YRDATA	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP
count	3.582930e+05	358293.000000	3.582930e+05	3.582930e+05	3.582930e+05	3.582930e+05	3.582930e+05
mean	3.134504e+03	2004.400390	3.173910e+04	2.689896e+03	1.473310e+04	1.431610e+04	3.209838e+04
std	1.402406e+04	6.849252	1.816932e+05	1.926575e+04	8.418726e+04	8.637972e+04	1.937165e+05
min	0.000000e+00	1993.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	2.760000e+02	1998.000000	3.299000e+03	1.730000e+02	1.354000e+03	1.125000e+03	3.231000e+03
50%	9.480000e+02	2004.000000	9.498000e+03	5.380000e+02	4.354000e+03	3.513000e+03	9.433000e+03
75%	2.607000e+03	2010.000000	2.575700e+04	1.677000e+03	1.156600e+04	1.101400e+04	2.585600e+04
max	1.077381e+06	2016.000000	2.744836e+07	3.120314e+06	1.056801e+07	1.514124e+07	2.962010e+07

Drawing Histograms and Density plots

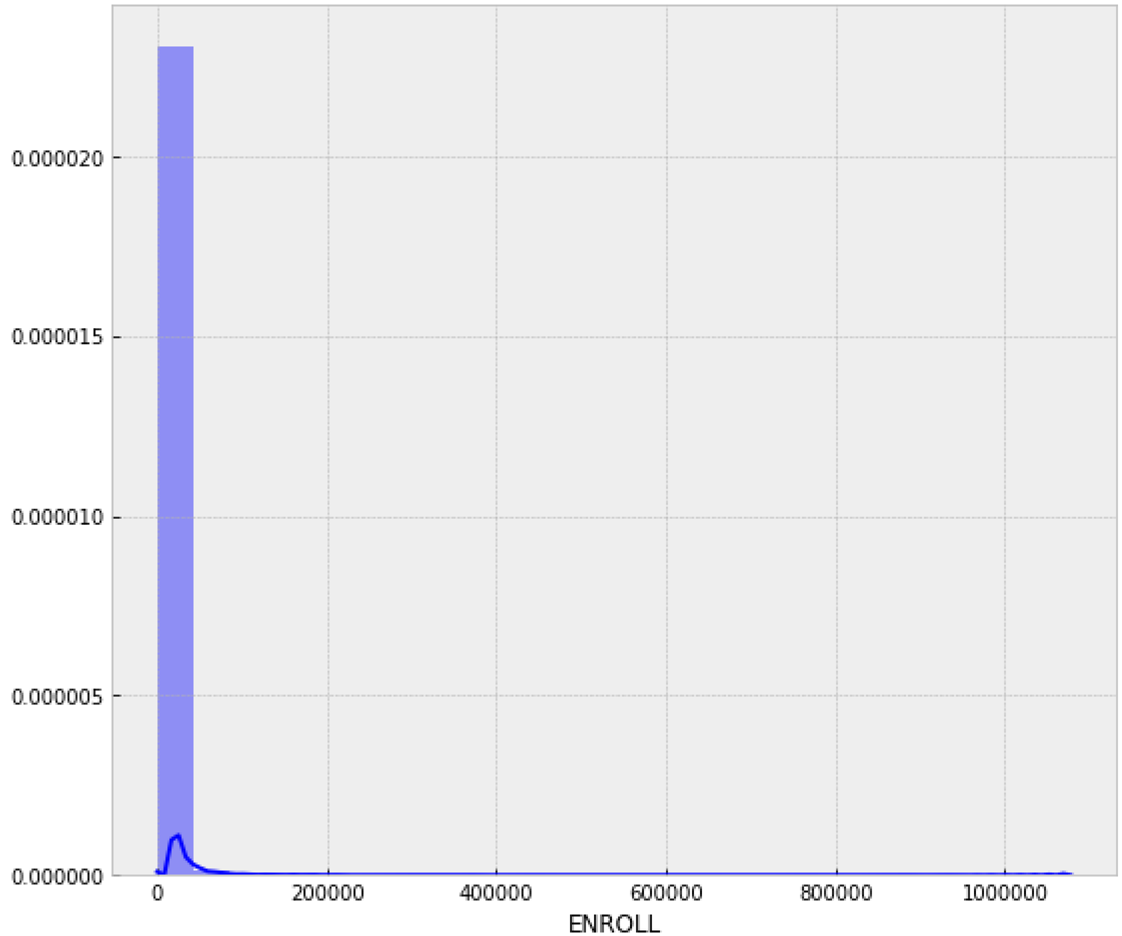
In [18]:

```
plt.figure(figsize=(9, 8))
#sns.distplot(findistdf['ENROLL'], color='b', bins=25, hist_kws={'alpha': 0.4});
sns.distplot(findistdf['ENROLL'], color='b',hist = True,  bins=25) #, hist_kws={'alpha': 0.4});
```

```
C:\Installed\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

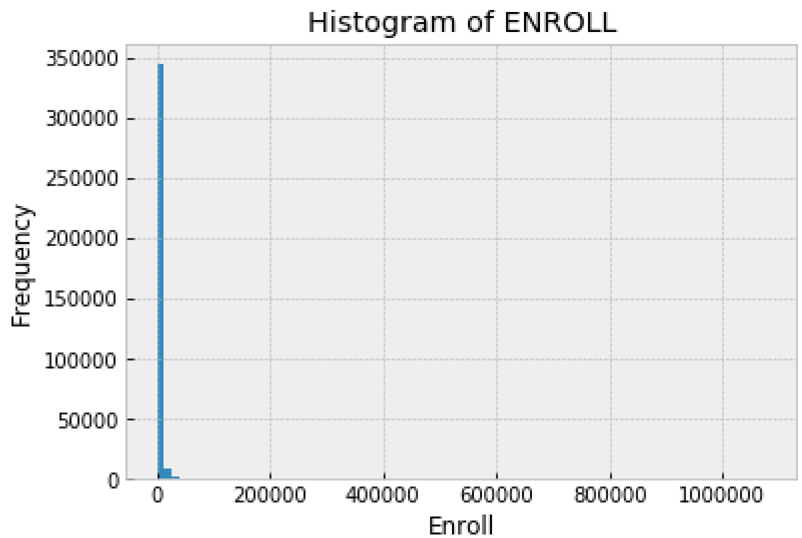
Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2253014b5f8>
```



In [19]:
```
findistdf['ENROLL'].hist(bins = 80)
#plt.locator_params(nbins=20)
plt.xlabel('Enroll')
plt.ylabel('Frequency')
plt.title('Histogram of ENROLL')
```

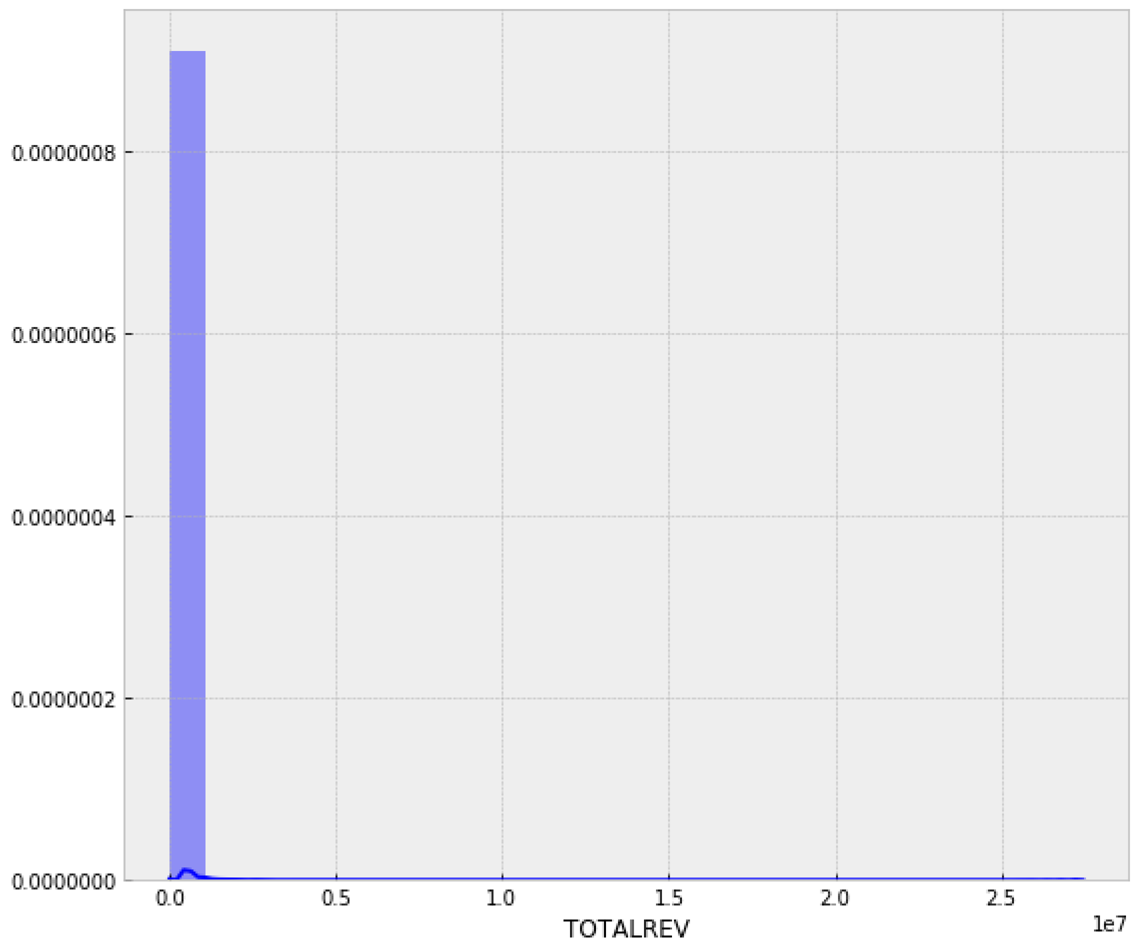
Out[19]:
```
Text(0.5,1,'Histogram of ENROLL')
```



In [20]:
```
plt.figure(figsize=(9, 8))
#sns.distplot(findistdf['ENROLL'], color='b', bins=25, hist_kws={'alpha': 0.4});
sns.distplot(findistdf['TOTALREV'], color='b',hist = True,  bins=25) #, hist_kws={'alpha': 0.4});
```

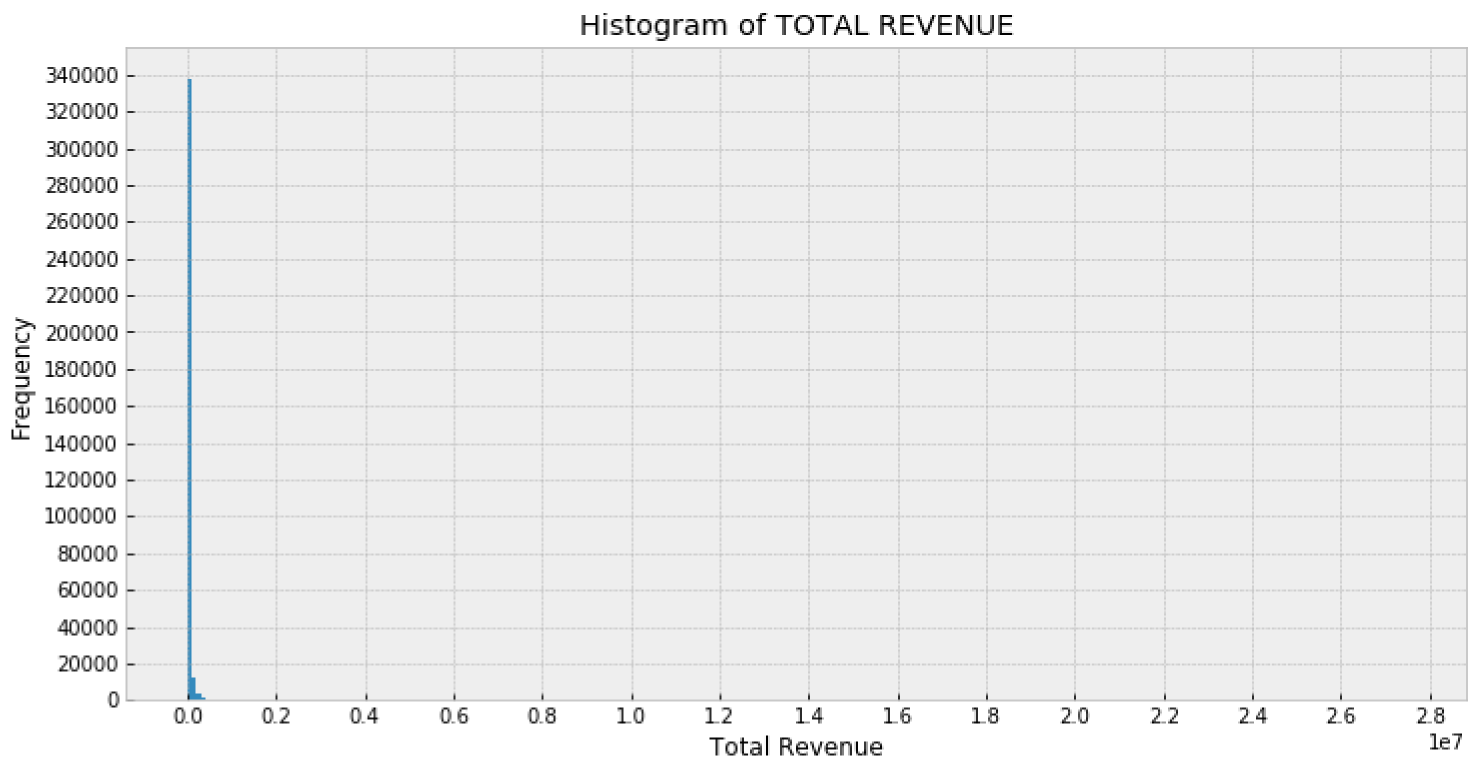
```
C:\Installed\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence
for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this
will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a differ
ent result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2252f574358>



In [21]:
```
# Trying to find apt number of bins from min to max
findistdf['TOTALREV'].hist(bins = 275,  figsize=[12,6])
plt.locator_params(nbins=20)
plt.xlabel('Total Revenue')
plt.ylabel('Frequency')
plt.title('Histogram of TOTAL REVENUE')
```

Out[21]: Text(0.5,1,'Histogram of TOTAL REVENUE')



Both ENROLL and TOTALREV variables are asymmetrically (positively) skewed with longer tail towards the higher values.

Clearly there are some outliers in ENROLL and TOTALREV that are skewing the distributions heavily.

In [22]:
```python
findistdf.groupby('STATE').TOTALREV.agg(['min', 'max', 'mean', 'var'])
```

Out[22]:

STATE	min	max	mean	var
ALABAMA	782	618181	4.349568e+04	4.077881e+09
ALASKA	158	914050	3.285153e+04	6.995753e+09
ARIZONA	0	635243	2.863350e+04	3.976721e+09
ARKANSAS	0	371708	1.339582e+04	6.637229e+08
CALIFORNIA	0	10329380	5.464825e+04	6.051548e+10
COLORADO	0	1271873	3.538293e+04	1.027157e+10
CONNECTICUT	78	527210	4.415065e+04	3.689717e+09
DELAWARE	3879	318466	7.314053e+04	4.044500e+09
DISTRICT_OF_COLUMBIA	678874	1382282	1.033762e+06	6.165597e+10
FLORIDA	5712	3959408	3.172400e+05	3.023165e+11
GEORGIA	739	1893150	7.196012e+04	2.694898e+10
HAWAII	1062475	3030519	2.047635e+06	4.478832e+11
IDAHO	41	281989	1.491776e+04	8.556664e+08
ILLINOIS	0	5760419	2.163508e+04	1.942673e+10
INDIANA	0	729047	3.179480e+04	2.305822e+09
IOWA	683	482554	1.250332e+04	6.858602e+08
KANSAS	551	666255	1.472987e+04	1.616821e+09
KENTUCKY	0	1323404	3.216628e+04	6.154377e+09
LOUISIANA	7144	625708	9.061099e+04	1.280243e+10
MAINE	0	119828	7.764532e+03	1.349948e+08
MARYLAND	16763	3159510	4.132408e+05	3.104588e+11
MASSACHUSETTS	0	1481699	3.228844e+04	4.637021e+09
MICHIGAN	0	1671978	2.475151e+04	3.685789e+09

STATE	min	max	mean	var
MINNESOTA	0	716799	2.087318e+04	2.691517e+09
MISSISSIPPI	0	291507	2.321156e+04	8.352367e+08
MISSOURI	0	510063	1.506467e+04	1.466022e+09
MONTANA	0	117079	2.835495e+03	4.497919e+07
NEBRASKA	1	687093	6.218597e+03	8.453300e+08
NEVADA	1294	3220684	1.803720e+05	2.960478e+11
NEW_HAMPSHIRE	2	186461	1.244669e+04	3.501079e+08
NEW_JERSEY	1	1163400	3.597258e+04	4.114898e+09
NEW_MEXICO	745	1051179	3.249878e+04	7.939642e+09
NEW_YORK	1	27448356	6.258730e+04	4.314818e+11
NORTH_CAROLINA	4938	2297008	9.167576e+04	2.673796e+10
NORTH_DAKOTA	10	177525	4.296540e+03	1.610324e+08
OHIO	1	980035	2.541799e+04	2.812349e+09
OKLAHOMA	0	478115	8.822205e+03	6.638011e+08
OREGON	39	697501	2.195237e+04	2.554278e+09
PENNSYLVANIA	0	3030964	3.618602e+04	9.705357e+09
RHODE_ISLAND	1732	461090	4.848231e+04	3.628086e+09
SOUTH_CAROLINA	0	855902	6.281708e+04	9.269236e+09
SOUTH_DAKOTA	17	230640	6.363154e+03	2.463003e+08
TENNESSEE	0	1470379	4.814285e+04	1.225541e+10
TEXAS	0	2480131	3.575125e+04	1.146961e+10
UTAH	1812	635282	8.064527e+04	1.400811e+10
VERMONT	0	84611	4.518641e+03	3.780746e+07
VIRGINIA	0	2733933	8.174012e+04	4.034570e+10
WASHINGTON	25	881789	3.143074e+04	3.719914e+09
WEST_VIRGINIA	2522	384864	4.753317e+04	2.279495e+09

STATE	min	max	mean	var
WISCONSIN	493	1310838	2.122801e+04	3.447978e+09
WYOMING	593	309591	2.482201e+04	1.315037e+09

In [23]:

```
findist_bystate = pd.DataFrame()
findist_bystate = findistdf.groupby('STATE', as_index = False)['TOTALREV', 'ENROLL'].max()
```

In [24]:

```
#Top 5 states with most total revenue
findist_bystate.sort_values('TOTALREV',ascending=False)[0:5]
```

Out[24]:

	STATE	TOTALREV	ENROLL
32	NEW_YORK	27448356	1077381.0
4	CALIFORNIA	10329380	747009.0
13	ILLINOIS	5760419	437418.0
9	FLORIDA	3959408	375836.0
28	NEVADA	3220684	325990.0

In [25]:
```
#Top 5 states with most total revenue
findist_bystate.sort_values('ENROLL',ascending=False)[0:5]
```

Out[25]:

	STATE	TOTALREV	ENROLL
32	NEW_YORK	27448356	1077381.0
4	CALIFORNIA	10329380	747009.0
13	ILLINOIS	5760419	437418.0
9	FLORIDA	3959408	375836.0
28	NEVADA	3220684	325990.0

Clearly California and NewYork are in a different league with respective to Total Revenue and Enroll numbers. So, let's see how the distribution will be if we separate these states from the data set

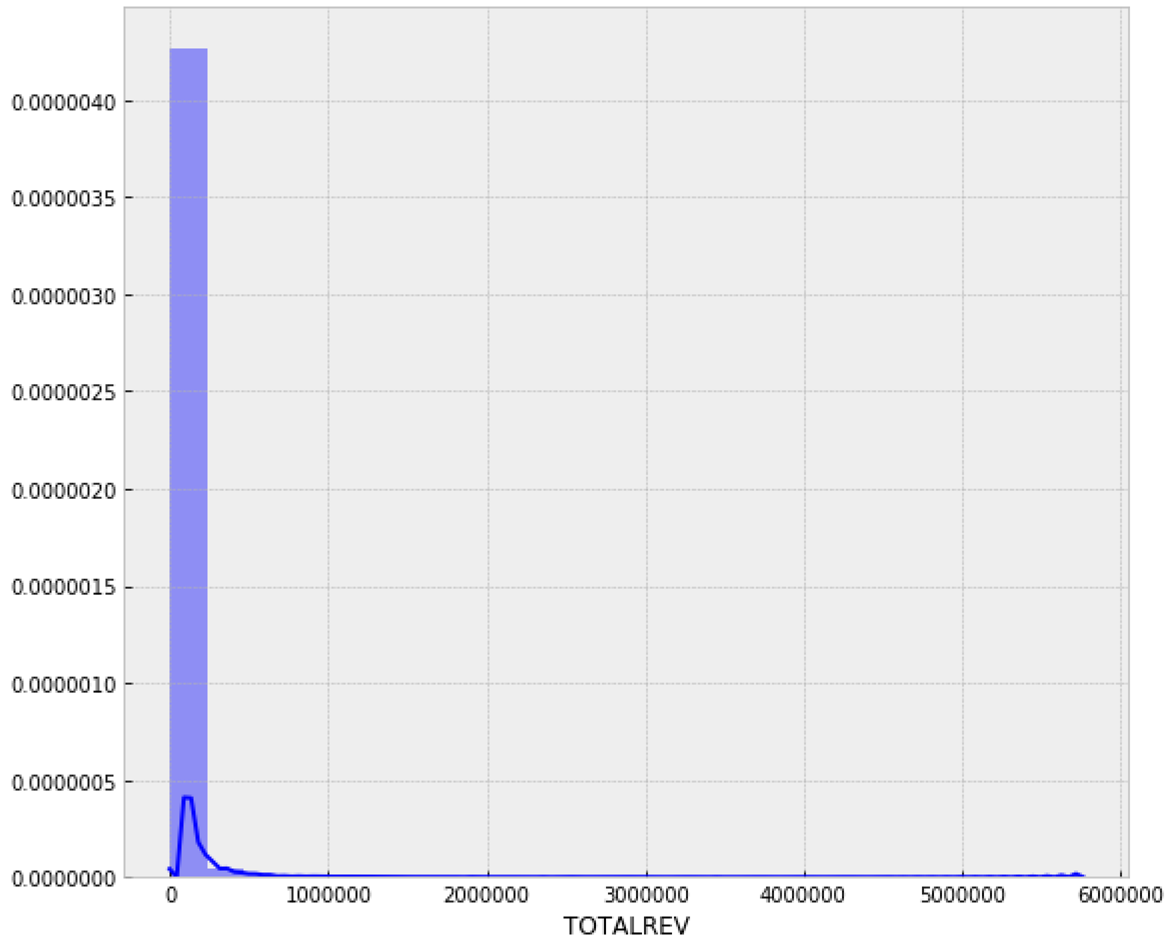
In [26]:
```
findistdf_orig3 = findistdf # taking backup copy of df

# separating the records of 'New York' and 'California' from the data set
findistdf = findistdf[(findistdf.STATE != 'NEW_YORK') & (findistdf.STATE != 'CALIFORNIA' )]

# removing recrods with 0 revenue's and enrollments

findistdf = findistdf[(findistdf.ENROLL >0) & (findistdf.TOTALREV >0) &  (findistdf.TFEDREV >0)
                      &  (findistdf.TSTREV >0) &  (findistdf.TLOCREV >0) &  (findistdf.TOTALEXP >0)   ]

len(findistdf)
```

Out[26]: 287744

Plotting Density plots, histograms

In [27]:
```
# Density plot for TOTALREV
plt.figure(figsize=(9, 8))
sns.distplot(findistdf['TOTALREV'], color='b', bins=25, hist_kws={'alpha': 0.4});
```

```
C:\Installed\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence
for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this
will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a differ
ent result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [28]:
```
# Trying to find apt number of bins from min to max
noofbins = np.arange(start=findistdf['TOTALREV'].min(), stop=findistdf['TOTALREV'].max(), step=50000)
print(len(noofbins))
```

```
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```
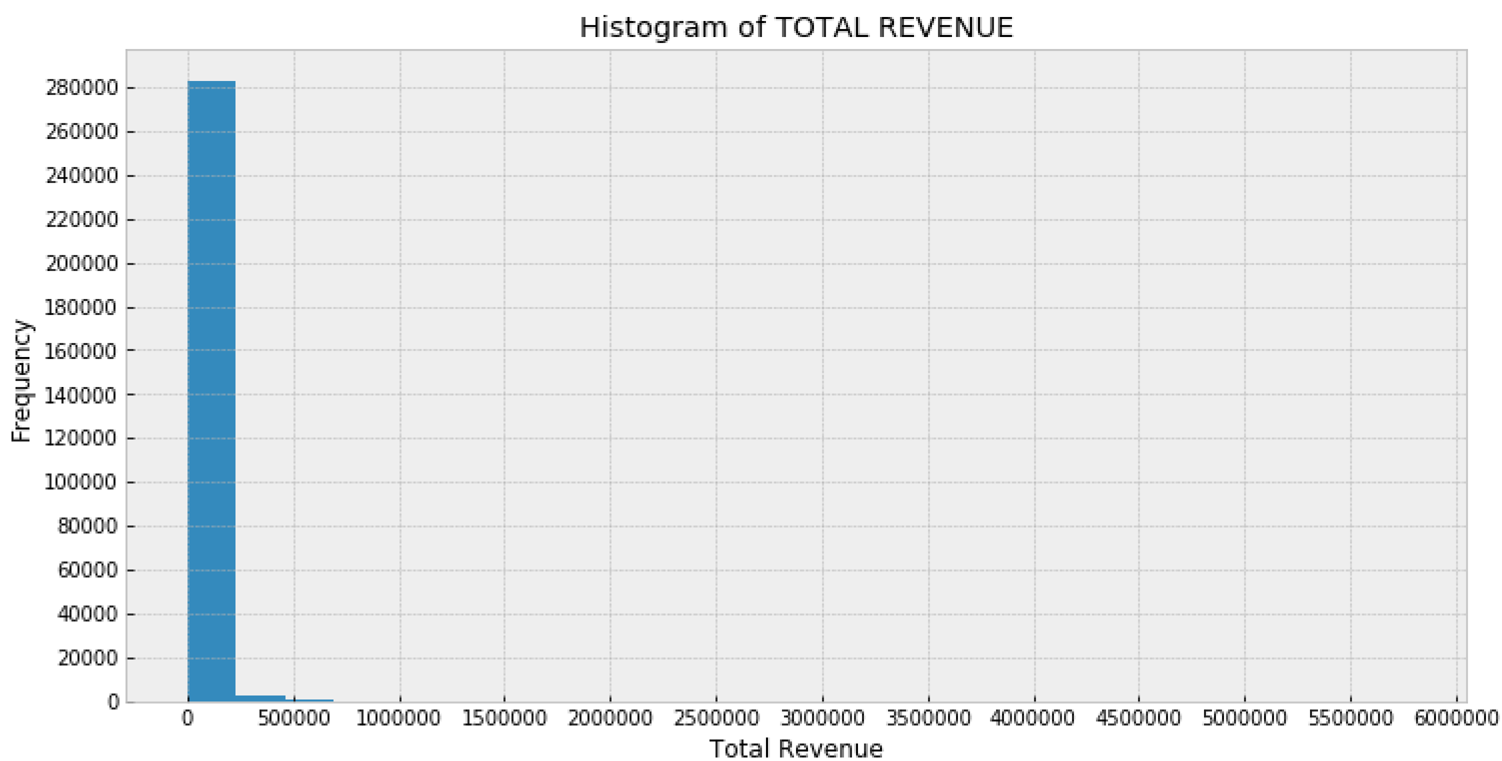
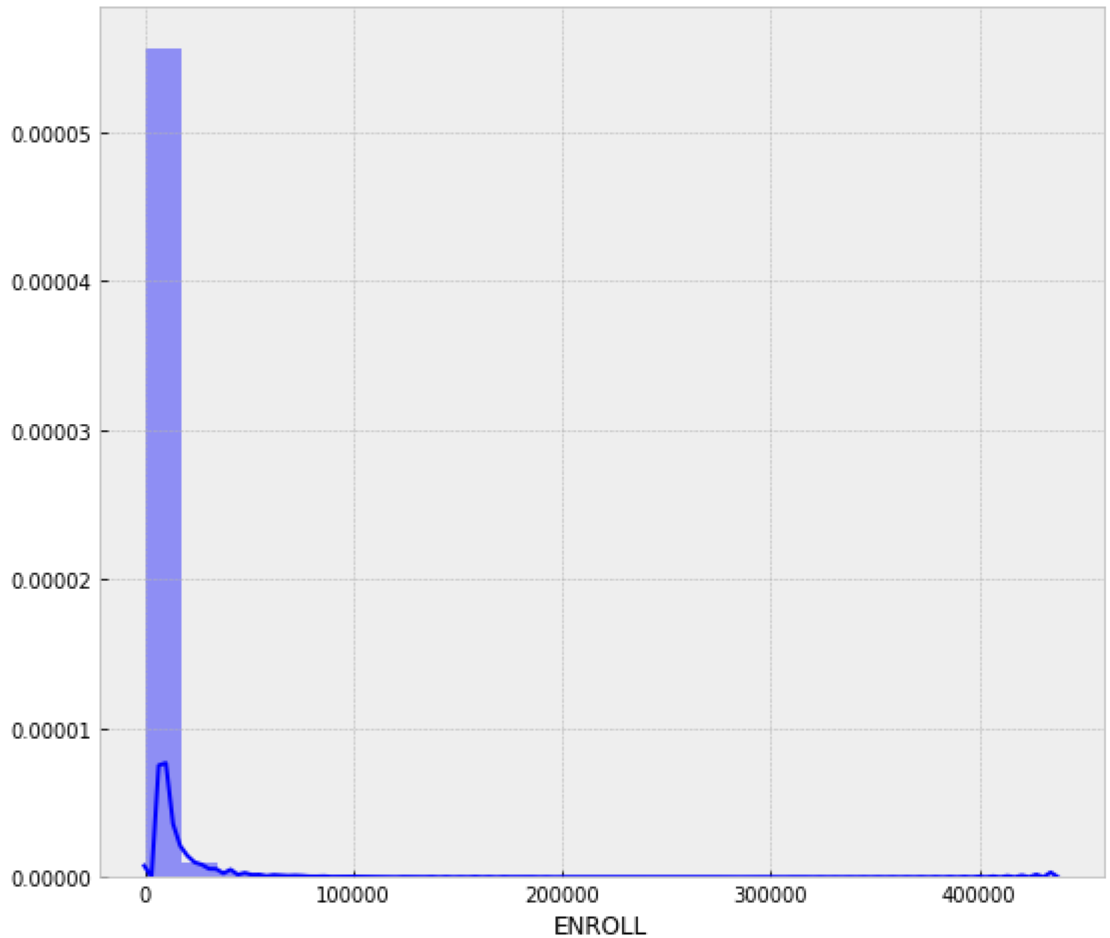

In [29]:
```

findistdf['TOTALREV'].hist(bins = 25,  figsize=[12,6])
plt.locator_params(nbins=20)
plt.xlabel('Total Revenue')
plt.ylabel('Frequency')
plt.title('Histogram of TOTAL REVENUE')
```

Out[29]:
```
Text(0.5,1,'Histogram of TOTAL REVENUE')
```



In [30]:
```
# Density plot for ENROLL
plt.figure(figsize=(9, 8))
sns.distplot(findistdf['ENROLL'], color='b', bins=25, hist_kws={'alpha': 0.4});
```

```
C:\Installed\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence
for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this
will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a differ
ent result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [31]:
```
# Trying to find apt number of bins from min to max
noofbins = np.arange(start=findistdf['ENROLL'].min(), stop=findistdf['ENROLL'].max(), step=10000)
print(len(noofbins))
```

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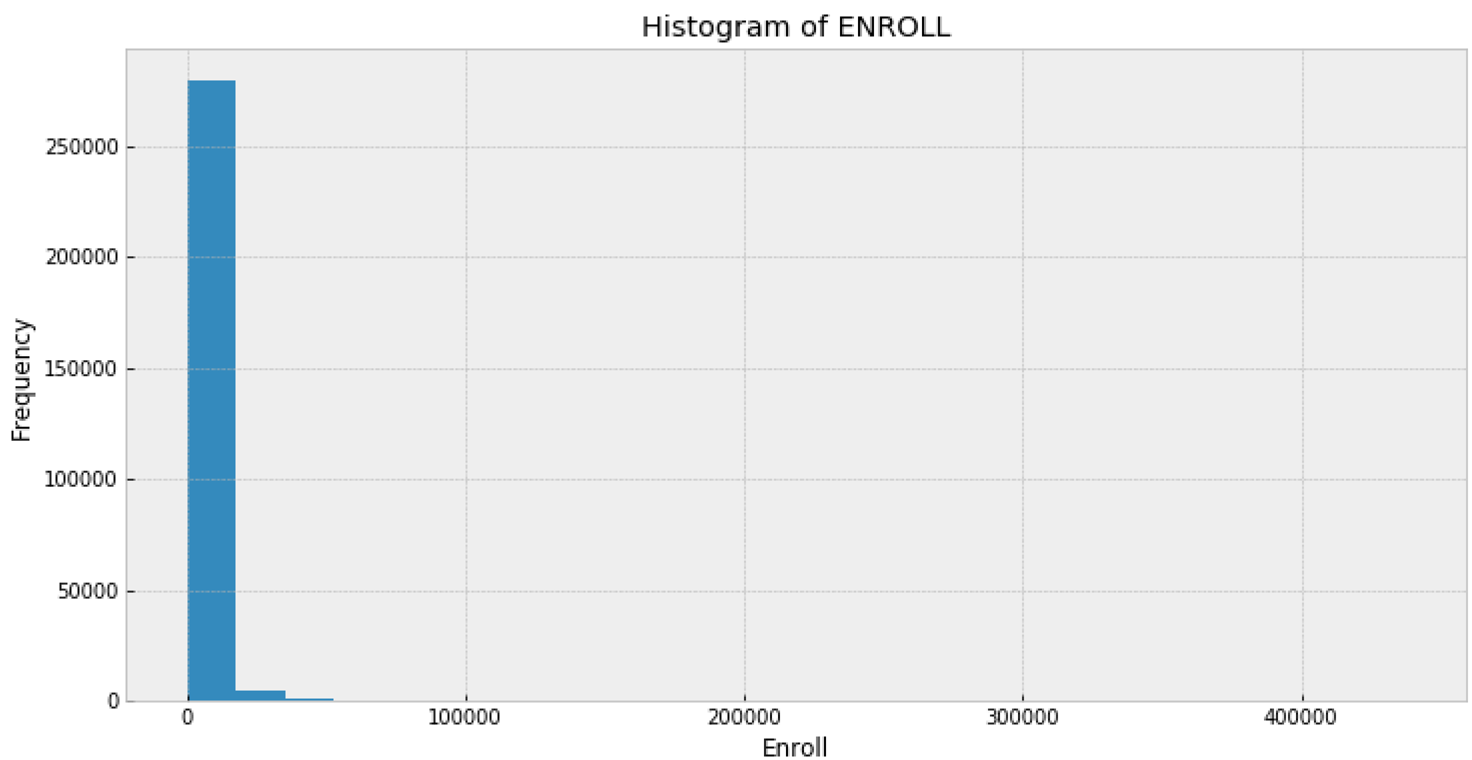
In [32]:
```
findistdf['ENROLL'].hist(bins = 25,  figsize=[12,6])
#plt.locator_params(nbins=20)
plt.xlabel('Enroll')
plt.ylabel('Frequency')
plt.title('Histogram of ENROLL')
```

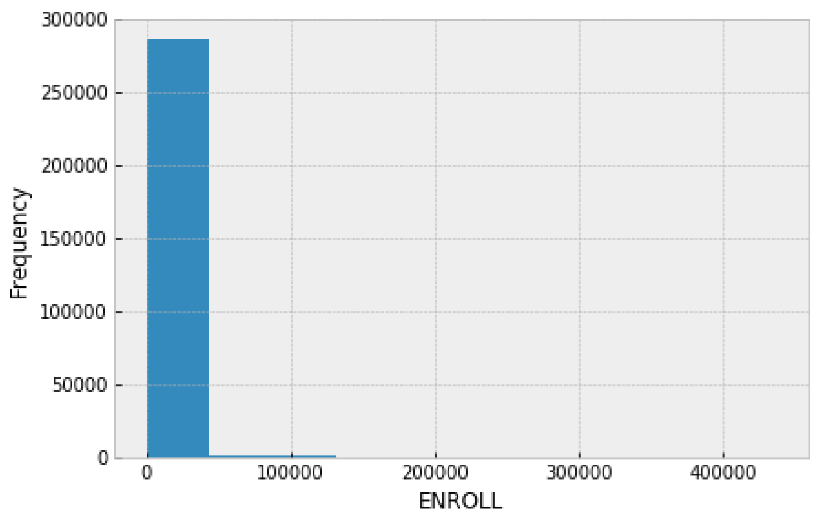
Out[32]: Text(0.5,1,'Histogram of ENROLL')

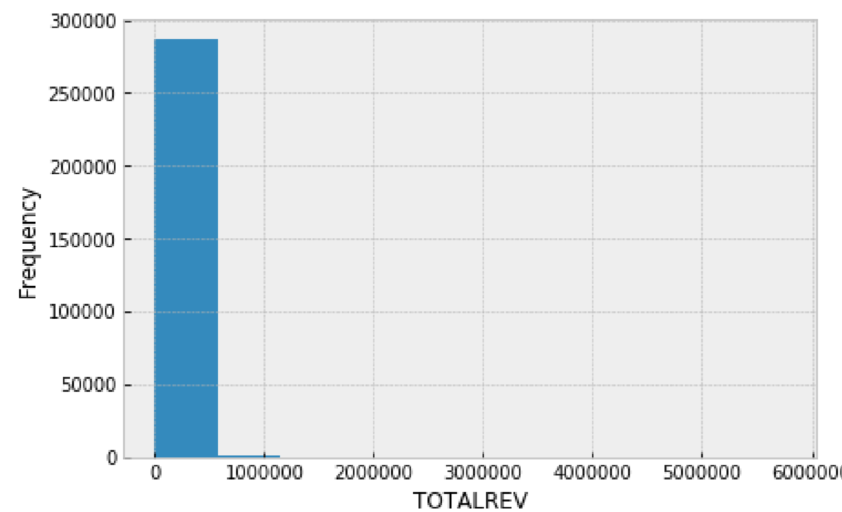


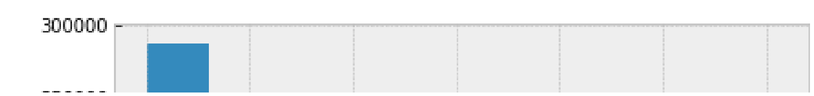
Still most of the numbers are packed at the lower end of the scale for the TOTALREV and ENROLL

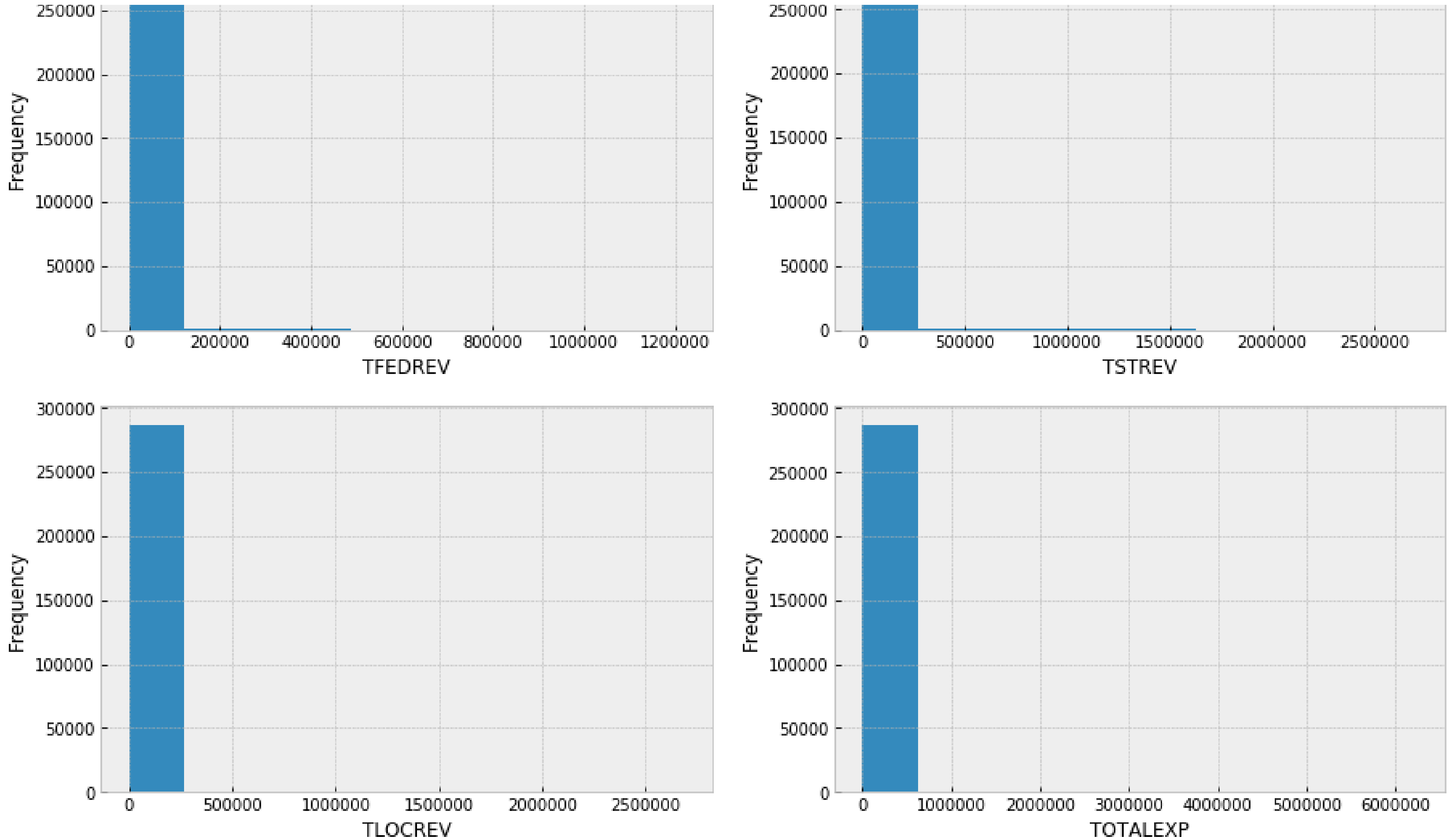
Plotting Histogram for the 5 variables

In [33]:
```python
colnames = ['ENROLL', 'TOTALREV', 'TFEDREV', 'TSTREV','TLOCREV', 'TOTALEXP']
plt.figure(figsize=(15,15))
for i in range(len(colnames)):

    if i == 0:
        plt.subplot(3,2,1)
    if i == 1:
        plt.subplot(3,2,2)
    if i == 2:
        plt.subplot(3,2,3)
    if i ==3:
        plt.subplot(3,2,4)
    if i == 4:
        plt.subplot(3,2,5)
    if i == 5:
        plt.subplot(3,2,6)

    #print(colnames[i])
    plt.hist(findistdf[colnames[i]].dropna())
    plt.ylabel('Frequency')
    plt.xlabel(findistdf[colnames[i]].name)
```









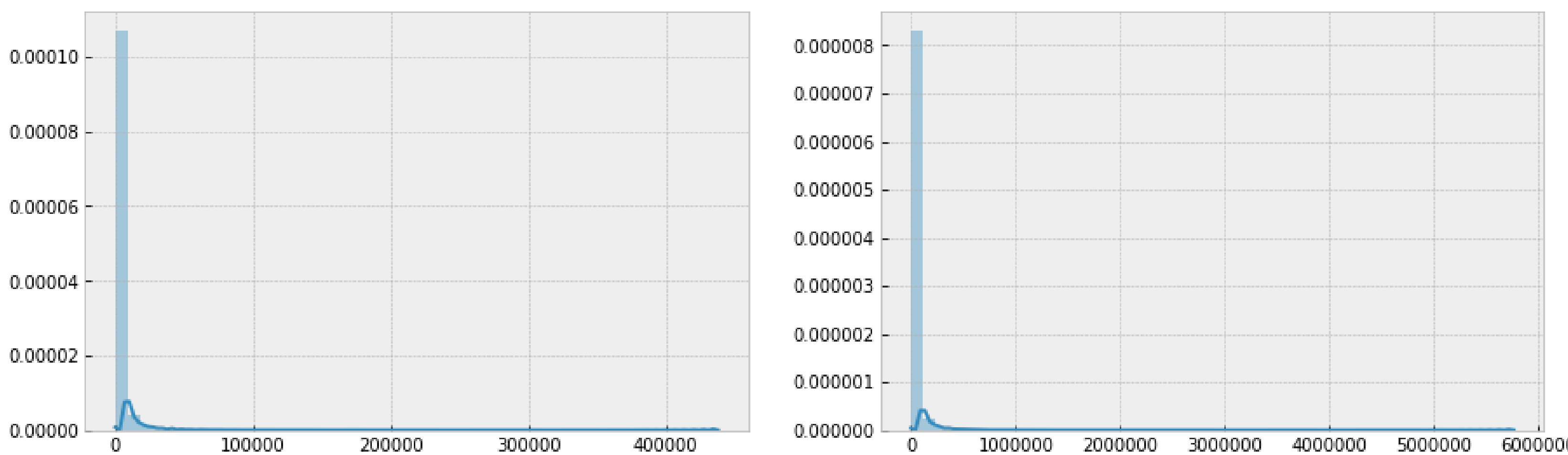

```
In [ ]:
```

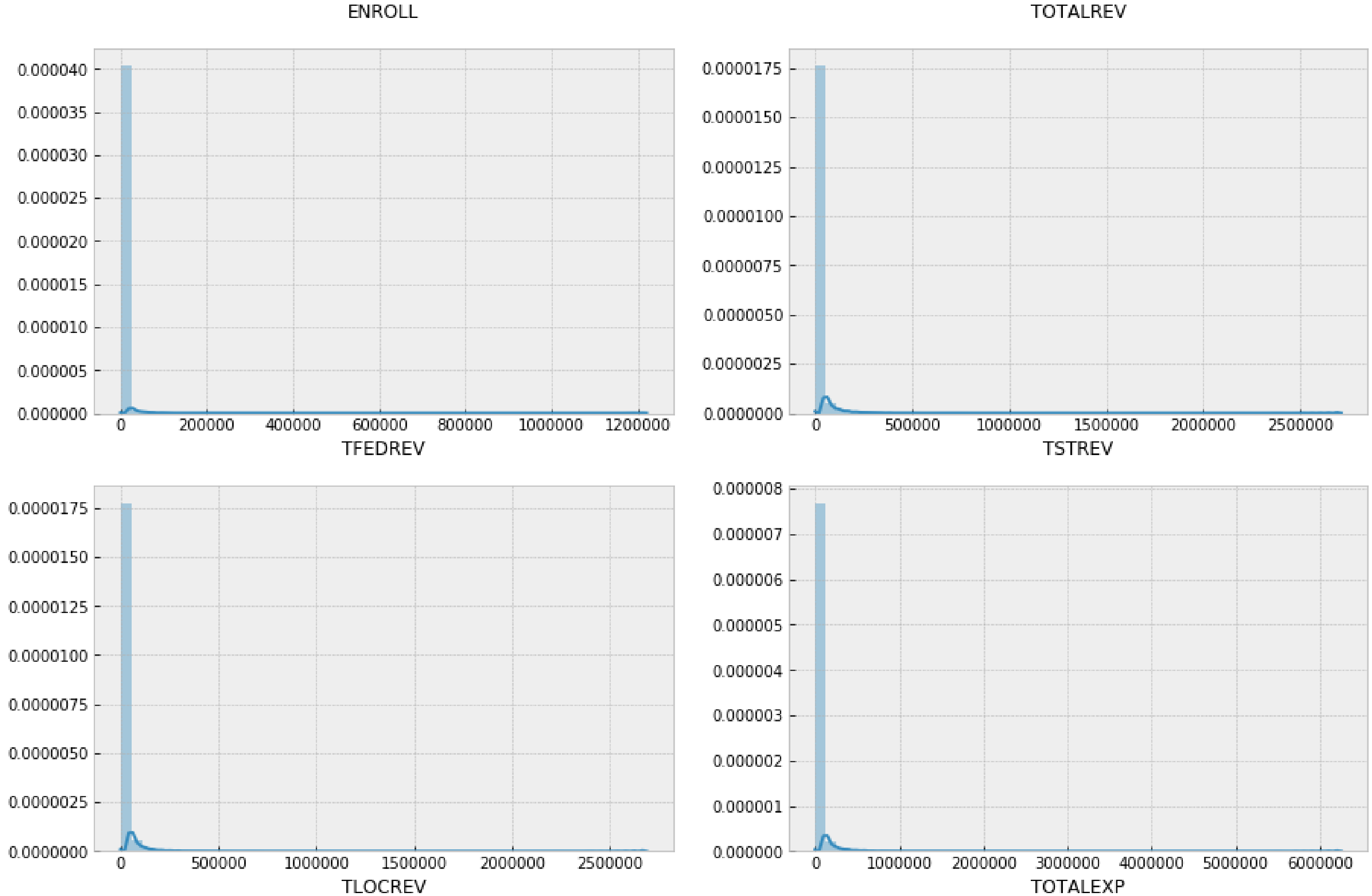
Plotting Desnity plots for the 5 variables

In [34]:

```
colnames = ['ENROLL', 'TOTALREV', 'TFEDREV', 'TSTREV','TLOCREV', 'TOTALEXP']
plt.figure(figsize=(15,15))
for i in range(len(colnames)):

    if i == 0:
        plt.subplot(3,2,1)
    if i == 1:
        plt.subplot(3,2,2)
    if i == 2:
        plt.subplot(3,2,3)
    if i ==3:
        plt.subplot(3,2,4)
    if i == 4:
        plt.subplot(3,2,5)
    if i == 5:
        plt.subplot(3,2,6)

    #print(colnames[i])
    sns.distplot(findistdf[colnames[i]].dropna())
```

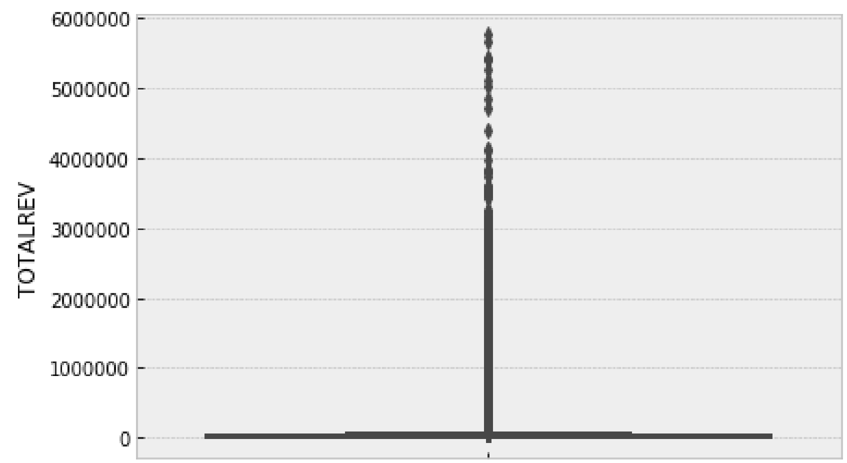
```
C:\Installed\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence
for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this
will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a differ
ent result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

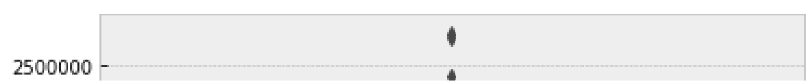


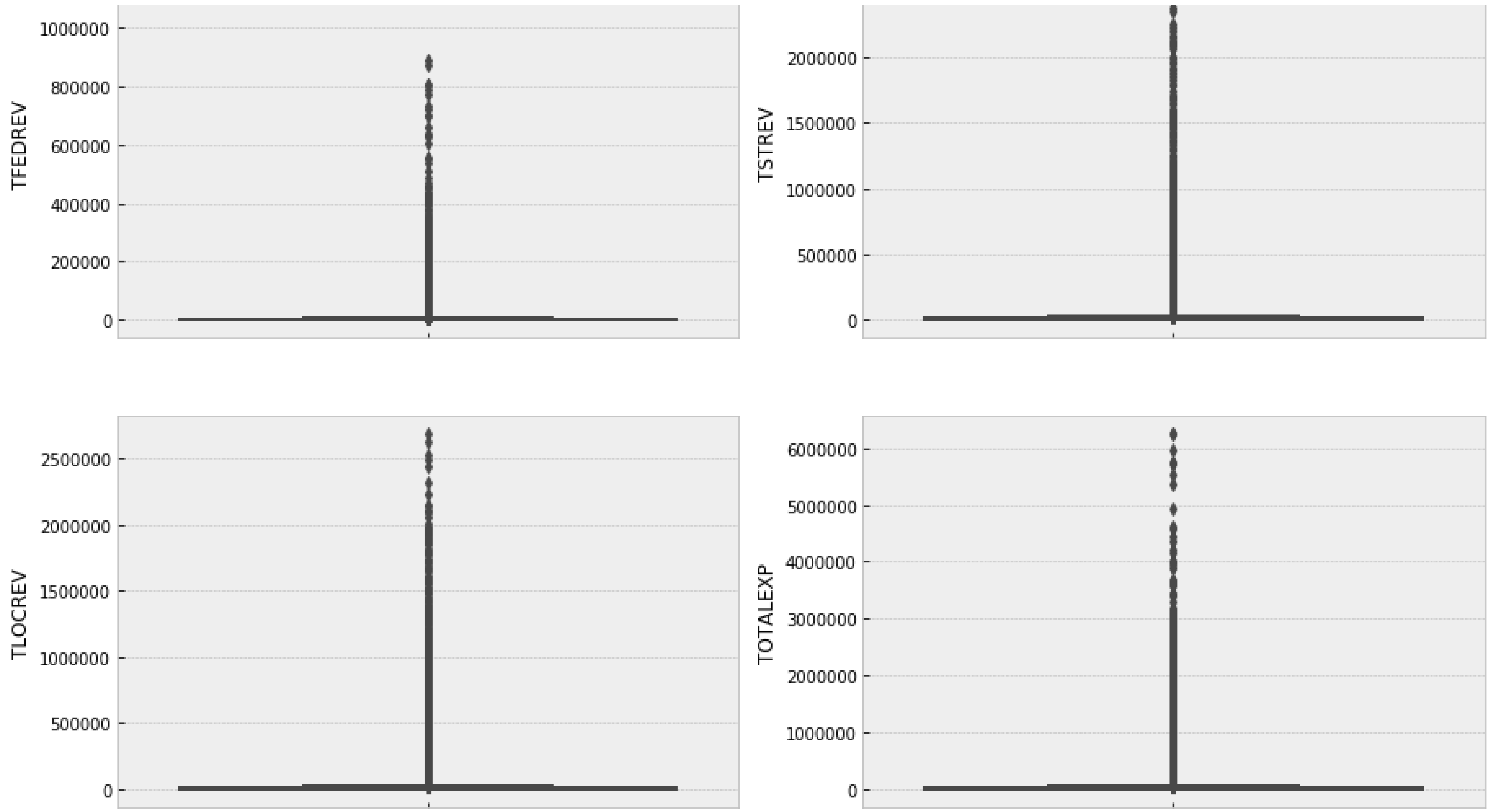


Plotting outliers using boxplot

In [35]:
```
plt.figure(figsize=(15,15))
for i in range(len(colnames)):

    if i == 0:
        plt.subplot(3,2,1)
    if i == 1:
        plt.subplot(3,2,2)
    if i == 2:
        plt.subplot(3,2,3)
    if i ==3:
        plt.subplot(3,2,4)
    if i == 4:
        plt.subplot(3,2,5)
    if i == 5:
        plt.subplot(3,2,6)

    #print(colnames[i])
    sns.boxplot(y=findistdf[colnames[i]].dropna())
    #column=findistdf[colnames[i]]
    #column.to_frame().boxplot(figsize=[4,8])
    #findistdf.boxplot(column=colnames[i], figsize=[4,8]);
```






TFEDREV
0
200000
400000
600000
800000
1000000
TSTREV
0
500000
1000000
1500000
2000000
TLOCREV
0
500000
1000000
1500000
2000000
2500000
TOTALEXP
0
1000000
2000000
3000000
4000000
5000000
6000000

Clearly the distribution of the metrics is not normal and they are absolutely skewed towards with the lower end of the scale with long tail on right end of the scale.

Let's transform the metrics into log form and see, how their distributions and histograms look like

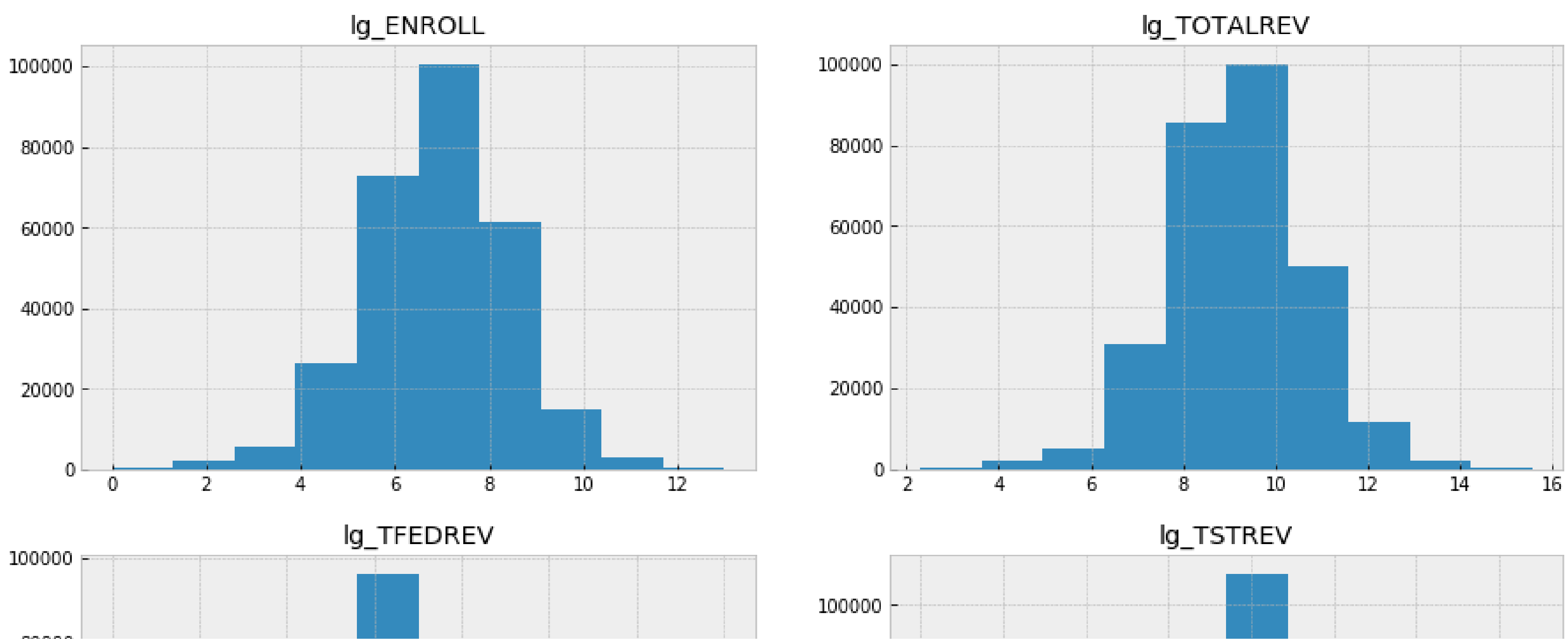
In [36]:
```
# Adding log transformed columns to the dataframe
findistdf['lg_ENROLL'] = findistdf['ENROLL'].apply(np.log)
findistdf['lg_TOTALREV'] = findistdf['TOTALREV'].apply(np.log)
findistdf['lg_TFEDREV'] = findistdf['TFEDREV'].apply(np.log)
findistdf['lg_TSTREV'] = findistdf['TSTREV'].apply(np.log)
findistdf['lg_TLOCREV'] = findistdf['TLOCREV'].apply(np.log)
findistdf['lg_TOTALEXP'] = findistdf['TOTALEXP'].apply(np.log)
findistdf.head()
```

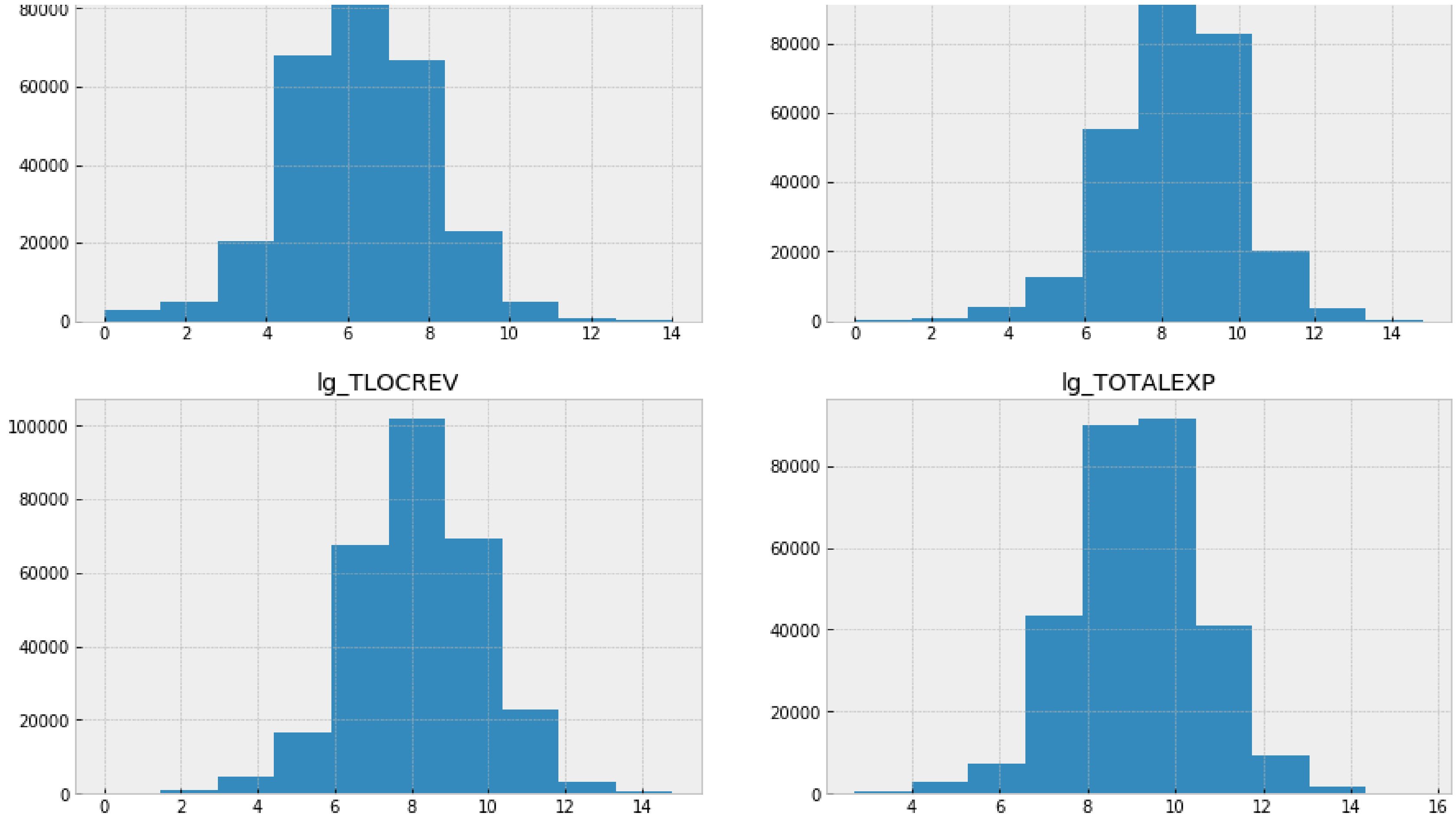
Out[36]:

	STATE	ENROLL	NAME	YRDATA	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP	lg_ENROLL	lg_TOTALREV	lg_TFED
0	ALABAMA	9609.0	AUTAUGA COUNTY SCHOOL DISTRICT	2016	80867	7447	53842	19578	76672	9.170455	11.300561	8.91
1	ALABAMA	30931.0	BALDWIN COUNTY SCHOOL DISTRICT	2016	338236	23710	145180	169346	299880	10.339514	12.731499	10.07
2	ALABAMA	912.0	BARBOUR COUNTY SCHOOL DISTRICT	2016	10116	2342	5434	2340	10070	6.815640	9.221874	7.75
3	ALABAMA	2842.0	EUFAULA CITY SCHOOL DISTRICT	2016	26182	3558	15900	6724	29843	7.952263	10.172827	8.17
4	ALABAMA	3322.0	BIBB COUNTY SCHOOL DISTRICT	2016	32486	3664	21846	6976	31662	8.108322	10.388565	8.20

Plotting histograms of log transformed columns

In [37]:
```
lgcolnames = ['lg_ENROLL', 'lg_TOTALREV', 'lg_TFEDREV', 'lg_TSTREV','lg_TLOCREV', 'lg_TOTALEXP']
plt.figure(figsize=(15,15))
for i in range(len(lgcolnames)):

    if i == 0:
        plt.subplot(3,2,1)
    if i == 1:
        plt.subplot(3,2,2)
    if i == 2:
        plt.subplot(3,2,3)
    if i ==3:
        plt.subplot(3,2,4)
    if i == 4:
        plt.subplot(3,2,5)
    if i == 5:
        plt.subplot(3,2,6)

    #print(colnames[i])
    plt.hist(findistdf[lgcolnames[i]].astype('float'))
    plt.title(findistdf[lgcolnames[i]].name)
```

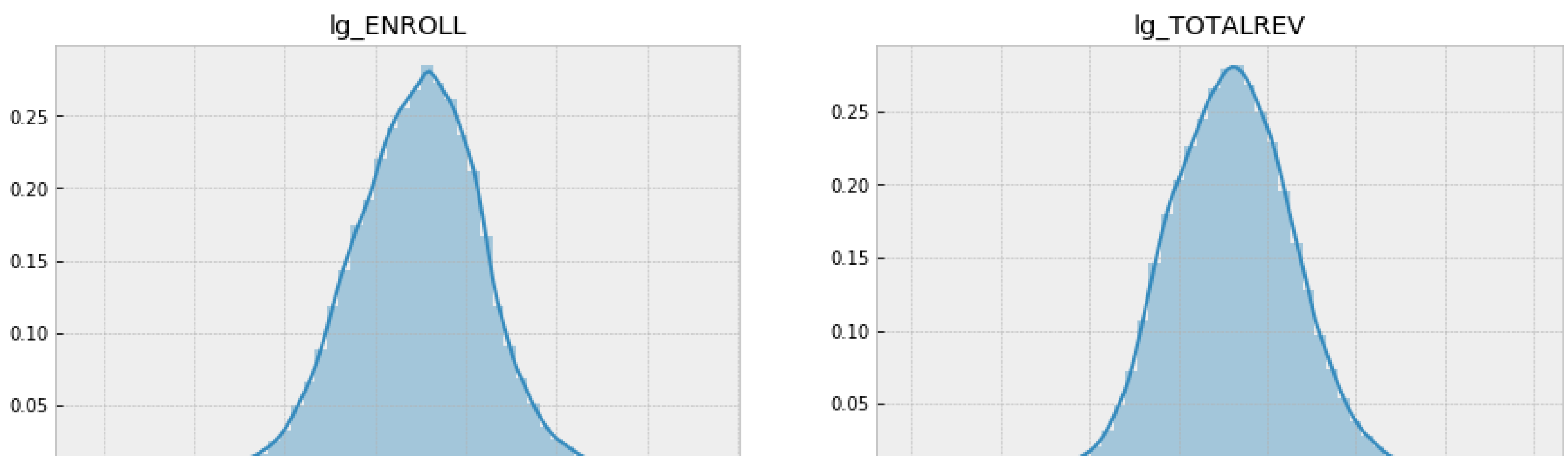


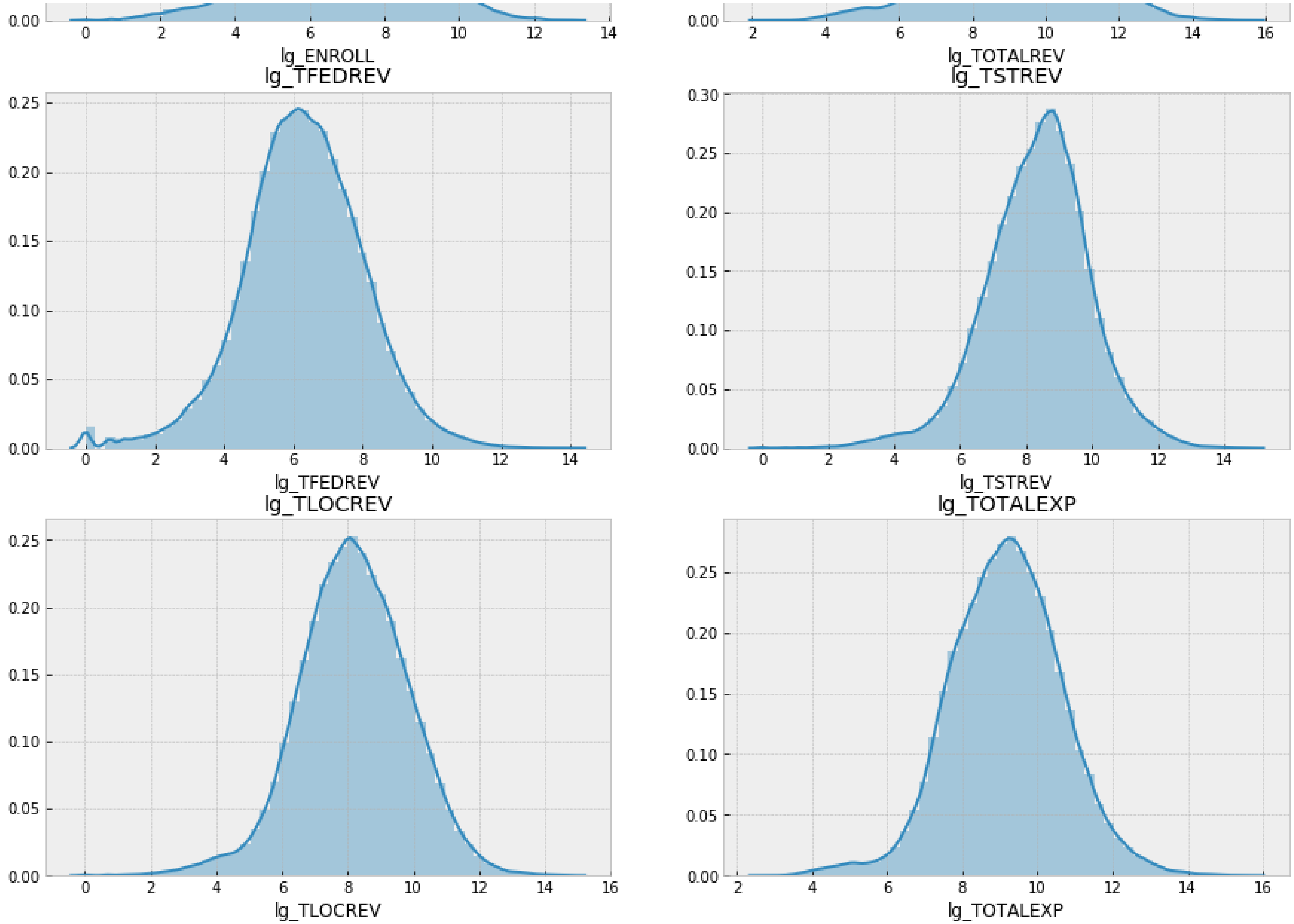


Histograms of log transformed variables doesn’t appear as much skewed as they were earlier without log transformations. All variables except for lg_TOTALEXP appear in unimodal distribution where as lg_TOTALEXP is in bimodal distribution.

In [38]:
```
plt.figure(figsize=(15,15))
for i in range(len(lgcolnames)):

    if i == 0:
        plt.subplot(3,2,1)
    if i == 1:
        plt.subplot(3,2,2)
    if i == 2:
        plt.subplot(3,2,3)
    if i ==3:
        plt.subplot(3,2,4)
    if i == 4:
        plt.subplot(3,2,5)
    if i == 5:
        plt.subplot(3,2,6)

    #print(colnames[i])
    sns.distplot(findistdf[lgcolnames[i]].dropna().astype('float'))
    plt.title(findistdf[lgcolnames[i]].name)
```

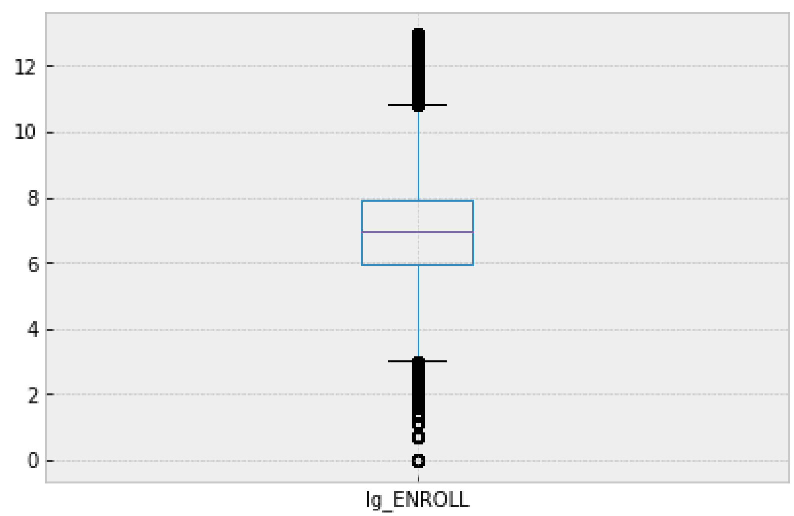
```
C:\Installed\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence
for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this
will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a differ
ent result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

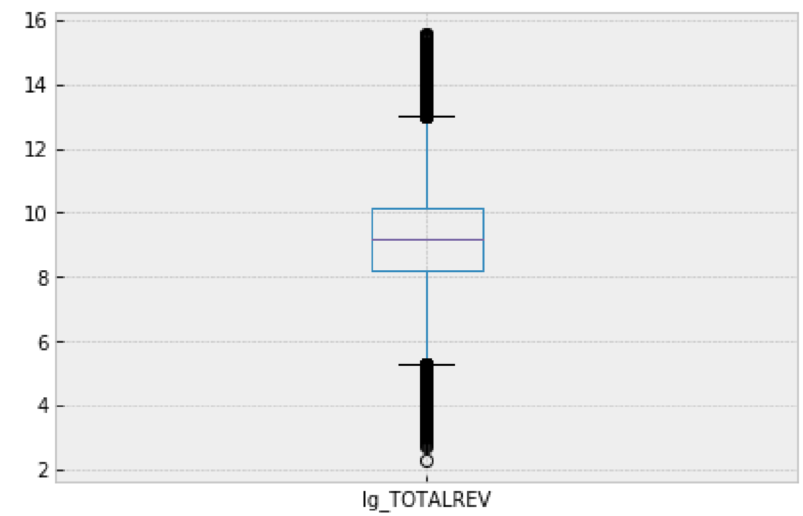


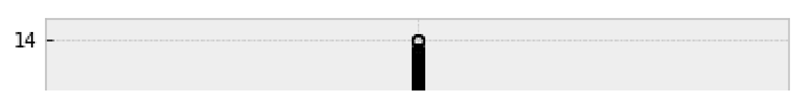


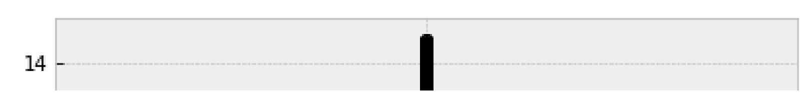
As per the above density plots, all the vairable appear close to log normal distribution

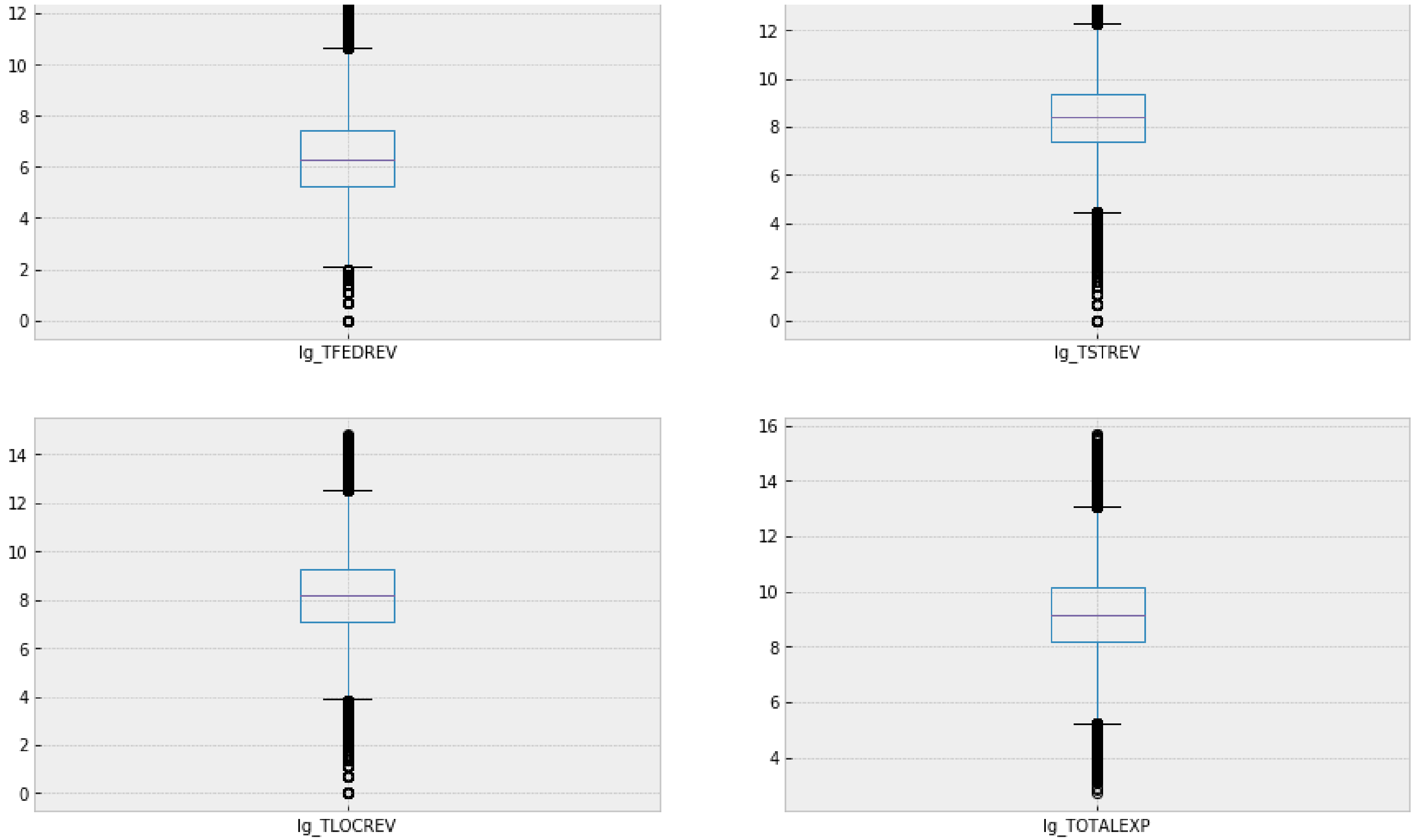
In [39]:
```python
plt.figure(figsize=(15,15))
for i in range(len(lgcolnames)):

    if i == 0:
        plt.subplot(3,2,1)
    if i == 1:
        plt.subplot(3,2,2)
    if i == 2:
        plt.subplot(3,2,3)
    if i ==3:
        plt.subplot(3,2,4)
    if i == 4:
        plt.subplot(3,2,5)
    if i == 5:
        plt.subplot(3,2,6)

    column=findistdf[lgcolnames[i]]
    column.to_frame().boxplot(figsize=[4,8])
```





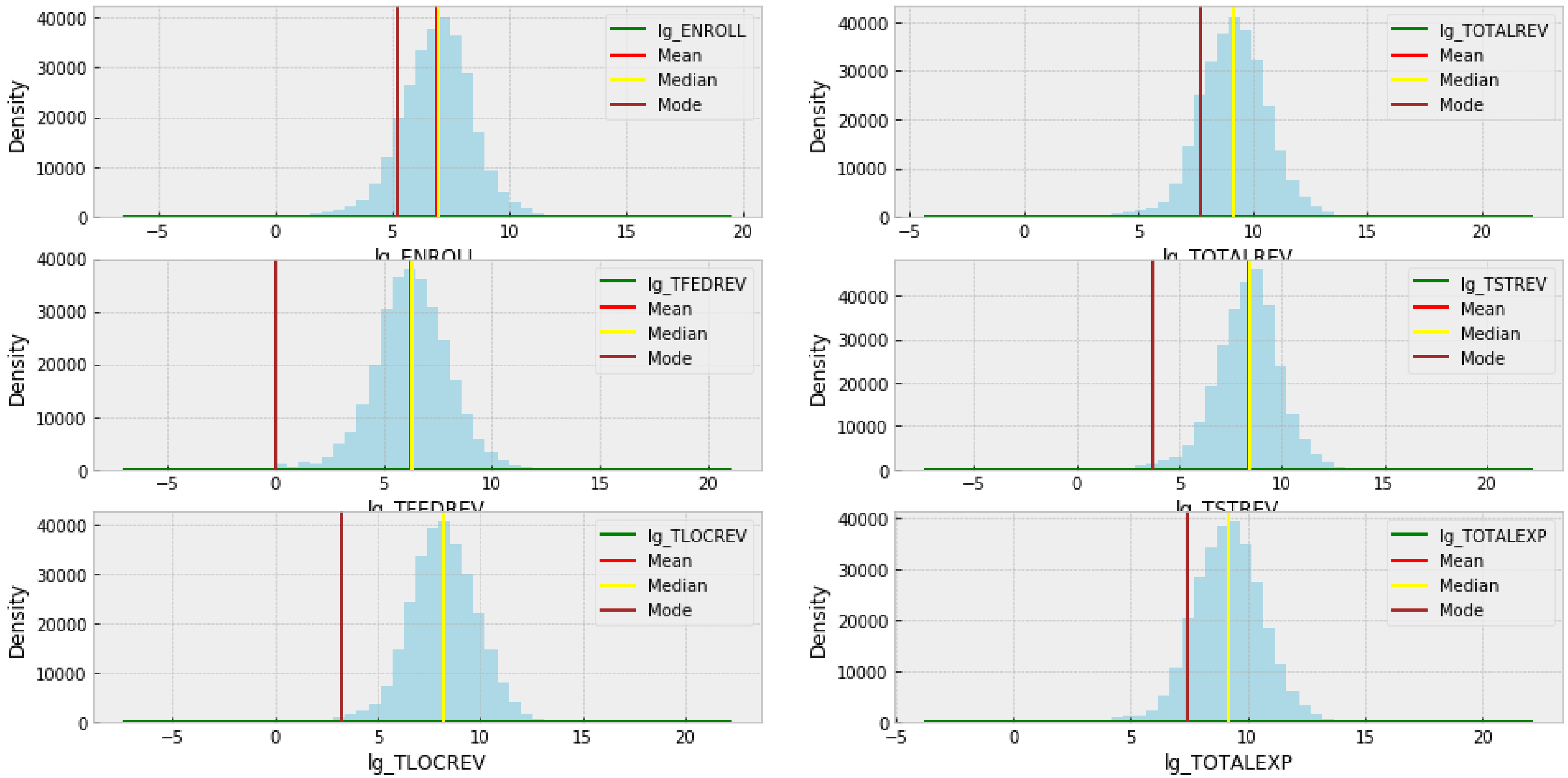






Log transformation gives a better representation of these variables with lesser outliers

In [40]:
```
#Plotting histogram and KDE for total revenue
plt.figure(figsize=(30, 30))
for i in range(len(lgcolnames)):

    if i == 0:
        plt.subplot(3,2,1)
    if i == 1:
        plt.subplot(3,2,2)
    if i == 2:
        plt.subplot(3,2,3)
    if i ==3:
        plt.subplot(3,2,4)
    if i == 4:
        plt.subplot(3,2,5)
    if i == 5:
        plt.subplot(3,2,6)

    axtr = findistdf[lgcolnames[i]].astype('float').hist(bins = 26, color = 'lightblue') #, normed=True)
    findistdf[lgcolnames[i]].plot(kind='kde', color='Green', ax=axtr,  figsize=[16,8])
    #plt.locator_params(nbins=20)
    #plt.title('Histogram - KDE for %s with mean(red), median(yellow) and mode(brown), %findistdf[lgcolnames[i]
    plt.xlabel(findistdf[lgcolnames[i]].name);
    plt.axvline(findistdf[lgcolnames[i]].mean(),color='red',label='Mean')
    plt.axvline(findistdf[lgcolnames[i]].median(),color='yellow',label='Median')
    plt.axvline(findistdf[lgcolnames[i]].mode()[0],color='brown',label='Mode')
    plt.legend()
#plt.title('Histogram - KDE with mean(red), median(yellow) and mode(brown)')
```



In [ ]:

Exploring data set by STATE and YEAR

In [41]:

```
findist_bystateyr = pd.DataFrame()
findist_bystateyr = findistdf.groupby(['YRDATA', 'STATE']).sum()
```

In [42]:
```python
# Displaying top 5 total revenues by state and year
findist_bystateyr.sort_values('TOTALREV',ascending=False)[0:5]
```

Out[42]:

YRDATA	STATE	ENROLL	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP	lg_ENROLL	lg_TOTALREV	lg_TFEDREV	lg_TSTR
2016	**TEXAS**	5053260.0	57724562	5666460	21937670	30120432	58859458	7242.432264	9874.110413	7159.541881	8807.299
2015	**TEXAS**	5004839.0	55046828	5550680	20903361	28592787	55822147	7232.728807	9847.412237	7121.440678	8722.951
2014	**TEXAS**	4949437.0	52271215	5389557	20452946	26428712	52651972	7227.241208	9813.737375	7108.461573	8738.947
2011	**TEXAS**	4800196.0	50448814	7542016	19510784	23396014	52221814	7239.639505	9827.987325	7568.709826	8848.164
2010	**TEXAS**	4728815.0	49998660	7710320	18799593	23488747	53344838	7238.895148	9833.663269	7655.391596	8829.589

In [43]:
```python
# Displaying bottom 5 total revenues by state and year
findist_bystateyr.sort_values('TOTALREV')[0:5]
```

Out[43]:

YRDATA	STATE	ENROLL	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP	lg_ENROLL	lg_TOTALREV	lg_TFEDREV	
1993	**SOUTH_DAKOTA**	107050.0	465650	52787	120851	292012	481665	535.762896	664.100837	471.248246	
1994	**SOUTH_DAKOTA**	108439.0	507927	51846	126591	329490	525289	536.448805	668.787000	470.863467	
1993	**NORTH_DAKOTA**	118536.0	549529	52163	231963	265403	557977	1281.962611	1705.264803	1046.491984	1
1994	**NORTH_DAKOTA**	118670.0	560962	50679	234002	276281	578406	1257.753819	1676.509178	1012.583536	1
1995	**NORTH_DAKOTA**	119132.0	600172	57770	244283	298119	580340	1214.217840	1623.333995	999.034394	1

In [ ]:

```

```

Calculating Mean, Mode, Spread, and Tails

In [44]:

```
# statistics for whole data set(including California & New York - school districts)
findistdf_orig2.describe()
```

Out[44]:

	ENROLL	YRDATA	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP
count	3.582930e+05	358293.000000	3.582930e+05	3.582930e+05	3.582930e+05	3.582930e+05	3.582930e+05
mean	3.134504e+03	2004.400390	3.173910e+04	2.689896e+03	1.473310e+04	1.431610e+04	3.209838e+04
std	1.402406e+04	6.849252	1.816932e+05	1.926575e+04	8.418726e+04	8.637972e+04	1.937165e+05
min	0.000000e+00	1993.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	2.760000e+02	1998.000000	3.299000e+03	1.730000e+02	1.354000e+03	1.125000e+03	3.231000e+03
50%	9.480000e+02	2004.000000	9.498000e+03	5.380000e+02	4.354000e+03	3.513000e+03	9.433000e+03
75%	2.607000e+03	2010.000000	2.575700e+04	1.677000e+03	1.156600e+04	1.101400e+04	2.585600e+04
max	1.077381e+06	2016.000000	2.744836e+07	3.120314e+06	1.056801e+07	1.514124e+07	2.962010e+07

In [45]:
```
def descchar(var):
    """
    Function to print descriptive charecteristics of the variable
        Input: dataframe.columnname
        Returns: descriptive charecteristics like - mean, median, mode, spread, interquartile range, skew
        """

    print('  Mean, Median, Mode of %s, %f %f %f ' %(var.name, var.mean(), var.median(), var.mode()[0]))
    print('  Spread - Variance, Standard deviation of %s, %f %f ' %(var.name, var.var(), var.std()))
    print('  Skew of %s, %f ' %(var.name, var.skew()))
    print('  Interquartile range of %s, %f %f %f' %(var.name, var.quantile(0.25), var.quantile(0.5), var.quant:
```

In [46]:
```
# statistics for entire data set with  California & New York school districts
for i in range(len(colnames)):
    print("Descriptive Characteristics for %s" % findistdf_orig2[colnames[i]].name)
    descchar(findistdf_orig2[colnames[i]])
```

```
Descriptive Characteristics for ENROLL
  Mean, Median, Mode of ENROLL, 3134.504099 948.000000 0.000000
  Spread - Variance, Standard deviation of ENROLL, 196674167.451108 14024.056740
  Skew of ENROLL, 39.215369
  Interquartile range of ENROLL, 276.000000 948.000000 2607.000000
Descriptive Characteristics for TOTALREV
  Mean, Median, Mode of TOTALREV, 31739.097055 9498.000000 0.000000
  Spread - Variance, Standard deviation of TOTALREV, 33012411727.751137 181693.180191
  Skew of TOTALREV, 75.790358
  Interquartile range of TOTALREV, 3299.000000 9498.000000 25757.000000
Descriptive Characteristics for TFEDREV
  Mean, Median, Mode of TFEDREV, 2689.895753 538.000000 0.000000
  Spread - Variance, Standard deviation of TFEDREV, 371169206.807162 19265.752173
  Skew of TFEDREV, 62.346503
  Interquartile range of TFEDREV, 173.000000 538.000000 1677.000000
Descriptive Characteristics for TSTREV
  Mean, Median, Mode of TSTREV, 14733.104367 4354.000000 0.000000
  Spread - Variance, Standard deviation of TSTREV, 7087494107.262826 84187.256205
  Skew of TSTREV, 64.036625
  Interquartile range of TSTREV, 1354.000000 4354.000000 11566.000000
Descriptive Characteristics for TLOCREV
  Mean, Median, Mode of TLOCREV, 14316.096912 3513.000000 0.000000
  Spread - Variance, Standard deviation of TLOCREV, 7461456055.094042 86379.720161
  Skew of TLOCREV, 88.592093
  Interquartile range of TLOCREV, 1125.000000 3513.000000 11014.000000
Descriptive Characteristics for TOTALEXP
  Mean, Median, Mode of TOTALEXP, 32098.381944 9433.000000 0.000000
  Spread - Variance, Standard deviation of TOTALEXP, 37526083710.425728 193716.503454
  Skew of TOTALEXP, 79.133328
  Interquartile range of TOTALEXP, 3231.000000 9433.000000 25856.000000
```

In [47]:
```
# statistics for data set without California & New York school districts
findistdf.describe()
```

Out[47]:

	ENROLL	YRDATA	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP	lg_ENROLL	lg_TOTALRE
count	287744.000000	287744.000000	2.877440e+05	2.877440e+05	2.877440e+05	2.877440e+05	2.877440e+05	287744.000000	287744.0000
mean	3170.830384	2004.461594	3.025546e+04	2.472747e+03	1.398188e+04	1.380084e+04	3.056100e+04	6.912037	9.1708
std	10435.217797	6.848307	1.033309e+05	1.225883e+04	4.819758e+04	5.112197e+04	1.057474e+05	1.520550	1.4830
min	1.000000	1993.000000	1.000000e+01	1.000000e+00	1.000000e+00	1.000000e+00	1.500000e+01	0.000000	2.3025
25%	388.000000	1999.000000	3.653000e+03	1.870000e+02	1.623000e+03	1.224000e+03	3.592000e+03	5.961005	8.2033
50%	1073.000000	2004.000000	9.715000e+03	5.390000e+02	4.608000e+03	3.524000e+03	9.660000e+03	6.978214	9.1814
75%	2720.000000	2010.000000	2.520025e+04	1.649000e+03	1.150125e+04	1.072525e+04	2.534300e+04	7.908387	10.1346
max	437418.000000	2016.000000	5.760419e+06	1.220298e+06	2.710361e+06	2.687925e+06	6.253045e+06	12.988645	15.5665

In [48]:
```
# statistics for data set without California & New York school districts
for i in range(len(colnames)):
    print("Descriptive Characteristics for %s" % findistdf[colnames[i]].name)
    descchar(findistdf[colnames[i]])
```

```
Descriptive Characteristics for ENROLL
  Mean, Median, Mode of ENROLL, 3170.830384 1073.000000 180.000000
  Spread - Variance, Standard deviation of ENROLL, 108893770.472233 10435.217797
  Skew of ENROLL, 16.793895
  Interquartile range of ENROLL, 388.000000 1073.000000 2720.000000
Descriptive Characteristics for TOTALREV
  Mean, Median, Mode of TOTALREV, 30255.458977 9715.000000 2276.000000
  Spread - Variance, Standard deviation of TOTALREV, 10677274625.544109 103330.898697
  Skew of TOTALREV, 18.316904
  Interquartile range of TOTALREV, 3653.000000 9715.000000 25200.250000
Descriptive Characteristics for TFEDREV
  Mean, Median, Mode of TFEDREV, 2472.746674 539.000000 1.000000
  Spread - Variance, Standard deviation of TFEDREV, 150278906.593238 12258.829740
  Skew of TFEDREV, 32.430302
  Interquartile range of TFEDREV, 187.000000 539.000000 1649.000000
Descriptive Characteristics for TSTREV
  Mean, Median, Mode of TSTREV, 13981.876206 4608.000000 40.000000
  Spread - Variance, Standard deviation of TSTREV, 2323006348.923632 48197.576173
  Skew of TSTREV, 19.203716
  Interquartile range of TSTREV, 1623.000000 4608.000000 11501.250000
Descriptive Characteristics for TLOCREV
  Mean, Median, Mode of TLOCREV, 13800.836066 3524.000000 25.000000
  Spread - Variance, Standard deviation of TLOCREV, 2613455677.474381 51121.968638
  Skew of TLOCREV, 19.163061
  Interquartile range of TLOCREV, 1224.000000 3524.000000 10725.250000
Descriptive Characteristics for TOTALEXP
  Mean, Median, Mode of TOTALEXP, 30560.999228 9660.000000 1638.000000
  Spread - Variance, Standard deviation of TOTALEXP, 11182506231.429939 105747.369856
  Skew of TOTALEXP, 19.065186
  Interquartile range of TOTALEXP, 3592.000000 9660.000000 25343.000000
```

Skew is far greater than 1, highlighting that the numbers for every column are skewed heavily towards right with long tail towards higher scale

In [ ]:

Plotting PMFS

In [49]:
```
#Top 5 states with most total revenue
findist_bystate.sort_values('TOTALREV',ascending=False)[0:5]
```

Out[49]:

	STATE	TOTALREV	ENROLL
32	NEW_YORK	27448356	1077381.0
4	CALIFORNIA	10329380	747009.0
13	ILLINOIS	5760419	437418.0
9	FLORIDA	3959408	375836.0
28	NEVADA	3220684	325990.0

In [50]:
```
# Bottom 5 states with most total revenue
findist_bystate.sort_values('TOTALREV',ascending=True)[0:5]
```

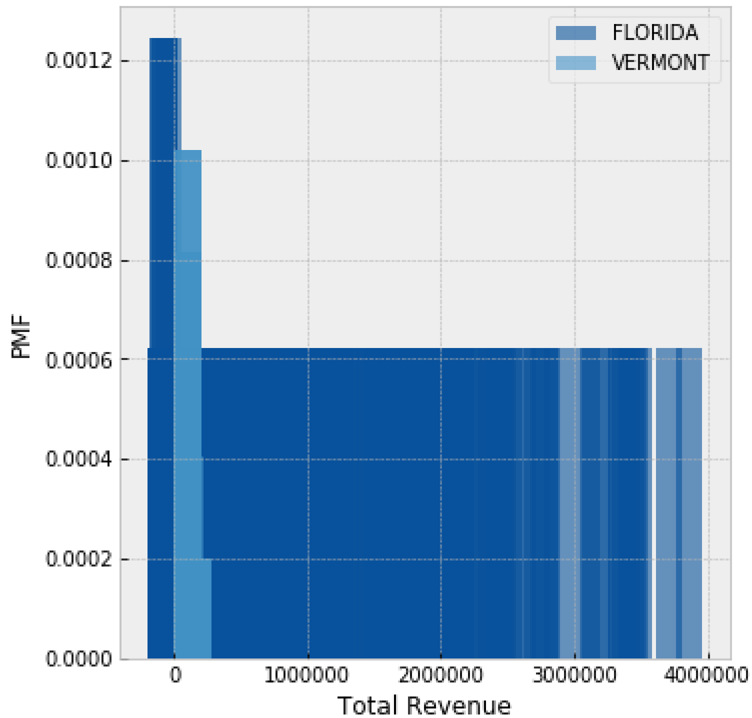
Out[50]:

	STATE	TOTALREV	ENROLL
45	VERMONT	84611	3992.0
26	MONTANA	117079	11348.0
19	MAINE	119828	8266.0
34	NORTH_DAKOTA	177525	12561.0
29	NEW_HAMPSHIRE	186461	17737.0

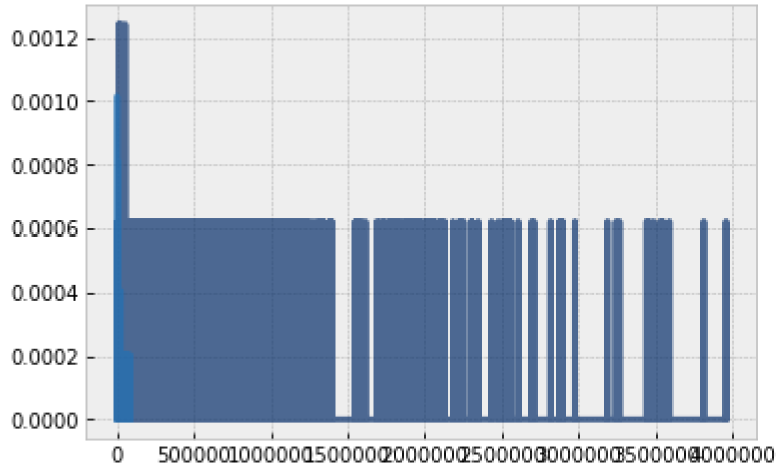
In [51]:
```
# Comparing 2 states -FLORIDA and VERMONT
flfindistdf =  findistdf[findistdf.STATE == 'FLORIDA']
vfindistdf =  findistdf[findistdf.STATE == 'VERMONT']
```

In [52]:
```
import thinkstats2
import thinkplot


flfindistdfpmf = thinkstats2.Pmf(flfindistdf['TOTALREV'], label='FLORIDA')
vfindistdfpmf = thinkstats2.Pmf(vfindistdf['TOTALREV'], label='VERMONT')
```

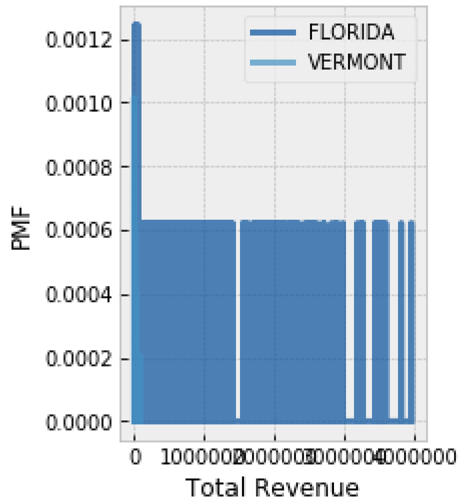
In [53]:
```
width=200000
axis = [0, 800, 0, 0.0005]

thinkplot.PrePlot(2, cols =2)
thinkplot.Hist(flfindistdfpmf, align = 'right', width = width)
thinkplot.Hist(vfindistdfpmf, align = 'left', width = width)
thinkplot.Config(xlabel = 'Total Revenue', ylabel = 'PMF')
```



In [54]:
```
thinkplot.Pmf(flfindistdfpmf)

thinkplot.Pmf(vfindistdfpmf)
```



In [55]:
```
thinkplot.PrePlot(2)
thinkplot.subplot(2)
#axis = [0, 800, 0, 0.0005]
thinkplot.Pmfs([flfindistdfpmf,vfindistdfpmf ])
thinkplot.Show(xlabel = 'Total Revenue', ylabel = 'PMF')
```




```
<Figure size 576x432 with 0 Axes>
```

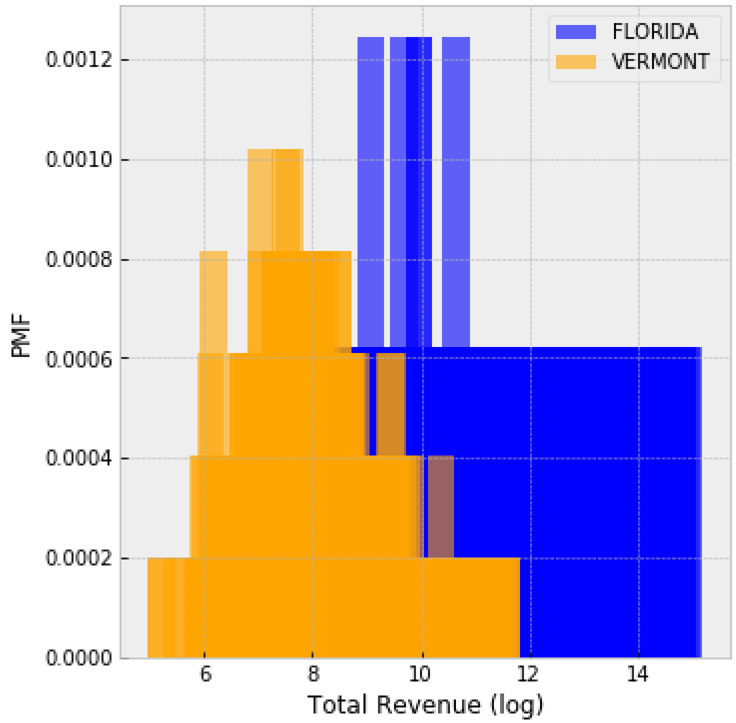
Lets plot PMF of log transformed columns

In [56]:
```
findistdf.columns
```

Out[56]:
```
Index(['STATE', 'ENROLL', 'NAME', 'YRDATA', 'TOTALREV', 'TFEDREV', 'TSTREV',
       'TLOCREV', 'TOTALEXP', 'lg_ENROLL', 'lg_TOTALREV', 'lg_TFEDREV',
       'lg_TSTREV', 'lg_TLOCREV', 'lg_TOTALEXP'],
      dtype='object')
```

In [57]:
```
lgflfindistdfpmf = thinkstats2.Pmf(flfindistdf['lg_TOTALREV'], label='FLORIDA')
lgvfindistdfpmf = thinkstats2.Pmf(vfindistdf['lg_TOTALREV'], label='VERMONT')
```

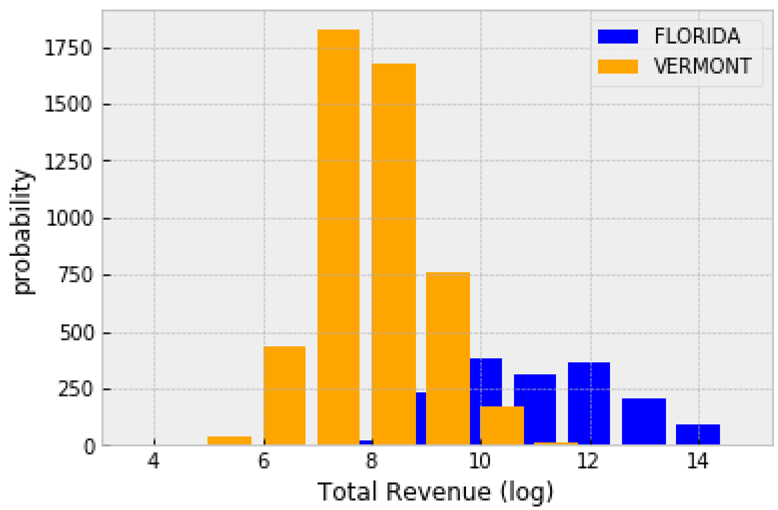
In [58]:
```
width= 0.5
#axis = [0, 800, 0, 0.0005]

thinkplot.PrePlot(2, cols =2)
thinkplot.Hist(lgflfindistdfpmf, align = 'right',color="blue",  width = width)
thinkplot.Hist(lgvfindistdfpmf, align = 'left',color="orange",  width = width)
thinkplot.Config(xlabel = 'Total Revenue (log)', ylabel = 'PMF')
```



In [ ]:

In [59]:
```
fltr4 = np.array(flfindistdf['lg_TOTALREV'].dropna())
vtr4 = np.array(vfindistdf['lg_TOTALREV'].dropna())

range_lb = int(min([np.min(fltr4), np.min(vtr4)]))
range_ub = int(max([np.max(fltr4), np.max(vtr4)]))

nbr_bins =  range_ub - range_lb

pmf_fltr4 = np.histogram(np.array(fltr4),
                                bins=nbr_bins, range=(range_lb, range_ub))
pmf_vtr4 = np.histogram(np.array(vtr4),
                                bins=nbr_bins, range=(range_lb, range_ub))

width = 0.001
plt.bar(np.arange(range_lb, range_ub), pmf_fltr4[0],  align = 'center', color="blue", label="FLORIDA")
plt.bar(np.arange(range_lb, range_ub) + width, pmf_vtr4[0], align = 'edge', color="orange", label="VERMONT")

plt.xlabel("Total Revenue (log)")
plt.ylabel("probability")
plt.legend(loc="best")
```

Out[59]: <matplotlib.legend.Legend at 0x225354ed668>



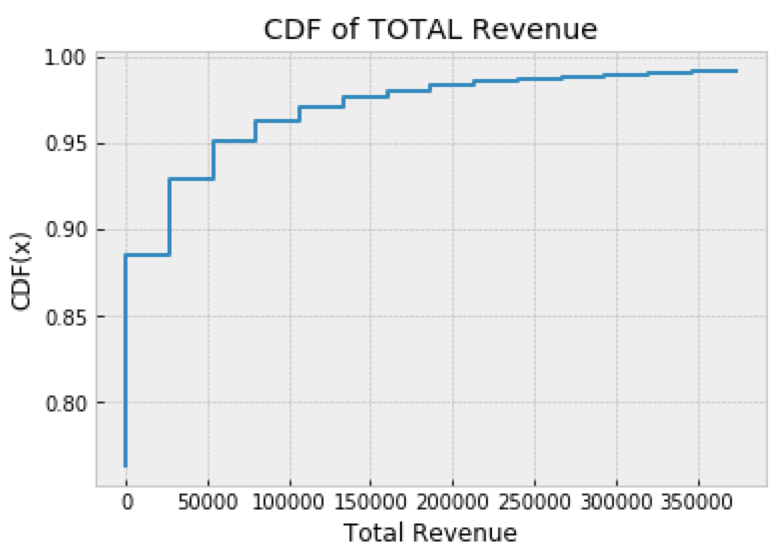
Based on the comparisons of PMF's Vermont - school districts are more likely to have lesser total revenues than Illinois school districts

In [ ]:

Calculating CDF

In [60]:
```
# CDF for total revenue
cdttlrev = np.sort(findistdf.TOTALREV) #ENROLL)
hist = np.histogram(cdttlrev, bins=15, range=(0,400000))
sz = len(cdttlrev)

plt.step(hist[1][:-1], np.cumsum(hist[0])/sz)
plt.xlabel("Total Revenue")
plt.ylabel("CDF(x)")
plt.title("CDF of TOTAL Revenue")
```

Out[60]:
```
Text(0.5,1,'CDF of TOTAL Revenue')
```

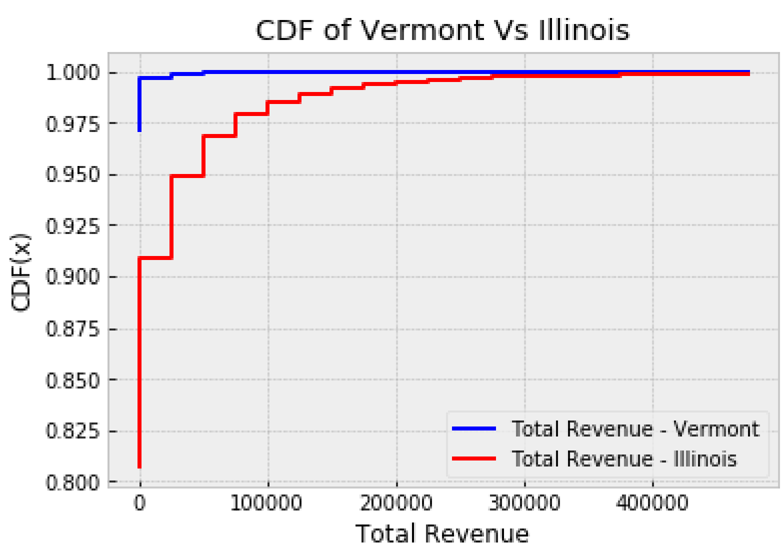


95% of the total revenues for all school districts are less than 50,000

In [61]:
```
# comparing CDF's of total revenue for school districts in different states

vfindistdf =  findistdf[findistdf.STATE == 'VERMONT']
ilfindistdf =  findistdf[findistdf.STATE == 'ILLINOIS']

actvtr = np.array(vfindistdf['TOTALREV'].dropna())
actiltr = np.array(ilfindistdf['TOTALREV'].dropna())
```

In [62]:
```
# CDF for Vermont state
vcdttlrev = np.sort(actvtr) #ENROLL)
histv = np.histogram(vcdttlrev, bins=20, range=(0,500000))
szv = len(vcdttlrev)

# CDF for Illionis state
ilcdttlrev = np.sort(actiltr) #ENROLL)
histil = np.histogram(ilcdttlrev, bins=20, range=(0,500000))
szil = len(ilcdttlrev)


plt.step(histv[1][:-1], np.cumsum(histv[0])/szv, color = 'blue', label = 'Total Revenue - Vermont')
plt.step(histil[1][:-1], np.cumsum(histil[0])/szil, color = 'red', label = 'Total Revenue - Illinois')
plt.xlabel("Total Revenue")
plt.ylabel("CDF(x)")
plt.title('CDF of Vermont Vs Illinois')
plt.legend()
```

Out[62]: <matplotlib.legend.Legend at 0x22539428400>



Overall school districts in Illinois have higher total revenue than Vermont and 98% of the total revenues for all school districts in Illinois is less than 100,000. Whereas for Vermont, almost 97% of the total revenues for school districts are below 50000$. Put it in another way, Illinois school districts have higher chance of having more Total Revenue.

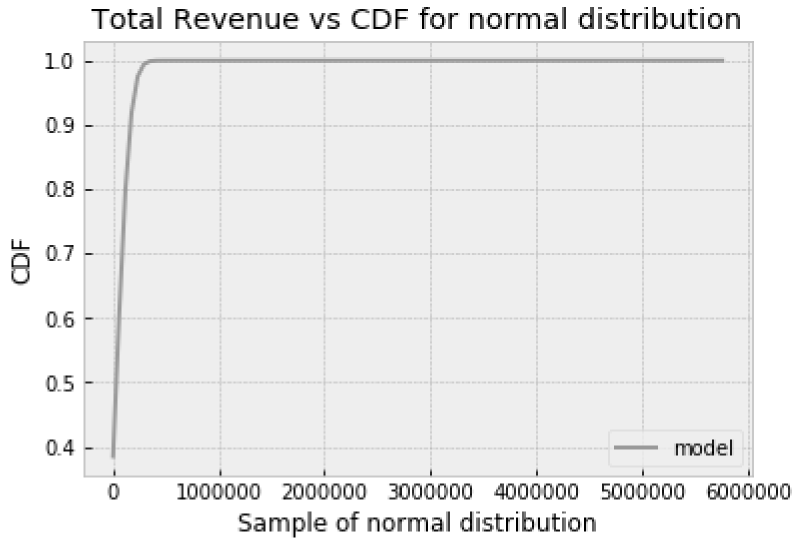
In [ ]:

```

```

Plotting analytical distributions

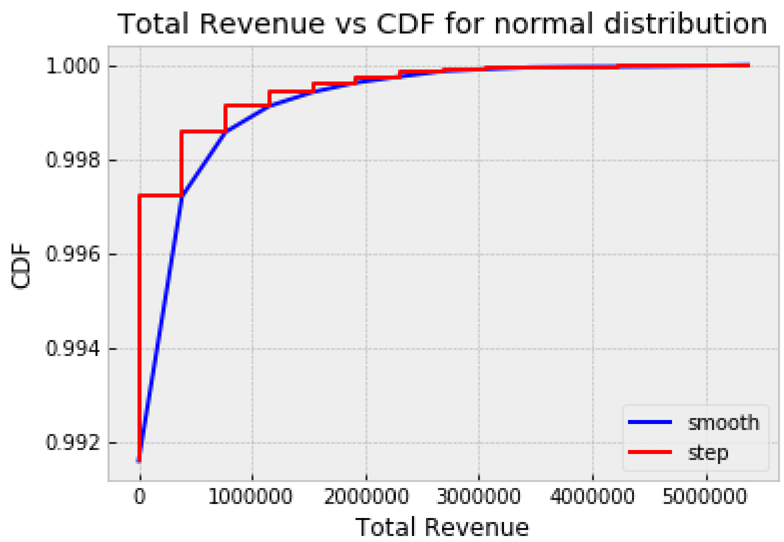
In [63]:
```
# PLotting analytical distributions for total revenue

# calculate the mean and standard deviation

mean_tr = np.mean(findistdf.TOTALREV)
mean_tr

std_tr = np.std(findistdf.TOTALREV)
std_tr

# plot a normal distribution with the mean and standard deviation of total revenue

low = min(findistdf.TOTALREV)
high = max(findistdf.TOTALREV)


xs = np.linspace(low, high, 100)
ps = stats.norm.cdf(xs, mean_tr, std_tr)

plt.plot(xs, ps, label='model', color='0.6')

plt.title('Total Revenue vs CDF for normal distribution')
plt.xlabel('Sample of normal distribution')
plt.ylabel('CDF')
plt.legend()
```

Out[63]:
```
<matplotlib.legend.Legend at 0x2253a063780>
```


Total Revenue vs CDF for normal distribution
CDF
1.0
0.9
0.8
0.7
0.6
0.5
0.4
model
0
1000000
2000000
3000000
4000000
5000000
6000000
Sample of normal distribution

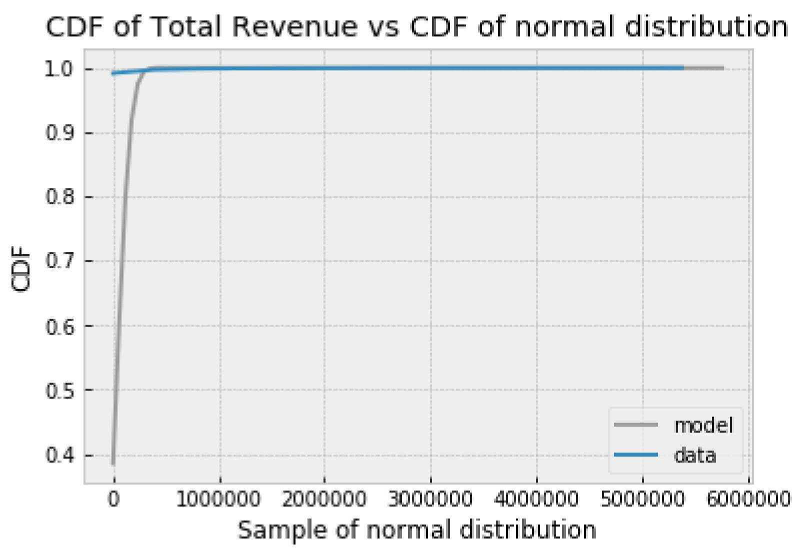
In [64]:
```
# CDF for total revenue
cdttlrev = np.sort(findistdf.TOTALREV) #ENROLL)
hist = np.histogram(cdttlrev, bins=15, range=(0,max(findistdf.TOTALREV)))
sz = len(cdttlrev)


plt.plot(hist[1][:-1], np.cumsum(hist[0])/sz, color = 'b', label = 'smooth')

plt.step(hist[1][:-1], np.cumsum(hist[0])/sz, color = 'r', label = 'step')

plt.title('Total Revenue vs CDF for normal distribution')
plt.xlabel('Total Revenue')
plt.ylabel('CDF')
plt.legend()
```

Out[64]: <matplotlib.legend.Legend at 0x2253f19a550>



In [65]:
```
# Overlapping distribution plots of normal distribution and cdf distribution of total revenues

plt.plot(xs, ps, label='model', color='0.6')
plt.plot(hist[1][:-1], np.cumsum(hist[0])/sz, label='data')

plt.title('CDF of Total Revenue vs CDF of normal distribution')
plt.xlabel('Sample of normal distribution')
plt.ylabel('CDF')

plt.legend()
```

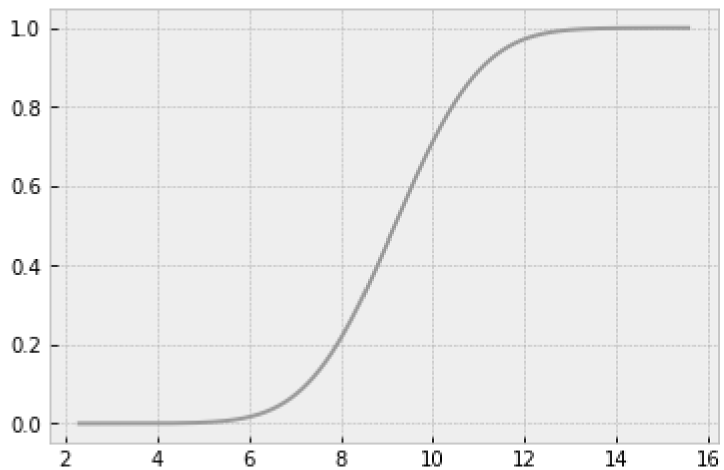
Out[65]: <matplotlib.legend.Legend at 0x2253f8cc5c0>



From the above overlapping plot of normal distribution vs total revenue, we can infer that Normal distribution doesn’t represent the total revenue. Let us try to see if log normal distribution is applicable.
To find out I will use the log transformed total revenue column - findistdf.lg_TOTALREV

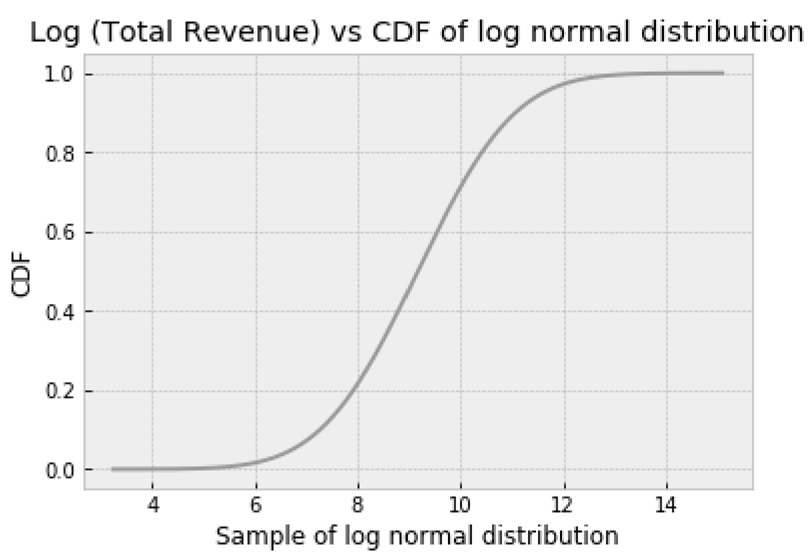
In [66]:
```
mean_ltr = np.mean(findistdf.lg_TOTALREV)
mean_ltr

std_ltr = np.std(findistdf.lg_TOTALREV)
std_ltr

# plot a normal distribution with the mean and standard deviation of total revenue

llow = min(findistdf.lg_TOTALREV)
lhigh = max(findistdf.lg_TOTALREV)


lxs = np.linspace(llow, lhigh, 10000)
lps = stats.norm.cdf(lxs, mean_ltr, std_ltr)

plt.plot(lxs,lps, label='model', color='0.6')
```

Out[66]: [<matplotlib.lines.Line2D at 0x22541cdb978>]



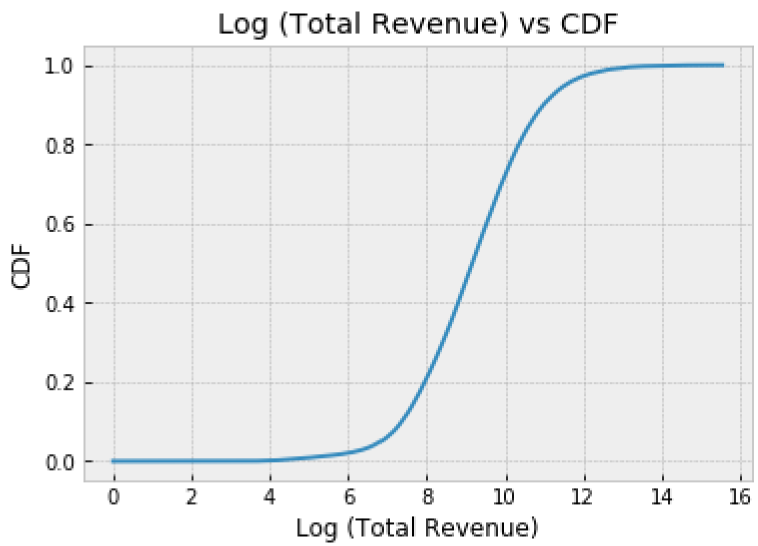
In [67]:
```
mean_ltr = np.mean(findistdf.lg_TOTALREV)
mean_ltr

std_ltr = np.std(findistdf.lg_TOTALREV)
std_ltr

# plot a normal distribution with the mean and standard deviation of total revenue

llow2 = mean_ltr - 4 * std_ltr
lhigh2 = mean_ltr + 4 * std_ltr


lxs2 = np.linspace(llow2, lhigh2, 10000)
lps2 = stats.norm.cdf(lxs2, mean_ltr, std_ltr)

plt.plot(lxs2,lps2, label='model', color='0.6')
plt.title('Log (Total Revenue) vs CDF of log normal distribution')
plt.xlabel('Sample of log normal distribution')
plt.ylabel('CDF')
```

Out[67]:
```
Text(0,0.5,'CDF')
```



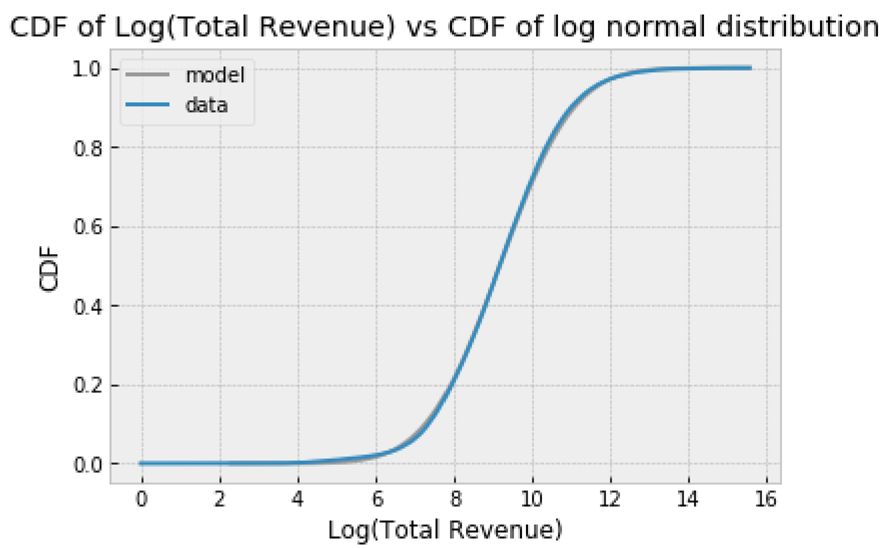
In [68]:
```
# CDF for log transformed total revenue
cdttlrev4 = np.sort(findistdf.lg_TOTALREV) #ENROLL)
hist = np.histogram(cdttlrev4, bins=1000, range=(0,max(findistdf.lg_TOTALREV)))
sz = len(cdttlrev4)


plt.plot(hist[1][:-1], np.cumsum(hist[0])/sz)

plt.title('Log (Total Revenue) vs CDF')
plt.xlabel('Log (Total Revenue)')
plt.ylabel('CDF')

#plt.legend()
```

Out[68]: Text(0,0.5,'CDF')



In [69]:
```
# Overlapping distribution plots of log normal distribution and cdf distribution of log (total revenues)

plt.plot(lxs,lps, label='model', color='0.6')
plt.plot(hist[1][:-1], np.cumsum(hist[0])/sz, label='data')

plt.title('CDF of Log(Total Revenue) vs CDF of log normal distribution')
plt.xlabel('Log(Total Revenue)')
plt.ylabel('CDF')
plt.legend()
```

Out[69]:
```
<matplotlib.legend.Legend at 0x22541ee9ac8>
```

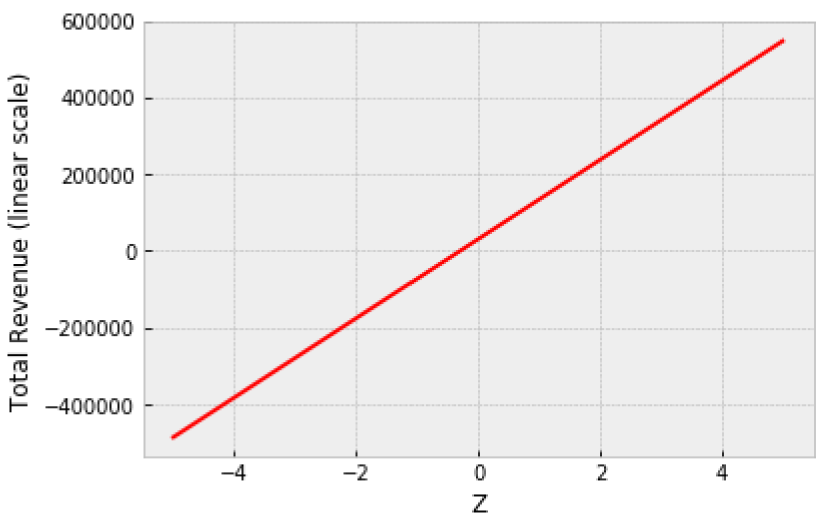


From the above overlapping plot of log normal distribution vs log(total revenue), we can infer that log normal distribution perfectly fits for the variable total revenue

Probability plots for total revenue and Log (total revenue)

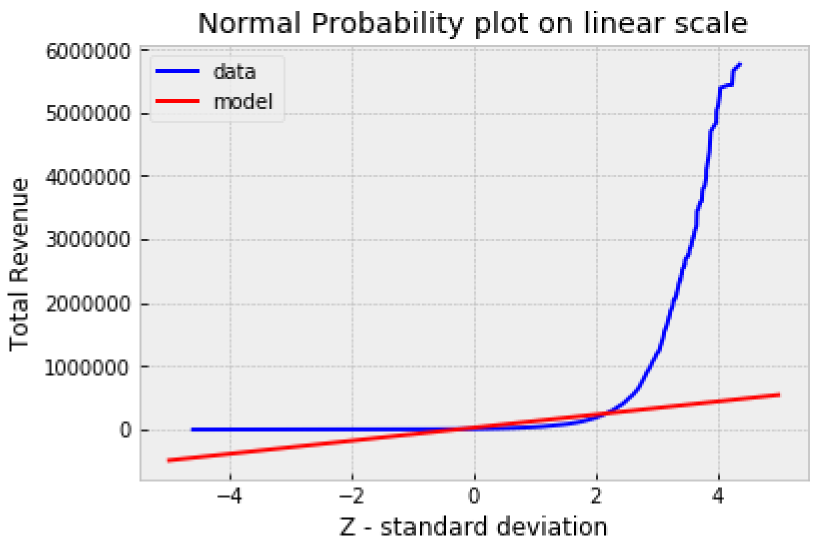
In [70]:
```
xs = [-5, 5]
# y(x) = mean + std * x, here mean and standard deviation are from Total Revenue
ys = mean_tr + std_tr * np.sort(xs)
plt.plot(xs, ys, color='red', label='model')

plt.xlabel('Z')
plt.ylabel('Total Revenue (linear scale)')
```

Out[70]:
```
Text(0,0.5,'Total Revenue (linear scale)')
```



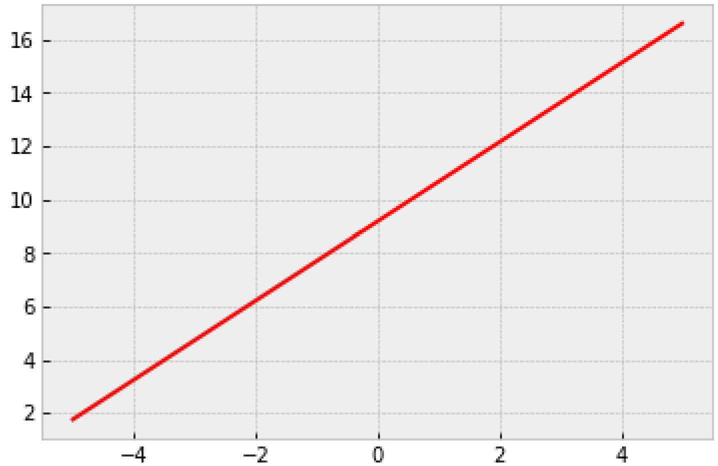
In [71]:
```
n = len(findistdf.TOTALREV)
xs2 = np.sort(np.random.normal(0, 1, n))
ys2 = np.sort(np.array(findistdf.TOTALREV))

plt.plot(xs2, ys2, color='blue', label='data')
plt.plot(xs, ys, color='red', label='model')

plt.title('Normal Probability plot on linear scale')
plt.xlabel("Z - standard deviation")
plt.ylabel('Total Revenue')
plt.legend()
```

Out[71]: <matplotlib.legend.Legend at 0x2253fb13fd0>



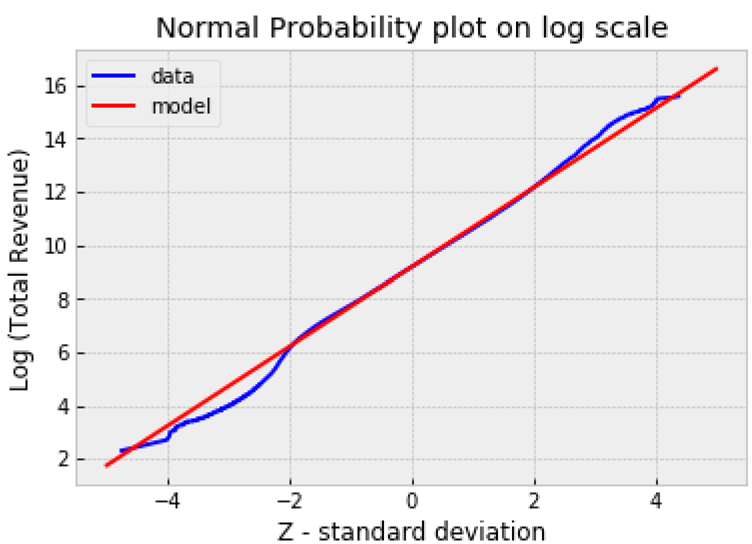
In [72]:
```
# Normal probability plot of log normal form

xs = [-5, 5]
# y(x) = mean + std * x, here mean and standard deviation are from log transformed Total Revenue
ys = mean_ltr + std_ltr * np.sort(xs)
plt.plot(xs, ys, color='red', label='model')
```

Out[72]: [<matplotlib.lines.Line2D at 0x2254151e588>]



In [73]:
```
n = len(findistdf.lg_TOTALREV)
xs2 = np.sort(np.random.normal(0, 1, n))
ys2 = np.sort(np.array(findistdf.lg_TOTALREV))

plt.plot(xs2, ys2, color='blue', label='data')
plt.plot(xs, ys, color='red', label='model')

plt.title('Normal Probability plot on log scale')
plt.xlabel("Z - standard deviation")
plt.ylabel("Log (Total Revenue)")

plt.legend()
```

Out[73]:
```
<matplotlib.legend.Legend at 0x22541859828>
```



From the above two normal probability plots, we can infer that data deviates substantially from normal model where as log normal model fits perfectly to the data with in 2 standard deviations (between -2 to 2) but deviates from the log normal model significantly for the school districts with lower and higher end of the (log) total revenue scale.

In [ ]:

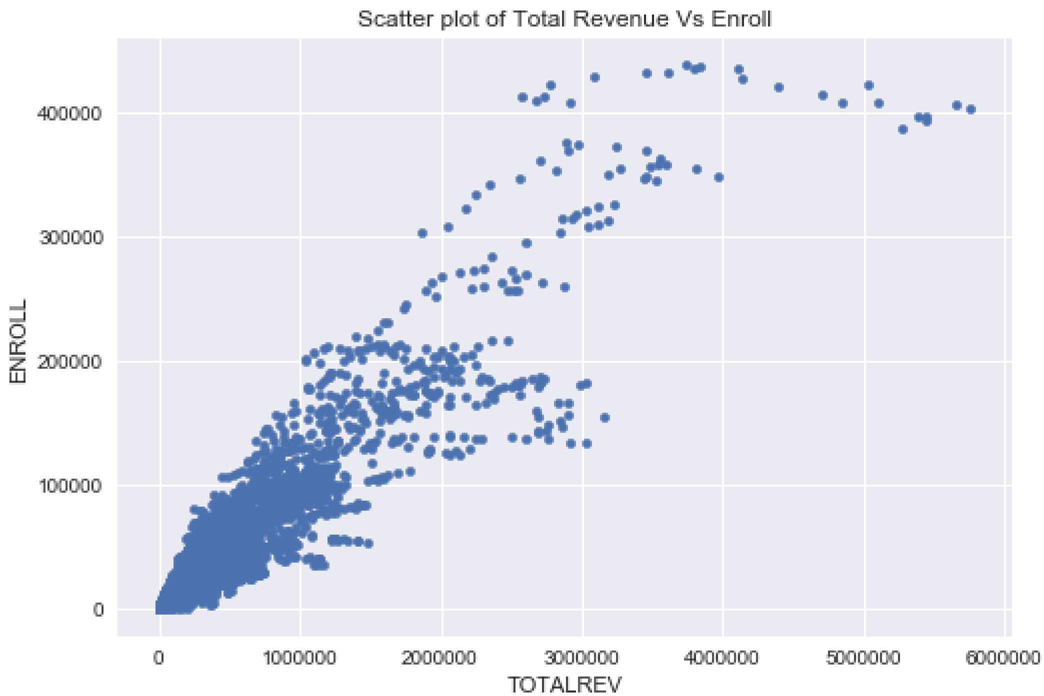
Scatter plots and Correlation analysis

In [74]:
```
findistdf.head()
```

Out[74]:

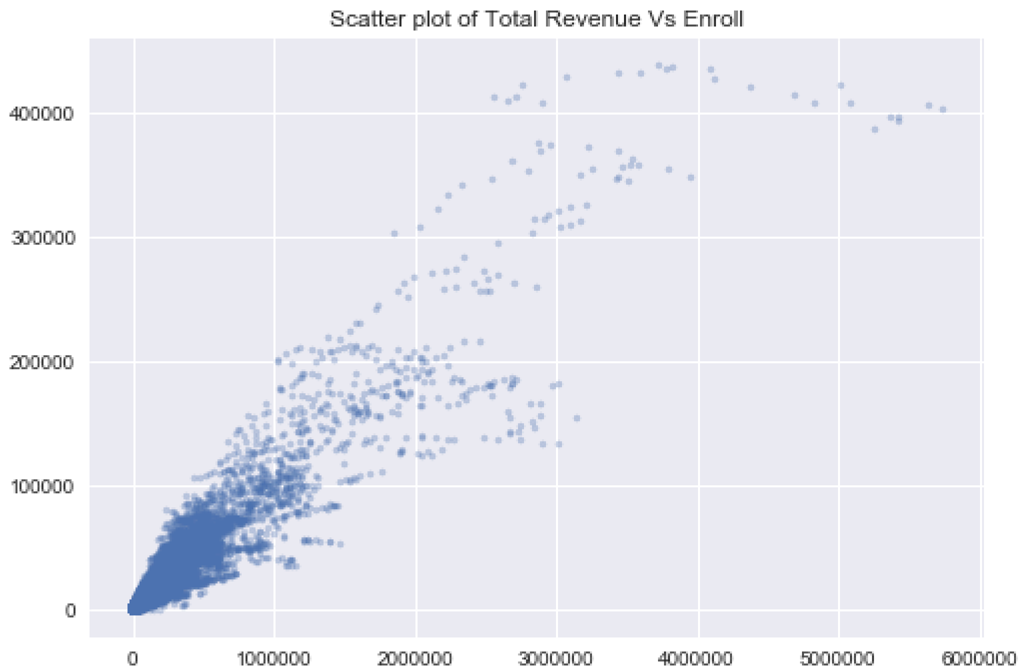
	STATE	ENROLL	NAME	YRDATA	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP	lg_ENROLL	lg_TOTALREV	lg_TFED
0	ALABAMA	9609.0	AUTAUGA COUNTY SCHOOL DISTRICT	2016	80867	7447	53842	19578	76672	9.170455	11.300561	8.91
1	ALABAMA	30931.0	BALDWIN COUNTY SCHOOL DISTRICT	2016	338236	23710	145180	169346	299880	10.339514	12.731499	10.07
2	ALABAMA	912.0	BARBOUR COUNTY SCHOOL DISTRICT	2016	10116	2342	5434	2340	10070	6.815640	9.221874	7.75
3	ALABAMA	2842.0	EUFAULA CITY SCHOOL DISTRICT	2016	26182	3558	15900	6724	29843	7.952263	10.172827	8.17
4	ALABAMA	3322.0	BIBB COUNTY SCHOOL DISTRICT	2016	32486	3664	21846	6976	31662	8.108322	10.388565	8.20

In [75]:
```
#plt.style.use('ggplot')
plt.style.use('seaborn')
findistdf.plot(x= 'TOTALREV', y = 'ENROLL', kind = 'scatter' )
plt.title('Scatter plot of Total Revenue Vs Enroll')
plt.show()
```



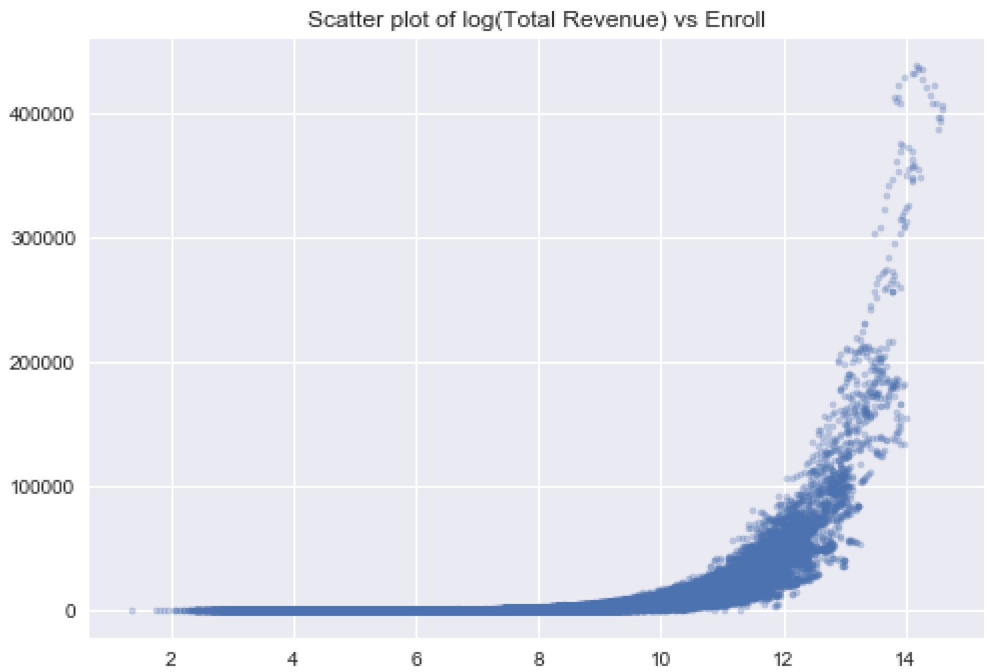
The above chart shows that school districts with higher total revenue has better enrollment than the school districts with lower total revenue, agrees with one of our assumptions.

In [76]:
```
# Scatter plot with jitter
jitter = 20000
TOTALREV = findistdf.TOTALREV + np.random.uniform(-jitter, jitter)
plt.scatter(TOTALREV, findistdf.ENROLL, alpha = 0.3, s = 10)
plt.title('Scatter plot of Total Revenue Vs Enroll')
plt.show()
```



In [77]:

```
# Scatter plot between log(total revenue) and enroll

jitter = 1
lg_TOTALREV = findistdf.lg_TOTALREV + np.random.uniform(-jitter, jitter)
plt.scatter(lg_TOTALREV, findistdf.ENROLL, alpha = 0.3, s = 10)
plt.title('Scatter plot of log(Total Revenue) vs Enroll')
plt.show()
```



In [78]:
```
# Scatter plot between log(total revenue) and log(enroll)

jitter = 0.3
ENROLL4 =  findistdf.lg_ENROLL + np.random.uniform(-jitter, jitter)
TOTALREV4 = findistdf.lg_TOTALREV + np.random.uniform(-jitter, jitter)
plt.scatter(TOTALREV4, ENROLL4, alpha = .2, s = 10)
plt.title('Scatter plot of log(Total Revenue) vs Enroll')
plt.show()
```

Characterizing Relationships

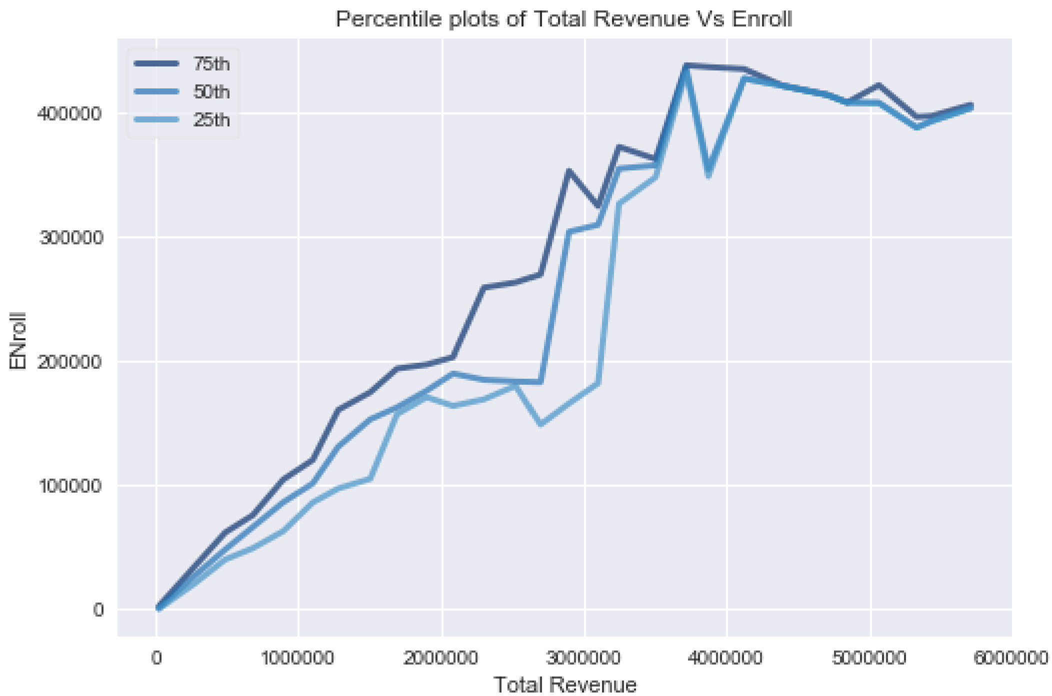
In [79]:
```
findistdf2 = findistdf.dropna(subset = ['ENROLL',  'TOTALREV'])
bins = np.arange(0, 30000000, 200000)
indicies = np.digitize(findistdf2.TOTALREV, bins)

grps = findistdf2.groupby(indicies)
```

In [80]:
```
for i, group in grps:
    print(i, len(group))
```

```
1 281561
2 3932
3 1093
4 394
5 220
6 171
7 87
8 56
9 41
10 37
11 31
12 24
13 18
14 21
15 17
16 10
17 3
18 9
19 3
20 3
21 2
22 1
24 1
25 1
26 2
27 2
28 2
29 2
```

In [81]:
```
mean_tr = [group.TOTALREV.mean() for i, group in grps]
cdfs = [thinkstats2.Cdf(group.ENROLL) for i, group in grps]
```

In [82]:
```
for percent in [75, 50, 25]:
    enroll_percentiles = [cdf.Percentile(percent) for cdf in cdfs]
    label = '%dth' % percent
    thinkplot.Plot(mean_tr, enroll_percentiles, label=label)
    thinkplot.Config(xlabel='Total Revenue',  ylabel='ENroll',legend=True)
    plt.title('Percentile plots of Total Revenue Vs Enroll')
```



Above percentiles plotof of Total Revenue Vs Enroll, relationship is linear upto 3500000$, after that relationship is going in the wrong direction.

In [83]:
```
descchar(findistdf['TOTALREV'])
```

```
Mean, Median, Mode of TOTALREV, 30255.458977 9715.000000 2276.000000
Spread - Variance, Standard deviation of TOTALREV, 10677274625.544109 103330.898697
Skew of TOTALREV, 18.316904
Interquartile range of TOTALREV, 3653.000000 9715.000000 25200.250000
```

Covariance and Correlation

In [84]:
```
# Covariance

def Cov(xs, ys, meanx=None, meany=None):
    xs = np.asarray(xs)
    ys = np.asarray(ys)

    if meanx is None:
        meanx = np.mean(xs)
    if meany is None:
        meany = np.mean(ys)

    cov = np.dot(xs-meanx, ys-meany) / len(xs)
    return cov

Cov(findistdf2.TOTALREV, findistdf2.ENROLL)
```

Out[84]:
```
1024052236.613642
```

In [85]:
```
# Calculating Correlation between total revenue and Enroll in school districts
def Corr(xs, ys):
    xs = np.asarray(xs)
    ys = np.asarray(ys)

    meanx, varx = thinkstats2.MeanVar(xs)
    meany, vary = thinkstats2.MeanVar(ys)

    corr = Cov(xs, ys, meanx, meany) / np.sqrt(varx * vary)
    return corr

Corr(findistdf2.TOTALREV, findistdf2.ENROLL)
```

Out[85]:
```
0.9497119340376089
```

Correlation value of 0.95 indicates that total revenue and enroll variables are strongly and positively correlated; and it implies that school districts with higher total revenue tend to have higher enrollments in those schools. But our distributions are highly skewed and are not normal distributions, so let’s find out the Spearman's Rank correlation as well.

In [86]:
```
def SpearmanCorr(xs, ys):
    xranks = pd.Series(xs).rank()
    yranks = pd.Series(ys).rank()
    return Corr(xranks, yranks)

SpearmanCorr(findistdf2.TOTALREV, findistdf2.ENROLL)
```

Out[86]:
```
0.9560835084463589
```

In [ ]:

Hypothesis Testing

Defining Null Hypothesis: My earlier assumption is that school districts with higher total revenue will have higher enrollments in the school. Based on that, my Null hypothesis is that there is no relationship between Total revenue and school enrollments for school districts. The p-value for this correlation testing is to find out the probability of having such a high observed correlation of 0.95 by pure chance should be significant (pvalue > 0.05).

Let us find out with Hypothesis testing.

In [87]:

```
findistdf.head()
```

Out[87]:

	STATE	ENROLL	NAME	YRDATA	TOTALREV	TFEDREV	TSTREV	TLOCREV	TOTALEXP	lg_ENROLL	lg_TOTALREV	lg_TFED
0	ALABAMA	9609.0	AUTAUGA COUNTY SCHOOL DISTRICT	2016	80867	7447	53842	19578	76672	9.170455	11.300561	8.91
1	ALABAMA	30931.0	BALDWIN COUNTY SCHOOL DISTRICT	2016	338236	23710	145180	169346	299880	10.339514	12.731499	10.07
2	ALABAMA	912.0	BARBOUR COUNTY SCHOOL DISTRICT	2016	10116	2342	5434	2340	10070	6.815640	9.221874	7.75
3	ALABAMA	2842.0	EUFAULA CITY SCHOOL DISTRICT	2016	26182	3558	15900	6724	29843	7.952263	10.172827	8.17
4	ALABAMA	3322.0	BIBB COUNTY SCHOOL DISTRICT	2016	32486	3664	21846	6976	31662	8.108322	10.388565	8.20

In [88]:
```
findist_bystate_mn = pd.DataFrame()
findist_bystate_mn = findistdf.groupby('STATE', as_index = False)['TOTALREV', 'ENROLL'].mean()
findist_bystate_mn.sort_values('TOTALREV',ascending=False)[0:5]
```

Out[88]:

	STATE	TOTALREV	ENROLL
9	HAWAII	2.047635e+06	183417.458333
18	MARYLAND	4.132408e+05	35081.586806
7	FLORIDA	3.172400e+05	37111.053483
26	NEVADA	1.803720e+05	21480.924020
30	NORTH_CAROLINA	9.168736e+04	11389.473421

In [89]:
```
findist_bystate_mn.sort_values('ENROLL',ascending=False)[0:5]
```

Out[89]:

	STATE	TOTALREV	ENROLL
9	HAWAII	2.047635e+06	183417.458333
7	FLORIDA	3.172400e+05	37111.053483
18	MARYLAND	4.132408e+05	35081.586806
26	NEVADA	1.803720e+05	21480.924020
41	UTAH	8.064527e+04	12644.656670

In [90]:
```
Hyp_df = findistdf.dropna(subset = ['ENROLL',  'TOTALREV'])
Hyp_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 287744 entries, 0 to 358292
Data columns (total 15 columns):
STATE          287744 non-null object
ENROLL         287744 non-null float64
NAME           287744 non-null object
YRDATA         287744 non-null int64
TOTALREV       287744 non-null int64
TFEDREV        287744 non-null int64
TSTREV         287744 non-null int64
TLOCREV        287744 non-null int64
TOTALEXP       287744 non-null int64
lg_ENROLL      287744 non-null float64
lg_TOTALREV    287744 non-null float64
lg_TFEDREV     287744 non-null float64
lg_TSTREV      287744 non-null float64
lg_TLOCREV     287744 non-null float64
lg_TOTALEXP    287744 non-null float64
dtypes: float64(7), int64(6), object(2)
memory usage: 35.1+ MB
```

In [91]:
```
# Pearson correlation
pecorr, p = stats.pearsonr(Hyp_df.TOTALREV, Hyp_df.ENROLL)
pecorr, p
```

Out[91]:
```
(0.9497119340376095, 0.0)
```

In [92]:
```
# Spearman correlation
corr2, p2 = stats.spearmanr(Hyp_df.TOTALREV, Hyp_df.ENROLL)
corr2, p2
```

Out[92]:
```
(0.9560835084463587, 0.0)
```

In [93]:
```
trenr_df = Hyp_df[['TOTALREV', 'ENROLL']]
```

In [94]:
```
stat, p, dof, expected = stats.chi2_contingency(trenr_df)
stat, p, dof, expected
```

Out[94]:
```
(108740524.95546971, 0.0, 287743, array([[8.18934126e+04, 8.58258740e+03],
        [3.34147679e+05, 3.50193205e+04],
        [9.98187977e+03, 1.04612023e+03],
        ...,
        [1.23614918e+04, 1.29550816e+03],
        [6.90078449e+03, 7.23215508e+02],
        [2.81317395e+03, 2.94826049e+02]]))
```

Method for testing this null hypothesis is to randomly generate values for total revenue and enroll with the same mean and standard deviation of the current data set and calculate the Correlation and P- value for that sample data set. Repeat the process for some iterations (100)

In [95]:

```
def samplepermute(iters = 100):
    '''
    Function to permutate the TOTALREV randomly and calculate Correlation, p value and Covariance of that  data
    iters is number of iterations of test
    returns:
    smpcorr - sample correlation
    smppval - sample pvalue
    count/iters - % of samples that have sampled correlation greater than observed correlation
    '''
    smpcorr = []
    smppval = []
    count = 0
    df = pd.DataFrame()
    for j in range(iters):


        corr, p = stats.pearsonr(np.random.permutation(Hyp_df.TOTALREV),Hyp_df.ENROLL)
        cov  = Cov(np.random.permutation(Hyp_df.TOTALREV), Hyp_df.ENROLL)


        if abs(corr) >= pecorr:
            count += 1
        smpcorr.append(corr)
        smppval.append(p)
    return smpcorr, smppval, count/iters
```

In [96]:

```
test2corr, test2p, test2count = samplepermute( iters = 100)
test2count
```

Out[96]: 0.0

The probability of having such a high (observed - 0.95) correlation between Total Revenue & Enroll by chance is 0. Hence null hypothesis that there is no correlation between Total Revenue and Enroll is false.

In [ ]:

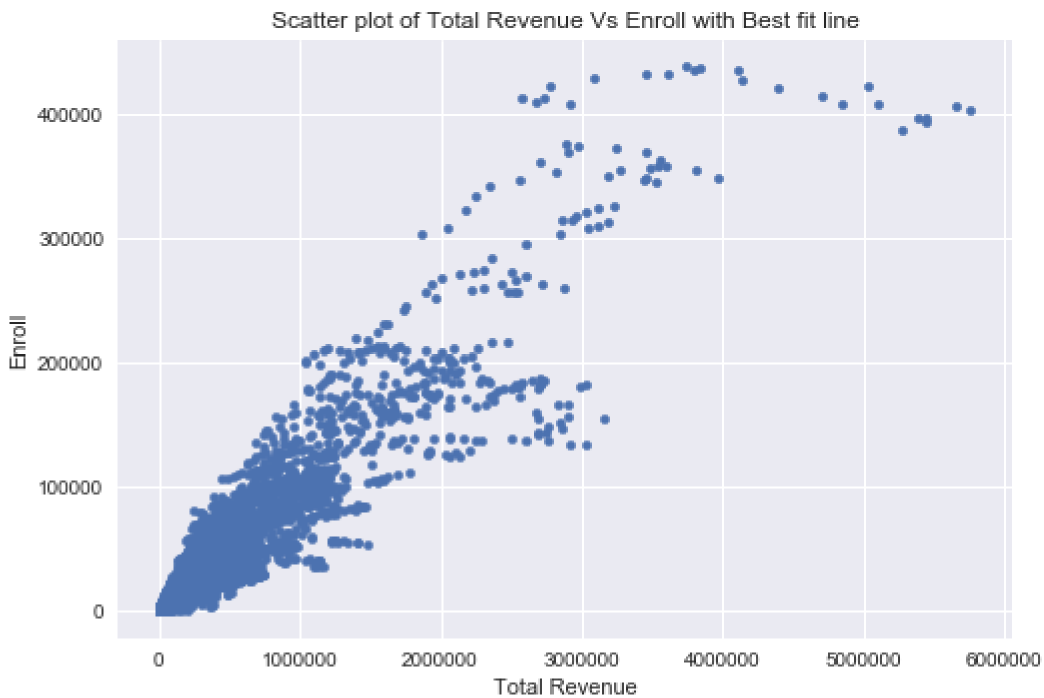
```

```

Regression Analysis

In [97]:

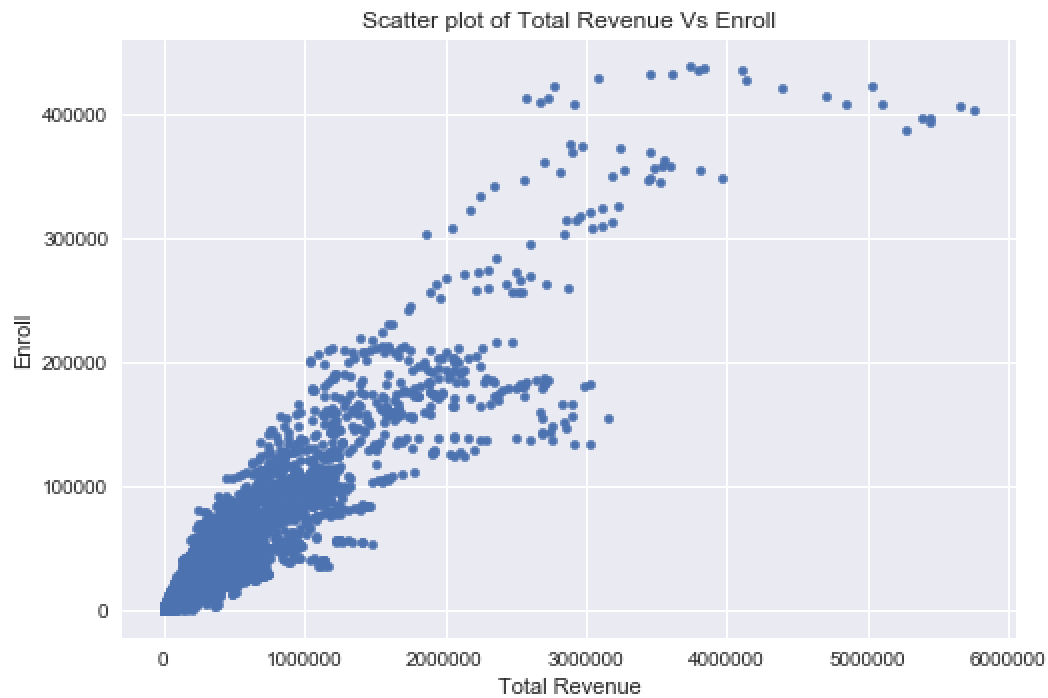
```
findistdf1 = findistdf.dropna(subset = ['ENROLL',  'TOTALREV'])
```

In [98]:
```
#PLotting scatter plot between Total Revenue and Enroll
#plt.style.use('ggplot')
plt.style.use('seaborn')
findistdf1.plot(x= 'TOTALREV', y = 'ENROLL', kind = 'scatter' )
plt.xlabel('Total Revenue')
plt.ylabel('Enroll')
plt.title('Scatter plot of Total Revenue Vs Enroll with Best fit line')
plt.show()
```



Linear Least Square Model

In [99]:
```
# plotting scatter plot again
plt.style.use('seaborn')
findistdf1.plot(x= 'TOTALREV', y = 'ENROLL', kind = 'scatter' )
plt.xlabel('Total Revenue')
plt.ylabel('Enroll')
plt.title('Scatter plot of Total Revenue Vs Enroll')
plt.show()
```

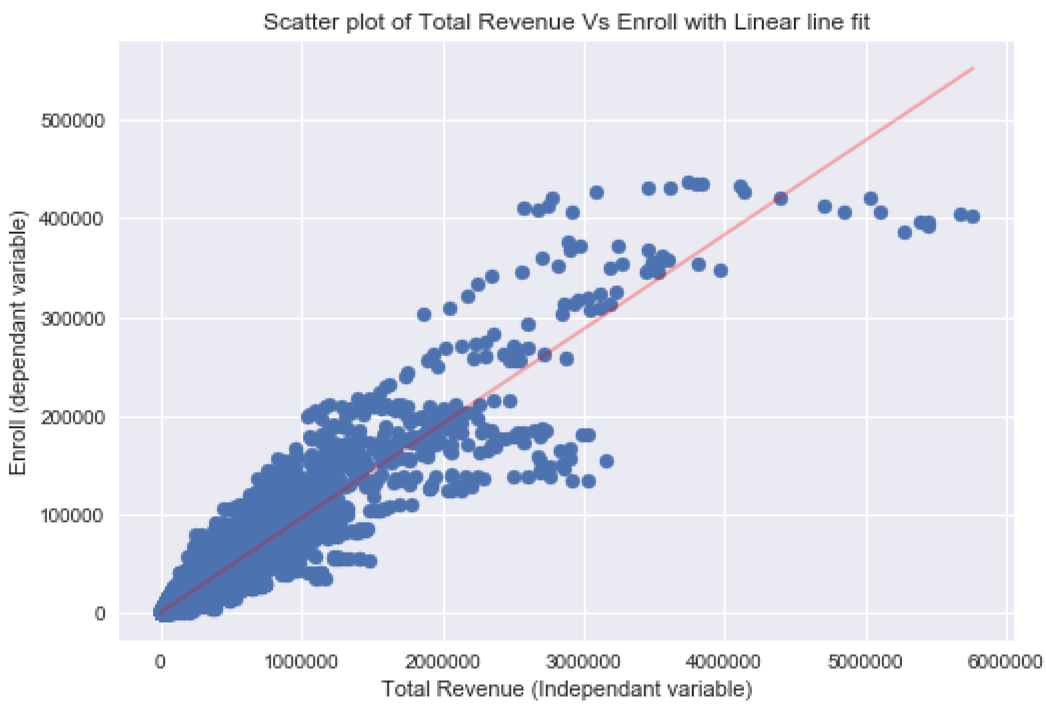


In [100]:
```
#Calculating slope & iter

meantr = np.mean(findistdf1.TOTALREV)
meanenr = np.mean(findistdf1.ENROLL)

slope = (meantr * meanenr - np.mean(findistdf1.TOTALREV * findistdf1.ENROLL))/ (meantr**2 -  np.mean(findistdf

inter = meanenr - meantr*slope

meantr, meanenr, slope, inter
```

Out[100]:
```
(30255.458977424376, 3170.830383952402, 0.09590984885567204, 269.0338863686443)
```

In [101]:
```
# Drawing best fit line

plt.scatter(findistdf1.TOTALREV, findistdf1.ENROLL)
TR_minmax = [np.min(findistdf1.TOTALREV), np.max(findistdf1.TOTALREV)]


Regressionline = [slope*t + inter for t in TR_minmax ]

plt.plot(TR_minmax, Regressionline, color = "red", alpha =0.3)
plt.xlabel('Total Revenue (Independant variable)')
plt.ylabel('Enroll (dependant variable)')
plt.title('Scatter plot of Total Revenue Vs Enroll with Linear line fit')
```

Out[101]:
```
Text(0.5,1,'Scatter plot of Total Revenue Vs Enroll with Linear line fit')
```



Above plot confirms the linear relationship between Total Revenue and Enroll

Goodness of Linear Least Square fit

Calculating Residuals, RMSE, Coeffecient of Determination

Goodness of linear least square fit can be found by comparing the Root mean square error between with model and without model.

In [102]:
```
# PLotting residuals
def Residuals(xs, ys, inter, slope):
    xs = np.asarray(xs)
    ys = np.asarray(ys)
    res = ys - (inter + slope * xs)
    return res

findistdf1['residual'] = Residuals(findistdf1.TOTALREV, findistdf1.ENROLL, inter, slope)
#len(findistdf1['residual'])
```

In [103]:
```
# Function to calculate Root mean squared error
def RMSE(ys, pred_ys):
    yactual = np.array(ys)
    ypred = np.array(pred_ys)
    error = (yactual - ypred)**2
    errmean = np.mean(error)
    errsqrt = sqrt(errmean)
    return errsqrt

xs = np.array(findistdf1.TOTALREV)
# predicted value for enroll using linear least square
pred_ys = [inter + (slope * x) for x in np.array(findistdf1.TOTALREV)]
RMSE(findistdf1.ENROLL, pred_ys)
```

Out[103]:
```
3267.521506975128
```

In [104]:
```
# Calculating Root Mean Square Error (RMSE) - Standard deviation of residuals
np.std(findistdf1['residual']), np.std(findistdf1['ENROLL'])
```

Out[104]:
```
(3267.521506975102, 10435.199664236075)
```

Without any model, RMSE of predicted Enroll numbers is represented by its standard deviation – which here in this case is 10435.

With Linear Least Square fit model, RMSE of predicted Enroll numbers from known Total Revenues is calculated by finding the residuals from prediction (Observed Enroll – Predicted Enroll) and finding the standard deviation from the residual. In this case it is 3267.

As predicting Enrollment numbers with Linear Least Square model results in lesser standard deviation, in this case knowing the total revenue and predicting enrollment numbers from it has significantly helped for better prediction and reducing the error.

In [105]:
```
# Coeffecient of Determination:
resid_var = np.var(findistdf1['residual'])
enroll_var = np.var(findistdf1['ENROLL'])

CoeffD = 1 - resid_var/enroll_var
CoeffD
```

Out[105]:
```
0.9019527576534582
```

CoeffD of 0.90 indicates that total revenue helps predict almost 90% of the variance in the enrollment numbers for school districts.

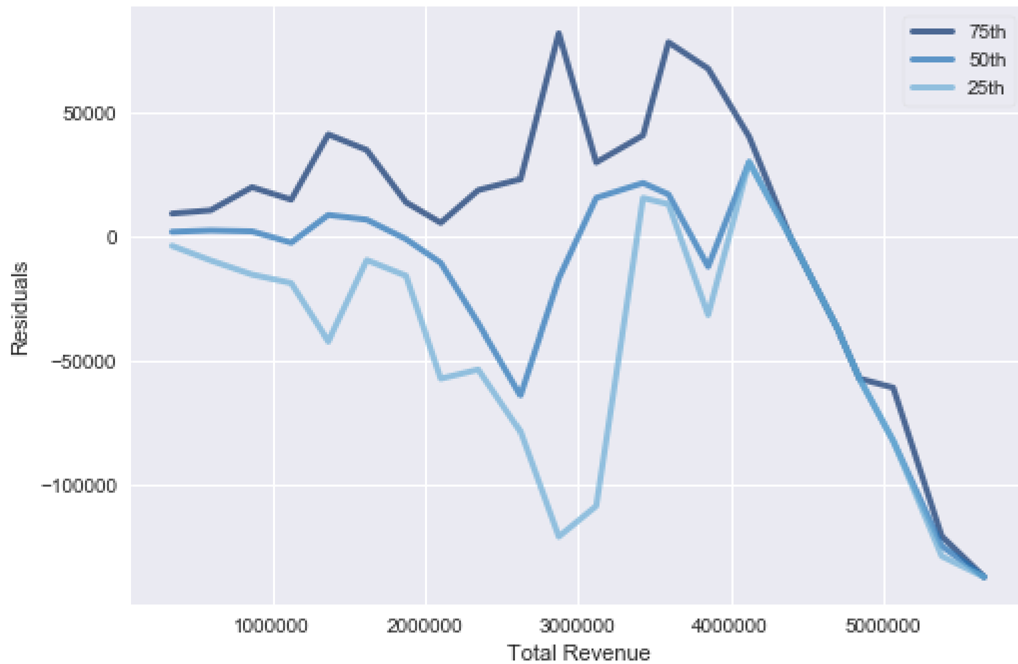
Plotting residuals

In [106]:
```
bins = np.arange(min(findistdf1.TOTALREV), max(findistdf1.TOTALREV), 250000)
indices = np.digitize(findistdf1.TOTALREV, bins)
groups = findistdf1.groupby(indices)

trbin_means = [group.TOTALREV.mean() for _, group in groups][1:-1]
#len(trbin_means) = 50
```

In [107]:
```
cdfs = [thinkstats2.Cdf(group.residual) for _, group in groups][1:-1]
```

In [108]:
```
def PlotPercentiles(trbin_means, cdfs):
    thinkplot.PrePlot(3)
    for percent in [75, 50, 25]:
        weight_percentiles = [cdf.Percentile(percent) for cdf in cdfs]
        label = '%dth' % percent
        thinkplot.Plot(trbin_means, weight_percentiles, label=label)
```

In [109]:
```
PlotPercentiles(trbin_means, cdfs)

thinkplot.Config(xlabel="Total Revenue", ylabel='Residuals')
```



The residual plots are not straight lines, indicates that relationship between total revenue and enroll is non - linear. The gap between inter quartile residuals is most at the total revenue of 3 Million.

In [ ]:
```

```

In [110]:
```
# Plotting best fit line with stats modules
plt.plot(findistdf1.TOTALREV, findistdf1.ENROLL, 'o', label='original data')
plt.plot(findistdf1.TOTALREV, inter + slope*findistdf1.TOTALREV, 'r', label='fitted line')
plt.legend()
plt.show()
```

In [ ]:
```

```

Testing Linear Model

In [111]:
```
#To estimate the sampling distribution of inter and slope, I'll use resampling.

def SampleRows(df, nrows, replace=False):
    """Choose a sample of rows from a DataFrame.

    df: DataFrame
    nrows: number of rows
    replace: whether to sample with replacement

    returns: DataDf
    """
    indices = np.random.choice(df.index, nrows, replace=replace)
    sample = df.loc[indices]
    return sample

def ResampleRows(df):
    """Resamples rows from a DataFrame.

    df: DataFrame

    returns: DataFrame
    """
    return SampleRows(df, len(df), replace=True)
```

In [112]:
```
def SamplingDistributions(findistdf1, iters=101):
    inters = []
    slopes = []
    for _ in range(iters):
        sample = ResampleRows(findistdf1)
        TOTALREV = sample.TOTALREV
        ENROLL = sample.ENROLL

        slope = (meantr * meanenr - np.mean(findistdf1.TOTALREV * findistdf1.ENROLL))/ (meantr**2 -  np.mean(f
        slopes.append(slope)
        inter = meanenr - meantr*slope
        inters.append(inter)

    return inters, slopes
```

In [113]:
```
inters, slopes = SamplingDistributions(findistdf1, iters=100)
```

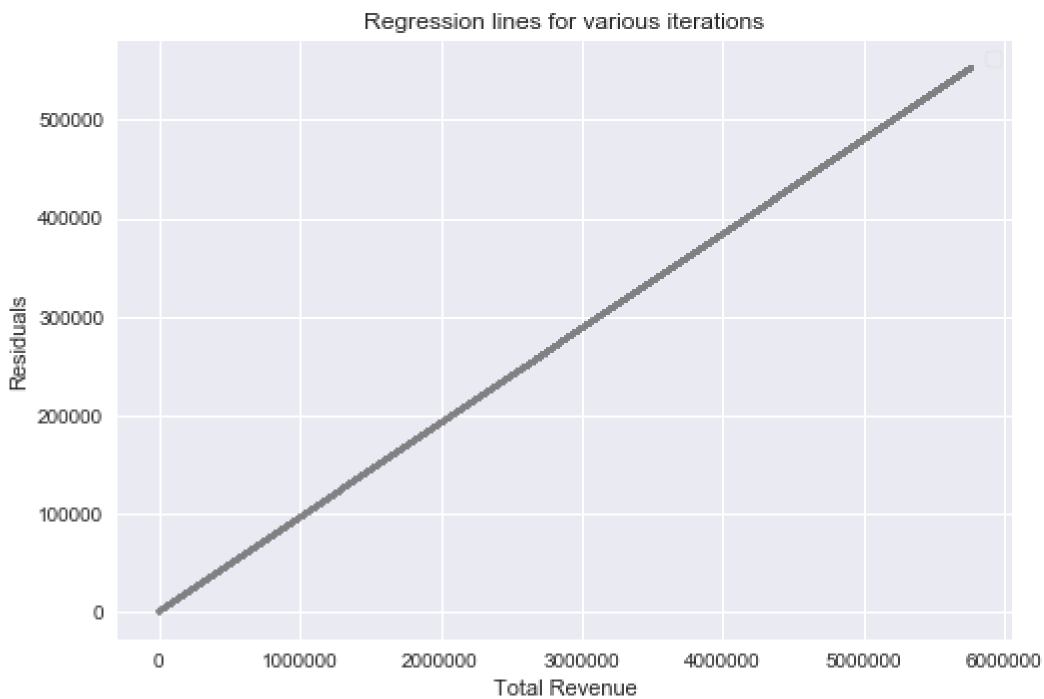
In [114]:
```
slope_cdf = thinkstats2.Cdf(slopes)
pvalue = slope_cdf[0]
pvalue
```

Out[114]: 0.0

Probability that the slope in the sampling distribution falls below 0 (p-value) is 0; as it is less than 0.001 indicating that the relation between Total Revenue and Enroll is statistically significant and not by chance.

In [115]:
```
for slope, inter in zip(slopes, inters):
    fxs = np.sort(findistdf1.TOTALREV)
    fys =  inter + slope * fxs
    thinkplot.Plot(fxs, fys, color='gray', alpha=0.01)

thinkplot.Config(xlabel="Total Revenue", ylabel='Residuals', title = "Regression lines for various iterations"
```

```
No handles with labels found to put in legend.
```



After repeated sampling the regression line roughly stayed in the same place, so it is a low variance model

In [ ]:

Regression Analysis - Ordinary Least Square Model

In [116]:

```
import statsmodels.formula.api as smf

formula = 'findistdf1.ENROLL ~ findistdf1.TOTALREV'
model = smf.ols(formula, data=findistdf1)
results = model.fit()
results.summary()
```

Out[116]:

OLS Regression Results

Dep. Variable:	findistdf1.ENROLL	**R-squared:**	0.902
Model:	OLS	**Adj. R-squared:**	0.902
Method:	Least Squares	**F-statistic:**	2.647e+06
Date:	Sun, 03 Mar 2019	**Prob (F-statistic):**	0.00
Time:	16:59:57	**Log-Likelihood:**	-2.7367e+06
No. Observations:	287744	**AIC:**	5.473e+06
Df Residuals:	287742	**BIC:**	5.473e+06
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	269.0339	6.347	42.387	0.000	256.594	281.474
findistdf1.TOTALREV	0.0959	5.9e-05	1626.956	0.000	0.096	0.096

Omnibus:	167866.320	**Durbin-Watson:**	1.533
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2577381320.624
Skew:	0.853	**Prob(JB):**	0.00
Kurtosis:	466.649	**Cond. No.**	1.12e+05

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.12e+05. This might indicate that there are strong multicollinearity or other numerical problems.

In [117]:
```
inter = results.params['Intercept']
slope = results.params['findistdf1.TOTALREV']
inter, slope
```

Out[117]:
```
(269.0338863686441, 0.09590984885567201)
```

Interpreting the coefficients: slope value of 0.095 infers that unit increase in total revenue is associated with 0.095 unit increase in enroll numbers for the school districts.

In [118]:
```
slope_pvalue = results.pvalues['findistdf1.TOTALREV']
slope_pvalue
```

Out[118]:
```
0.0
```

As P-value is less than 0.001, the estimated slope is significant

In [119]:
```
# Coefficient of determination
results.rsquared
```

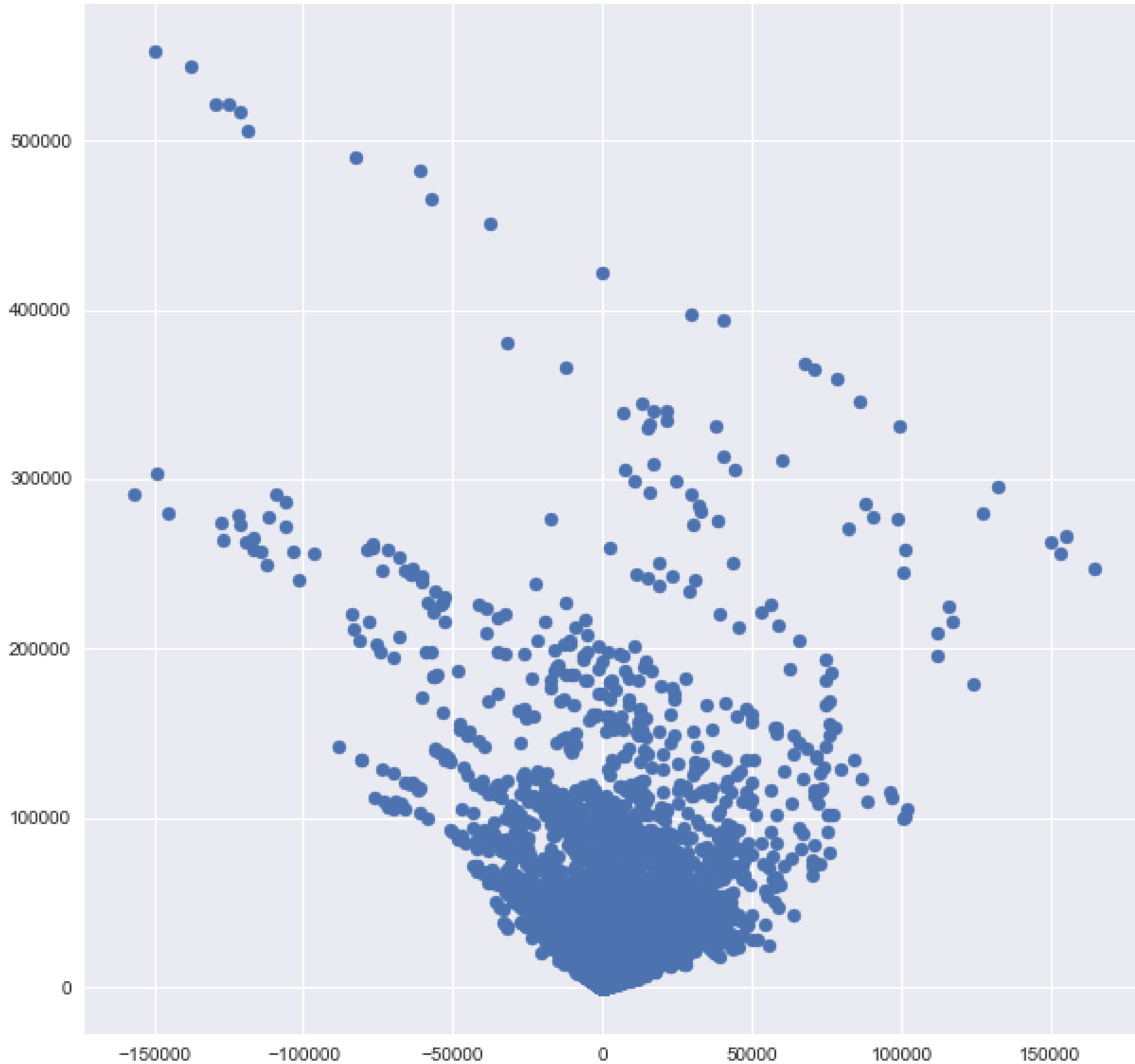
Out[119]:
```
0.9019527576534563
```

R- Square value of 0.90 shows that variation in enrollment can be explained by variation in Total Revenue upto 90%. As more variance is being explained by the model, once again proves the fit of the model.

In [120]:

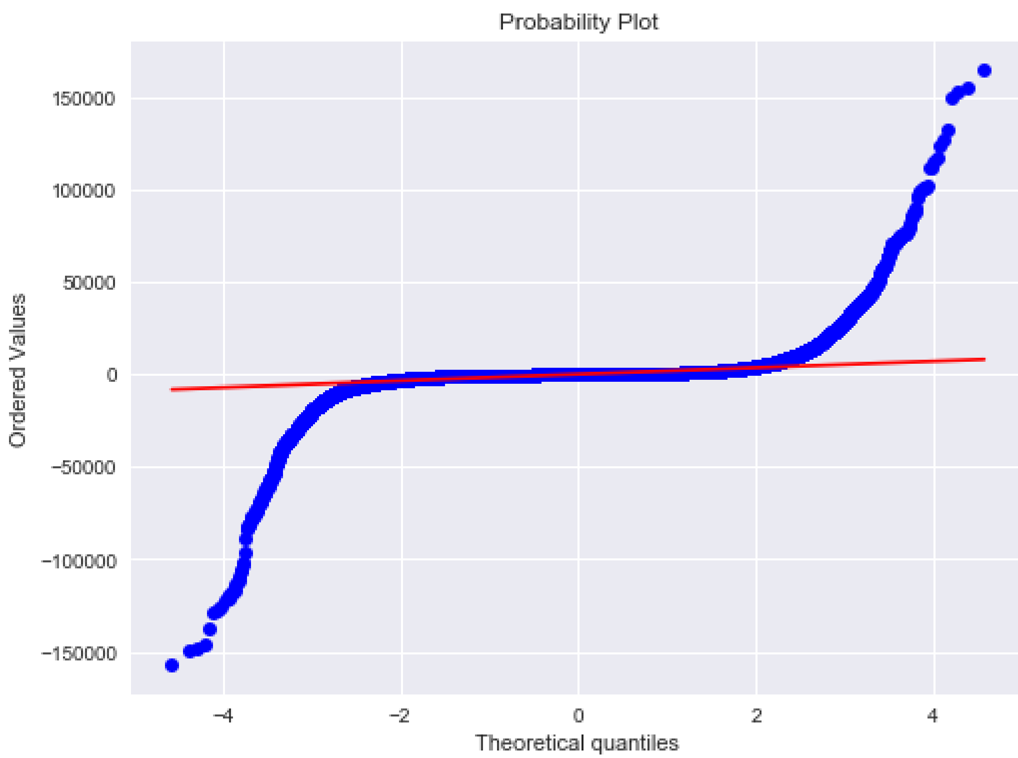
```
#plotting residuals

pred_val = results.fittedvalues.copy()
true_val = findistdf1['ENROLL'].values.copy()
residual = true_val - pred_val
```

In [121]:
```
fig, ax = plt.subplots(figsize=(10,10))
residplot = ax.scatter(residual, pred_val)
```



In [122]:
```
# Drawing normal probability plot

fig, ax = plt.subplots(figsize=(8,6))
_, (__, ___, r) = stats.probplot(residual, plot=ax, fit=True)

r**2
#stats.probplot(residual, plot=ax, fit=True)
```

Out[122]: 0.28856453419639605



Above normality plot indicates that this model is good fit only between quartile -2 to +2. After that it significantly deviates from linear model.

In [123]:
```
# Confidence intervals
results.conf_int()
```

Out[123]:

	0	1
Intercept	256.593660	281.474113
findistdf1.TOTALREV	0.095794	0.096025

In [124]:
```
# p-values for the model coefficients
results.pvalues
```

Out[124]:
```
Intercept             0.0
findistdf1.TOTALREV    0.0
dtype: float64
```

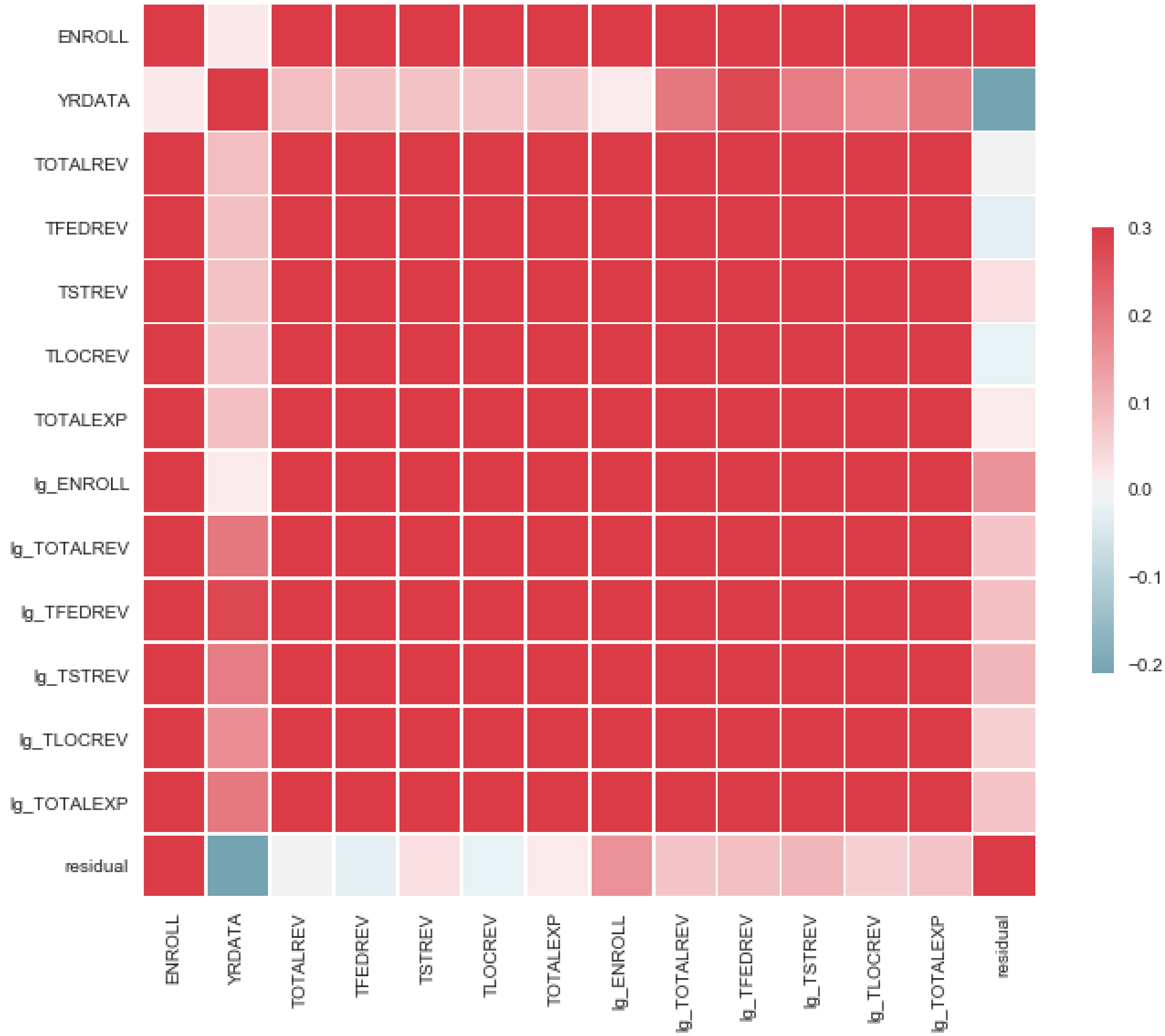
Again p-values are way less than 0.05, indicating that the relation between dependent and independent variables is genuine.

Correlation matrix

In [125]:
```
# Compute the correlation matrix
corr = findistdf1.corr()
```

In [126]:
```
# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr,   cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[126]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x225357cbcf8>
```



In [ ]:

Multiple Linear Regression

In [127]:
```
# understanding whether the enrollment in school districts depends on Total Revenue and STATE as well
formula2 = 'findistdf1.ENROLL ~ findistdf1.TOTALREV + findistdf1.STATE'
model2 = smf.ols(formula2, data=findistdf1)
results2 = model2.fit()
results2.summary()
```

Out[127]:

OLS Regression Results

Dep. Variable:	findistdf1.ENROLL	**R-squared:**	0.909
Model:	OLS	**Adj. R-squared:**	0.909
Method:	Least Squares	**F-statistic:**	6.001e+04
Date:	Sun, 03 Mar 2019	**Prob (F-statistic):**	0.00
Time:	17:00:19	**Log-Likelihood:**	-2.7256e+06
No. Observations:	287744	**AIC:**	5.451e+06
Df Residuals:	287695	**BIC:**	5.452e+06
Df Model:	48		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1532.3320	56.355	27.191	0.000	1421.879	1642.785

In [ ]:

Comparing model 1 vs model2:

1) Adjusted R-square of model2 is .909, better than Adjusted R-square of model1 (0.902) - indicating that model2 can explain slightly more variation in dependent variable compared to model1.

2) AIC of model1 is 5.473e+06, which is slightly higher than AIC of model2 5.451e+06, indicating that model2 (enrollment as a function of total revenue and state) is slightly better model among the 2 models.

3) HAWAII has the highest absolute coefficient - indicating that ENROLL'ment numbers change hugely with a single unit of variation in TOTALREV for that state. In other words, we can probably see more enrollment numbers for every same number of units increase in total revenue compared to all other states (all remaining things being constant).

4) LOUISIANA has the lowest absolute coefficient value - indicating that ENROLL numbers will change at a slower rate compared to all other states for the same unit of increase in the total revenue (all remaining things being constant).

5) Overall adding STATE to the ordinary least square model, improved the model very slightly but not significantly. But interesting aspect of adding STATE to the equation is it gives us insights into how each is the relationship between Total Revenue and Enroll for each STATE.

In [ ]:

```

```

Outcome of EDA:

The assumption that I had before exploring this data set was that the school districts that are in higher revenue states will have more chance of higher enrollments in the school. After performing EDA, I did find statistical correlation between Total Revenues and Enrollment of the school districts. So my assumption was correct. One more observation that I made is not all states will respond similarly to the total revenue numbers. For example, take state like LOUISIANA, even though Total Revenues increase for this state, Enrollment numbers will not raise proportionally when compared to other states.

What was missing during the analysis?

Having demographic information of each school districts like population, family size, number of school going kids, family income etc. would have added more sense to the analysis. Also one of these or couple of these could be the confounding factors that I highlighted above with STATE – LOUISIANA.

Variables that could have helped in the analysis?

As states above, demographic information could have helped more in the analysis in finding the actual enrollment prediction for the school districts.

Assumptions made correct or incorrect?

No. The assumptions that I made that enrollments in school districts are based on Total Revenues of the state was correct, backed by the higher correlation factor and the linear models

Challenges faced

In the selected data, there were some other aggregated data sets available, which I wanted to explore and compare with the financial school district data set that I selected. But some of the variables that I wanted to explore like GRADES_ALL_G etc. are not available through those sheets. I feel enrollment numbers depend a lot on population or number of families living in that school district. Having a demographic data for these school district would have been an interesting analysis, I would like to try. But that information was not available readily, so I couldn't venture into that analysis. One more challenge is that some of the states like California, New York are too big to be compared with other smaller states like Vermont, but before realizing this when I performed EDA overall financial school district data set, numbers were highly skewed – and didn't find an ideal number of bins to represent these variables into proper histogram. Plotting PDF and CDF without using the thinkstats2, thinkplot modules has been a challenge, at some places I gave up trying to figure out other means and ended up using these modules. I would like to explore these in free time.

In [ ]:

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