updated_full_d102_final_project

December 13, 2021

1 Analysis of Bureau of Transportation Statistics on Utilization and Spending Trends

1.1 Section Headings

This notebook will be divided into two sections, `GLM/NPM Prediction` and `Causality Analysis`, as found in the analysis write-up. *Note that all methods regarding each section will be found below each respective heading. This includes shared methods such as EDA, Feature Engineering, Result Discussion, etc.*

Section 1: Generalized Linear Model vs. Non Parametric Model Prediction

`Research Question A`: *Predicting "State and Local Government Construction Spending - Transportation" in 2019 using past infrastructure data (up to 2018) in the US.*

Section 2: Causality Analysis

`Research Question B`: *Does investment in infrastructure have an causal impact on the utilization of infrastructure in the US? Specifically, does the change in state and local spending on land passenger terminals have a causal effect on the number of passenger rail passenger miles, and if so is it a positive or negative effect?*

2 1. GLM and Non Parametric Model Prediction

Prompt: (Comparing GLMs and nonparametric methods): Predicting "State and Local Government Construction Spending - Transportation" in 2019 using past infrastructure data (up to 2018) in the US.

2.1 1.1. GLM/NPM EDA

[1]:
```
#Import Libraries and raw data
import numpy as np
import pandas as pd
import re
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import gamma

import pymc3 as pm
```

```python
from pymc3 import glm
import statsmodels.api as sm
import arviz

import warnings
warnings.filterwarnings('ignore')

raw = pd.read_csv("Monthly_Transportation_Statistics.csv")
raw.head()
```

[1]:
```
   Index                    Date  Air Safety - General Aviation Fatalities  \
0      0  01/01/1947 12:00:00 AM                                       NaN
1      1  02/01/1947 12:00:00 AM                                       NaN
2      2  03/01/1947 12:00:00 AM                                       NaN
3      3  04/01/1947 12:00:00 AM                                       NaN
4      4  05/01/1947 12:00:00 AM                                       NaN

   Highway Fatalities Per 100 Million Vehicle Miles Traveled  \
0                                                NaN
1                                                NaN
2                                                NaN
3                                                NaN
4                                                NaN

   Highway Fatalities  U.S. Airline Traffic - Total - Seasonally Adjusted  \
0                 NaN                                                 NaN
1                 NaN                                                 NaN
2                 NaN                                                 NaN
3                 NaN                                                 NaN
4                 NaN                                                 NaN

   U.S. Airline Traffic - International - Seasonally Adjusted  \
0                                                NaN
1                                                NaN
2                                                NaN
3                                                NaN
4                                                NaN

   U.S. Airline Traffic - Domestic - Seasonally Adjusted  \
0                                                NaN
1                                                NaN
2                                                NaN
3                                                NaN
4                                                NaN

   Transit Ridership - Other Transit Modes - Adjusted  \
0                                                NaN
```

```
1                                                    NaN
2                                                    NaN
3                                                    NaN
4                                                    NaN

   Transit Ridership - Fixed Route Bus - Adjusted  …  \
0                                                NaN  …
1                                                NaN  …
2                                                NaN  …
3                                                NaN  …
4                                                NaN  …

   Heavy truck sales SAAR (millions)  \
0                                NaN
1                                NaN
2                                NaN
3                                NaN
4                                NaN

   U.S. Airline Traffic - Total - Non Seasonally Adjusted  \
0                                                NaN
1                                                NaN
2                                                NaN
3                                                NaN
4                                                NaN

   Light truck sales SAAR (millions)  \
0                                NaN
1                                NaN
2                                NaN
3                                NaN
4                                NaN

   U.S. Airline Traffic - International - Non Seasonally Adjusted  \
0                                                NaN
1                                                NaN
2                                                NaN
3                                                NaN
4                                                NaN

   Auto sales SAAR (millions)  \
0                         NaN
1                         NaN
2                         NaN
3                         NaN
4                         NaN
```

```
   U.S. Airline Traffic - Domestic - Non Seasonally Adjusted  \
0                                                        NaN
1                                                        NaN
2                                                        NaN
3                                                        NaN
4                                                        NaN

   Transborder - Total North American Freight  \
0                                         NaN
1                                         NaN
2                                         NaN
3                                         NaN
4                                         NaN

   Transborder - U.S. - Mexico Freight  \
0                                  NaN
1                                  NaN
2                                  NaN
3                                  NaN
4                                  NaN

   U.S. marketing air carriers on-time performance (percent)  \
0                                                        NaN
1                                                        NaN
2                                                        NaN
3                                                        NaN
4                                                        NaN

   Transborder - U.S. - Canada Freight
0                                  NaN
1                                  NaN
2                                  NaN
3                                  NaN
4                                  NaN

[5 rows x 136 columns]
```

[2]:
```
raw.columns, raw.shape
```

[2]:
```
(Index(['Index', 'Date', 'Air Safety - General Aviation Fatalities',
        'Highway Fatalities Per 100 Million Vehicle Miles Traveled',
        'Highway Fatalities',
        'U.S. Airline Traffic - Total - Seasonally Adjusted',
        'U.S. Airline Traffic - International - Seasonally Adjusted',
        'U.S. Airline Traffic - Domestic - Seasonally Adjusted',
        'Transit Ridership - Other Transit Modes - Adjusted',
        'Transit Ridership - Fixed Route Bus - Adjusted',
```

```
        …
        'Heavy truck sales SAAR (millions)',
        'U.S. Airline Traffic - Total - Non Seasonally Adjusted',
        'Light truck sales SAAR (millions)',
        'U.S. Airline Traffic - International - Non Seasonally Adjusted',
        'Auto sales SAAR (millions)',
        'U.S. Airline Traffic - Domestic - Non Seasonally Adjusted',
        'Transborder - Total North American Freight',
        'Transborder - U.S. - Mexico Freight',
        'U.S. marketing air carriers on-time performance (percent)',
        'Transborder - U.S. - Canada Freight'],
       dtype='object', length=136),
 (899, 136))
```

2.1.1 1.1.1. Determine a start date to subset the raw data

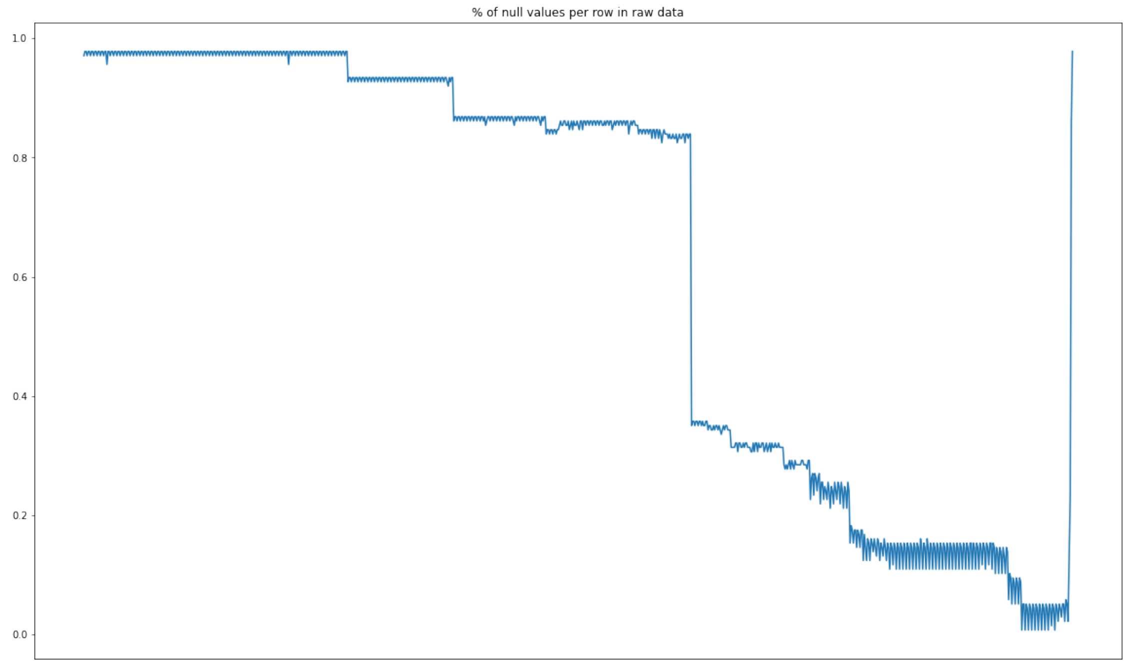
[3]:
```
#First and last date of data (regardless of nulls)
raw["Date"][0], list(raw["Date"])[-1]
```

[3]:
```
('01/01/1947 12:00:00 AM', '11/01/2021 12:00:00 AM')
```

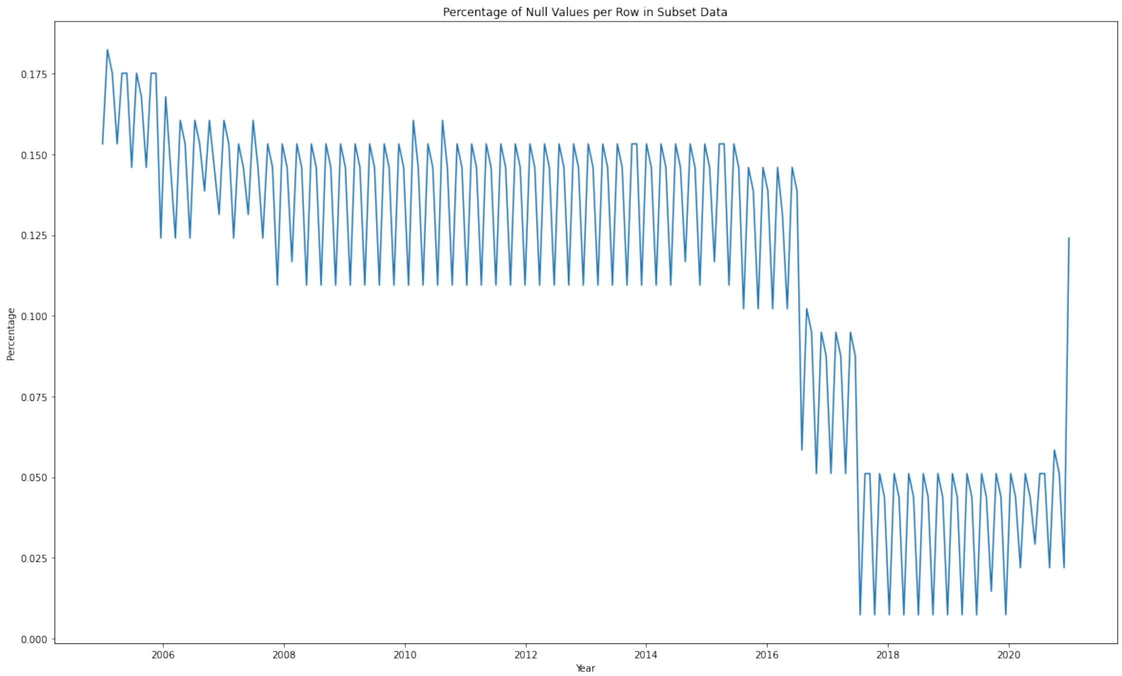
[4]:
```
#Eliminate time to only include MM/YYYY since dd is always 1

raw["Month"] = [date[:3]+date[6:10] for date in raw["Date"]]
```

[5]:
```
#Calculate the percentage of values in a row that are null
raw["pct_null"] = list(raw.isnull().sum(axis=1) / len(raw.columns))
```

[6]:
```
#Visualize pct of null values in each row vs. month
plt.figure(figsize=(20,12))
plt.plot(raw["Month"], raw["pct_null"])
plt.xticks([])
plt.title("% of null values per row in raw data")
plt.show();
```



[7]:
```
subset = raw[raw["pct_null"] < .2]
fig, ax = plt.subplots(figsize=(20, 12))
x=np.linspace(2005, 2021, 200)
#plt.figsize(20, 12)
plt.plot(x ,subset["pct_null"])
ax.set_ylabel("Percentage")
ax.set_xlabel("Year")
ax.set_title("Percentage of Null Values per Row in Subset Data");
```



Due to COVID-19, we also wanted to subset the data such that COVID affected dates (beginning in 01/2020) were not taken into consideration.

[8]:
```
#Find dates up until 01/2020 to prevent COVID as confounder
subset = subset[[int(list(subset["Month"])[i][3:])
                 < 2020 for i in range(len(subset))]]
subset.head()
```

[8]:
```
     Index                    Date  Air Safety - General Aviation Fatalities  \
696    696  01/01/2005 12:00:00 AM                                      56.0
697    697  02/01/2005 12:00:00 AM                                      43.0
698    698  03/01/2005 12:00:00 AM                                      37.0
699    699  04/01/2005 12:00:00 AM                                      37.0
700    700  05/01/2005 12:00:00 AM                                      50.0

     Highway Fatalities Per 100 Million Vehicle Miles Traveled  \
696                                                NaN
697                                                NaN
698                                                NaN
699                                                NaN
700                                                NaN

     Highway Fatalities  U.S. Airline Traffic - Total - Seasonally Adjusted  \
696                 NaN                                                 NaN
697                 NaN                                                 NaN
```

```
698              NaN                                                     NaN
699              NaN                                                     NaN
700              NaN                                                     NaN

     U.S. Airline Traffic - International - Seasonally Adjusted  \
696                                                NaN
697                                                NaN
698                                                NaN
699                                                NaN
700                                                NaN

     U.S. Airline Traffic - Domestic - Seasonally Adjusted  \
696                                                NaN
697                                                NaN
698                                                NaN
699                                                NaN
700                                                NaN

     Transit Ridership - Other Transit Modes - Adjusted  \
696                                         11611875.0
697                                         11445295.0
698                                         13310572.0
699                                         12907373.0
700                                         12763833.0

     Transit Ridership - Fixed Route Bus - Adjusted  …  \
696                                     416054551.0  …
697                                     403144202.0  …
698                                     473893673.0  …
699                                     443809746.0  …
700                                     455794647.0  …

     Light truck sales SAAR (millions)  \
696                          8921000.0
697                          8840000.0
698                          9168000.0
699                          9334000.0
700                          9415000.0

     U.S. Airline Traffic - International - Non Seasonally Adjusted  \
696                                                NaN
697                                                NaN
698                                                NaN
699                                                NaN
700                                                NaN

     Auto sales SAAR (millions)  \
```

```
696                  7448000.0
697                  7560000.0
698                  7761000.0
699                  7939000.0
700                  7513000.0

     U.S. Airline Traffic - Domestic - Non Seasonally Adjusted  \
696                                                       NaN
697                                                       NaN
698                                                       NaN
699                                                       NaN
700                                                       NaN

     Transborder - Total North American Freight  \
696                                         NaN
697                                         NaN
698                                         NaN
699                                         NaN
700                                         NaN

     Transborder - U.S. - Mexico Freight  \
696                                  NaN
697                                  NaN
698                                  NaN
699                                  NaN
700                                  NaN

     U.S. marketing air carriers on-time performance (percent)  \
696                                                       NaN
697                                                       NaN
698                                                       NaN
699                                                       NaN
700                                                       NaN

     Transborder - U.S. - Canada Freight    Month  pct_null
696                                  NaN  01/2005  0.153285
697                                  NaN  02/2005  0.182482
698                                  NaN  03/2005  0.175182
699                                  NaN  04/2005  0.153285
700                                  NaN  05/2005  0.175182

[5 rows x 138 columns]
```

2.1.2 1.1.2. Determine columns of interest

First, let's look at our research question in scope: *Research Question 2 (Comparing GLMs and nonparametric methods): Predicting infrastructure spending in 2019 using past infrastructure data* *(up to 2018) in the US.*

Columns to include:

1. Include all spending columns (since those our primary covariates)
2. Employment statistics (helps control for natural expansion/reduction of workforces as a result of high/low investment and spending in infrastructure
3. Consumer population and behavior statistics (such as highway death fatalities, rail passengers, transborder volume of passengers, airline traffic, truck sales to help control for population growth and volume of "consumers of infrastructure")
4. Real GDP/US economy valuation (helps control for a "budget constraint" or degree of liquidity for US budget for infrastructure.

As a result, columns that are not directly associated with the above points are dropped.

[9]:
```
cols_to_drop = ["Index",
                "Air Safety - General Aviation Fatalities",
                 "Highway Fatalities Per 100 Million Vehicle Miles Traveled",
                "Highway Fuel Price - On-highway Diesel",
                "Highway Fuel Price - Regular Gasoline",
                "Passenger Rail Yard Switching Miles",
                "Passenger Rail Total Reports",
                "U.S. Waterway Tonnage",
                "Amtrak On-time Performance",
                "Rail Fatalities at Highway-Rail Crossings",
                "U.S. Airline Traffic - Total - Non Seasonally Adjusted",
                "U.S. Airline Traffic - International - Non Seasonally Adjusted",
                "U.S. marketing air carriers on-time performance (percent)",
                 "pct_null"
                ]
subset = subset.drop(cols_to_drop, axis=1)
```

[10]:
```
subset
```

[10]:
```
                         Date  Highway Fatalities  \
696  01/01/2005 12:00:00 AM                 NaN
697  02/01/2005 12:00:00 AM                 NaN
698  03/01/2005 12:00:00 AM                 NaN
699  04/01/2005 12:00:00 AM                 NaN
700  05/01/2005 12:00:00 AM                 NaN
..                        …                   …
871  08/01/2019 12:00:00 AM                 NaN
872  09/01/2019 12:00:00 AM                 NaN
873  10/01/2019 12:00:00 AM              9155.0
874  11/01/2019 12:00:00 AM                 NaN
875  12/01/2019 12:00:00 AM                 NaN

     U.S. Airline Traffic - Total - Seasonally Adjusted  \
696                                                NaN
```

```
697                                                 NaN
698                                                 NaN
699                                                 NaN
700                                                 NaN
..                                                  …
871                                          77600000.0
872                                          77740000.0
873                                          77650000.0
874                                          78830000.0
875                                          78670000.0

     U.S. Airline Traffic - International - Seasonally Adjusted  \
696                                                 NaN
697                                                 NaN
698                                                 NaN
699                                                 NaN
700                                                 NaN
..                                                  …
871                                           9600000.0
872                                           9640000.0
873                                           9590000.0
874                                           9660000.0
875                                           9630000.0

     U.S. Airline Traffic - Domestic - Seasonally Adjusted  \
696                                                 NaN
697                                                 NaN
698                                                 NaN
699                                                 NaN
700                                                 NaN
..                                                  …
871                                          68230000.0
872                                          68280000.0
873                                          67920000.0
874                                          69370000.0
875                                          69200000.0

     Transit Ridership - Other Transit Modes - Adjusted  \
696                                          11611875.0
697                                          11445295.0
698                                          13310572.0
699                                          12907373.0
700                                          12763833.0
..                                                  …
871                                          20593034.0
872                                          18338805.0
873                                          19083744.0
```

```
874                                        16328180.0
875                                        16239029.0

     Transit Ridership - Fixed Route Bus - Adjusted  \
696                                     416054551.0
697                                     403144202.0
698                                     473893673.0
699                                     443809746.0
700                                     455794647.0
..                                              …
871                                     384027047.0
872                                     396062247.0
873                                     426327140.0
874                                     371791492.0
875                                     352319744.0

     Transit Ridership - Urban Rail - Adjusted  Freight Rail Intermodal Units  \
696                                311945546.0                      1004042.0
697                                305374953.0                       885038.0
698                                349880600.0                       846425.0
699                                335620384.0                      1095545.0
700                                342804244.0                       893384.0
..                                         …                             …
871                                410170062.0                      1089839.0
872                                410903169.0                      1329532.0
873                                448819797.0                      1063908.0
874                                405041309.0                      1019780.0
875                                401888202.0                      1189369.0

     Freight Rail Carloads  …  Truck tonnage index  \
696              1538344.0  …                 88.2
697              1340764.0  …                 86.3
698              1344164.0  …                 85.7
699              1704628.0  …                 86.6
700              1332755.0  …                 85.8
..                     …  …                  …
871              1055024.0  …                120.4
872              1239455.0  …                117.7
873               977406.0  …                118.1
874               955392.0  …                117.3
875              1143990.0  …                116.4

     U.S. Air Carrier Cargo (millions of revenue ton-miles) - Domestic  \
696                                       1.280516e+09
697                                       1.253130e+09
698                                       1.469765e+09
699                                       1.226824e+09
```

```
700                                          1.261165e+09
..                                                    …
871                                          1.410974e+09
872                                          1.304838e+09
873                                          1.433811e+09
874                                          1.413881e+09
875                                          1.555344e+09

     Heavy truck sales SAAR (millions)  Light truck sales SAAR (millions)  \
696                           519000.0                          8921000.0
697                           483000.0                          8840000.0
698                           484000.0                          9168000.0
699                           482000.0                          9334000.0
700                           486000.0                          9415000.0
..                                 …                                  …
871                           535000.0                         12501000.0
872                           554000.0                         12564000.0
873                           505000.0                         12330000.0
874                           456000.0                         12700000.0
875                           470000.0                         12367000.0

     Auto sales SAAR (millions)  \
696                   7448000.0
697                   7560000.0
698                   7761000.0
699                   7939000.0
700                   7513000.0
..                          …
871                   4609000.0
872                   4596000.0
873                   4395000.0
874                   4401000.0
875                   4502000.0

     U.S. Airline Traffic - Domestic - Non Seasonally Adjusted  \
696                                                NaN
697                                                NaN
698                                                NaN
699                                                NaN
700                                                NaN
..                                                   …
871                                         72720000.0
872                                         63980000.0
873                                         69920000.0
874                                         64820000.0
875                                         69720000.0
```

```
     Transborder - Total North American Freight  \
696                                         NaN
697                                         NaN
698                                         NaN
699                                         NaN
700                                         NaN
..                                          …
871                                1.051030e+11
872                                1.014349e+11
873                                1.071120e+11
874                                9.903155e+10
875                                9.634248e+10

     Transborder - U.S. - Mexico Freight  Transborder - U.S. - Canada Freight  \
696                                  NaN                                  NaN
697                                  NaN                                  NaN
698                                  NaN                                  NaN
699                                  NaN                                  NaN
700                                  NaN                                  NaN
..                                   …                                    …
871                         5.310121e+10                         5.200176e+10
872                         5.014872e+10                         5.128617e+10
873                         5.335177e+10                         5.376023e+10
874                         5.010448e+10                         4.892707e+10
875                         4.668673e+10                         4.965575e+10

       Month
696  01/2005
697  02/2005
698  03/2005
699  04/2005
700  05/2005
..       …
871  08/2019
872  09/2019
873  10/2019
874  11/2019
875  12/2019

[180 rows x 124 columns]
```

As a further measure of data accuracy, let's see which columns are missing a dangerous proportion of values. For reference, let's remove any columns missing more than 50% of its values.

[11]:
```
# Count number of na's in each column
series = subset.isna().sum()/len(subset)
missing_cols = series[series > .5]
```

```
missing_cols
```

[11]:
```
Highway Fatalities
0.738889
U.S. Airline Traffic - Total - Seasonally Adjusted
0.800000
U.S. Airline Traffic - International - Seasonally Adjusted
0.800000
U.S. Airline Traffic - Domestic - Seasonally Adjusted
0.800000
Highway Vehicle Miles Traveled - All Systems
0.866667
Highway Vehicle Miles Traveled - Total Rural
0.866667
Highway Vehicle Miles Traveled - Other Rural
0.866667
Highway Vehicle Miles Traveled - Rural Other Arterial
0.866667
Highway Vehicle Miles Traveled - Rural Interstate
0.866667
National Highway Construction Cost Index (NHCCI)
0.666667
Personal Spending on Transportation - Transportation Services - Seasonally
Adjusted            0.666667
Personal Spending on Transportation - Gasoline and Other Energy Goods -
Seasonally Adjusted    0.666667
Personal Spending on Transportation - Motor Vehicles and Parts - Seasonally
Adjusted           0.666667
Real Gross Domestic Product - Seasonally Adjusted
0.666667
U.S. Airline Traffic - Domestic - Non Seasonally Adjusted
0.800000
dtype: float64
```

[12]:
```
# Drop these columns
subset = subset.drop(list(missing_cols.keys()), axis=1)
subset.head()
```

[12]:
```
                       Date  \
696  01/01/2005 12:00:00 AM
697  02/01/2005 12:00:00 AM
698  03/01/2005 12:00:00 AM
699  04/01/2005 12:00:00 AM
700  05/01/2005 12:00:00 AM

     Transit Ridership - Other Transit Modes - Adjusted  \
696                                        11611875.0
```

```
697                                         11445295.0
698                                         13310572.0
699                                         12907373.0
700                                         12763833.0

     Transit Ridership - Fixed Route Bus - Adjusted  \
696                                     416054551.0
697                                     403144202.0
698                                     473893673.0
699                                     443809746.0
700                                     455794647.0

     Transit Ridership - Urban Rail - Adjusted  Freight Rail Intermodal Units  \
696                                311945546.0                      1004042.0
697                                305374953.0                       885038.0
698                                349880600.0                       846425.0
699                                335620384.0                      1095545.0
700                                342804244.0                       893384.0

     Freight Rail Carloads  \
696              1538344.0
697              1340764.0
698              1344164.0
699              1704628.0
700              1332755.0

     State and Local Government Construction Spending - Breakwater/Jetty  \
696                                         32000000.0
697                                         28000000.0
698                                         38000000.0
699                                         53000000.0
700                                         50000000.0

     State and Local Government Construction Spending - Dam/Levee  \
696                                         22000000.0
697                                         29000000.0
698                                         36000000.0
699                                         38000000.0
700                                         39000000.0

     State and Local Government Construction Spending - Conservation and
Development  \
696                                         98000000.0
697                                        101000000.0
698                                        116000000.0
699                                        132000000.0
700                                        142000000.0
```

```
     State and Local Government Construction Spending - Pump Station  …  \
696                                         45000000.0                …
697                                         52000000.0                …
698                                         49000000.0                …
699                                         53000000.0                …
700                                         53000000.0                …

     U.S. Air Carrier Cargo (millions of revenue ton-miles) - International  \
696                                       1.696944e+09
697                                       1.561959e+09
698                                       1.958162e+09
699                                       2.078222e+09
700                                       1.925489e+09

     Truck tonnage index  \
696                 88.2
697                 86.3
698                 85.7
699                 86.6
700                 85.8

     U.S. Air Carrier Cargo (millions of revenue ton-miles) - Domestic  \
696                                       1.280516e+09
697                                       1.253130e+09
698                                       1.469765e+09
699                                       1.226824e+09
700                                       1.261165e+09

     Heavy truck sales SAAR (millions)  Light truck sales SAAR (millions)  \
696                           519000.0                          8921000.0
697                           483000.0                          8840000.0
698                           484000.0                          9168000.0
699                           482000.0                          9334000.0
700                           486000.0                          9415000.0

     Auto sales SAAR (millions)  Transborder - Total North American Freight  \
696                   7448000.0                                         NaN
697                   7560000.0                                         NaN
698                   7761000.0                                         NaN
699                   7939000.0                                         NaN
700                   7513000.0                                         NaN

     Transborder - U.S. - Mexico Freight  Transborder - U.S. - Canada Freight  \
696                                  NaN                                  NaN
697                                  NaN                                  NaN
698                                  NaN                                  NaN
```

```
699                                    NaN                                    NaN
700                                    NaN                                    NaN

       Month
696  01/2005
697  02/2005
698  03/2005
699  04/2005
700  05/2005

[5 rows x 109 columns]
```

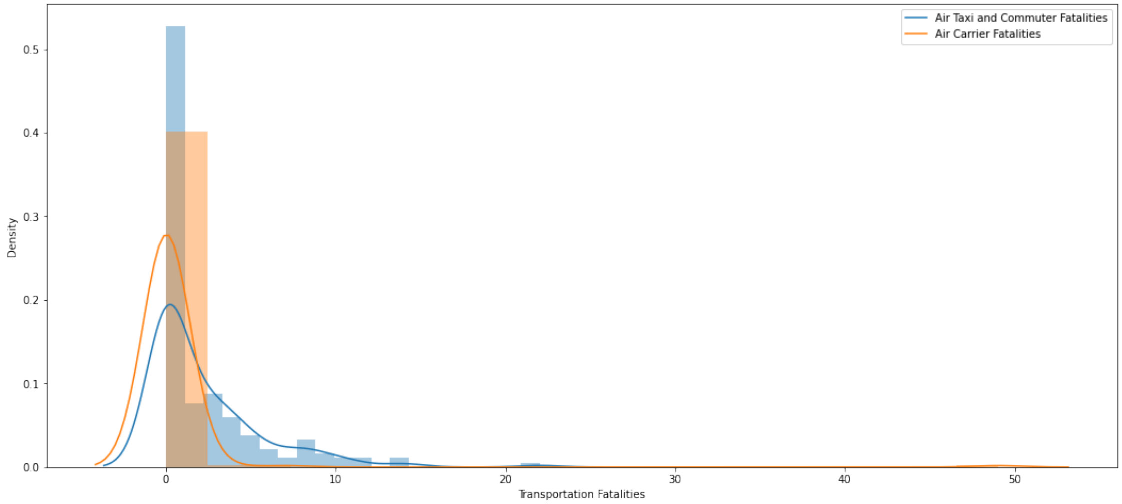
2.1.3 1.1.3. Adjust for null values

[13]:
```
subset.isna().sum()[subset.isna().sum() > 0]
```

[13]:
```
Air Safety - Air Taxi and Commuter Fatalities    13
Air Safety - Air Carrier Fatalities              14
Transborder - Total North American Freight       12
Transborder - U.S. - Mexico Freight              12
Transborder - U.S. - Canada Freight              12
dtype: int64
```

We see that there are 5 columns (out of 110 columns total) that are missing values. These columns are only missing around 13 values each, which comprises <10% of the number of total data points. It would not make sense to drop these columns, since they contain lots of data. Instead, we should adjust for null values by looking at their distributions and decide accordingly.

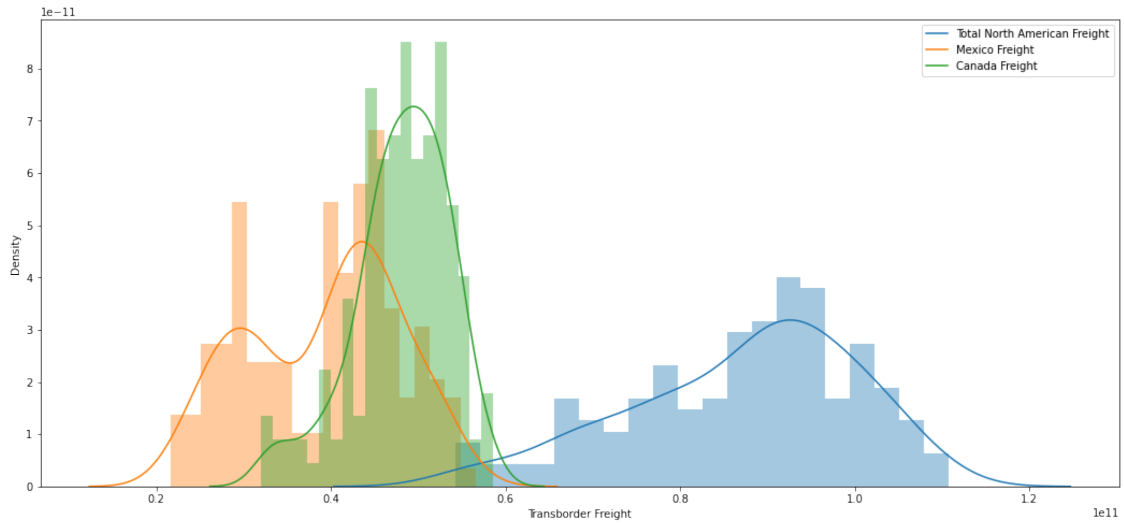
[14]:
```
plt.figure(figsize=(18, 8))
sns.distplot(subset["Air Safety - Air Taxi and Commuter Fatalities"],
             bins=20);
sns.distplot(subset["Air Safety - Air Carrier Fatalities"],
             bins=20);
plt.legend(labels=["Air Taxi and Commuter Fatalities","Air Carrier Fatalities"])
plt.xlabel("Transportation Fatalities");
```



[15]:
```
col = "Air Safety - Air Taxi and Commuter Fatalities"
subset[col] = subset[col].fillna(0)
col2 = "Air Safety - Air Carrier Fatalities"
subset[col2] = subset[col2].fillna(0)
```

From the above distribution plot, we see an overwhelming majority of points have a fatality number of 0. For this reason, we should replace the null values in both air safety columns with the **mode** or **mean** = 0.

[16]:
```
plt.figure(figsize=(18, 8))
sns.distplot(subset["Transborder - Total North American Freight"],
             bins=20);
sns.distplot(subset["Transborder - U.S. - Mexico Freight"],
             bins=20);
sns.distplot(subset["Transborder - U.S. - Canada Freight"],
             bins=20);
plt.xlabel("Transborder Freight")
plt.legend(labels=["Total North American Freight","Mexico Freight", "Canada␣
 ↪Freight"]);
```



From the above distribution plot, we see see that none of the transborder columns are normally distributed. This eliminates the option of replacing these values with the mean. Additionally, it looks as though all three distributions share one commonality: left skewed. Since an overall negative skew is apparent, we should replace all three columns' null values with the **median** since the median is most representative of the "balancing point" for all three distributions.

[17]:
```
cols = ["Transborder - Total North American Freight",
        "Transborder - U.S. - Mexico Freight",
        "Transborder - U.S. - Canada Freight"]

for col in cols:
    subset[col] = subset[col].fillna(np.median(subset[col].dropna()))
```

[18]:
```
# Now, the subset of data should have 0 nulls
check = subset.isna().sum()
check[check > 0]
```

[18]:
```
Series([], dtype: int64)
```

[19]:
```
subset.head()
```

[19]:
```
                         Date  \
696  01/01/2005 12:00:00 AM
697  02/01/2005 12:00:00 AM
698  03/01/2005 12:00:00 AM
699  04/01/2005 12:00:00 AM
700  05/01/2005 12:00:00 AM

     Transit Ridership - Other Transit Modes - Adjusted  \
696                                         11611875.0
```

```
697                                   11445295.0
698                                   13310572.0
699                                   12907373.0
700                                   12763833.0

     Transit Ridership - Fixed Route Bus - Adjusted  \
696                                   416054551.0
697                                   403144202.0
698                                   473893673.0
699                                   443809746.0
700                                   455794647.0

     Transit Ridership - Urban Rail - Adjusted  Freight Rail Intermodal Units  \
696                                311945546.0                      1004042.0
697                                305374953.0                       885038.0
698                                349880600.0                       846425.0
699                                335620384.0                      1095545.0
700                                342804244.0                       893384.0

     Freight Rail Carloads  \
696              1538344.0
697              1340764.0
698              1344164.0
699              1704628.0
700              1332755.0

     State and Local Government Construction Spending - Breakwater/Jetty  \
696                                         32000000.0
697                                         28000000.0
698                                         38000000.0
699                                         53000000.0
700                                         50000000.0

     State and Local Government Construction Spending - Dam/Levee  \
696                                         22000000.0
697                                         29000000.0
698                                         36000000.0
699                                         38000000.0
700                                         39000000.0

     State and Local Government Construction Spending - Conservation and
Development  \
696                                         98000000.0
697                                        101000000.0
698                                        116000000.0
699                                        132000000.0
700                                        142000000.0
```

	State and Local Government Construction Spending - Pump Station	… \
696	45000000.0	…
697	52000000.0	…
698	49000000.0	…
699	53000000.0	…
700	53000000.0	…

	U.S. Air Carrier Cargo (millions of revenue ton-miles) - International \
696	1.696944e+09
697	1.561959e+09
698	1.958162e+09
699	2.078222e+09
700	1.925489e+09

	Truck tonnage index \
696	88.2
697	86.3
698	85.7
699	86.6
700	85.8

	U.S. Air Carrier Cargo (millions of revenue ton-miles) - Domestic \
696	1.280516e+09
697	1.253130e+09
698	1.469765e+09
699	1.226824e+09
700	1.261165e+09

	Heavy truck sales SAAR (millions)	Light truck sales SAAR (millions) \
696	519000.0	8921000.0
697	483000.0	8840000.0
698	484000.0	9168000.0
699	482000.0	9334000.0
700	486000.0	9415000.0

	Auto sales SAAR (millions)	Transborder - Total North American Freight \
696	7448000.0	9.006379e+10
697	7560000.0	9.006379e+10
698	7761000.0	9.006379e+10
699	7939000.0	9.006379e+10
700	7513000.0	9.006379e+10

	Transborder - U.S. - Mexico Freight	Transborder - U.S. - Canada Freight \
696	4.091667e+10	4.886062e+10
697	4.091667e+10	4.886062e+10
698	4.091667e+10	4.886062e+10

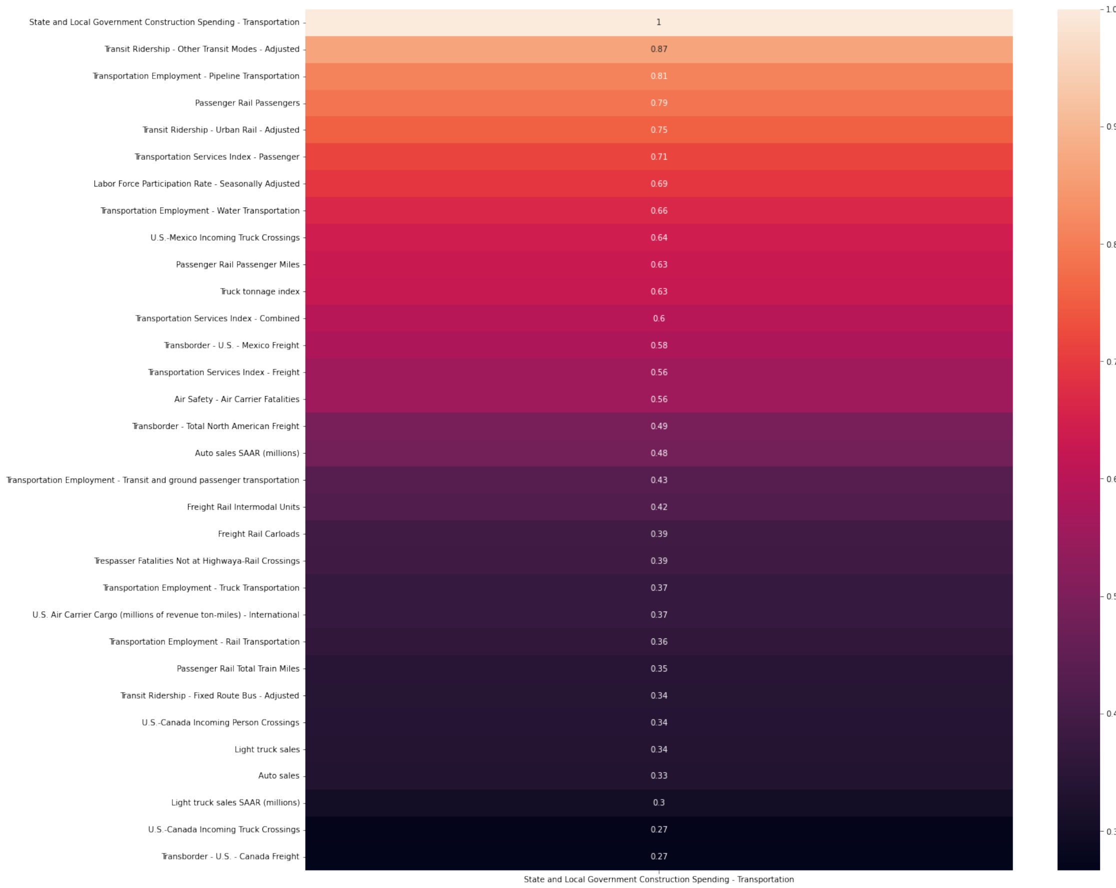
```
699                          4.091667e+10                            4.886062e+10
700                          4.091667e+10                            4.886062e+10

       Month
696  01/2005
697  02/2005
698  03/2005
699  04/2005
700  05/2005

[5 rows x 109 columns]
```

2.1.4 1.1.4 Feature Visualization: Qualitative and Quantitative Variables

A useful visualization would be to look at the correlation between state and local government transportation spending and the features that do not include spending (i.e. ridership statistics, population statistics, etc.) That way, we could see the overall association between spend and metrics relating consumer volume/behavior. Since we want to see which features are strongly correlated (positive or negative), we took the absolute value of the correlation coefficient and sorted them.

[20]:
```python
# Subset data to cons/dev gov spending and the remaining non-spend cols
col_list = list(subset.columns)
bools = [not "Spending" in col for col in col_list]
```

[21]:
```python
# Visualize heatmap of correlations between spending and non-spending features

cols_for_viz = [col_list[index] for index in np.where(bools)[0]]
for_viz = subset[cols_for_viz].drop(["Date", "Month"], axis=1)
y_col = "State and Local Government Construction Spending - Transportation"
for_viz[y_col] = np.log(subset[[y_col]])
corr = np.log(for_viz).corr()[[y_col]]
corr = abs(corr).sort_values(y_col, ascending=False)
plt.figure(figsize=(20, 20))
subset_corr = corr.loc[corr.mean(axis=1) > 0.2, corr.mean(axis=0) > 0.2]
sns.heatmap(subset_corr, annot=True);
```



Observations

Above, we see the relationship between conservation/development spending and non-spending variables found in the dataset. Overall, all of the non-spending variables were numerical (non-categorical). We also see that the top 5 metrics correlated with higher transportation spending in state and local governments were:

1. **Transit Ridership - Other Transit Modes**
2. **Transportation Employment - Pipeline Transportation**
3. **Passenger Rail Passengers**
4. **Transit Ridership - Urban Rail**
5. **Transportation Services Index - Passenger**

Overall, this can be summarized through the fact that we witness a high association between transportation spending and population in two regards: first, the number of users utilizing public transit, and second, the population/volume of workers in the transportation sector.

From here, it would be neat to follow up on perhaps why we see a high correlation between spending and variables such as **mobile transit** metrics (as seen through the top five list above) rather than other forms of transportation such as air carrier and cargo shipping. By answering these thoughts and developing a more firm understanding to which non-spending metric impacts/correlates with spending metrics the most, we will be able to select better features for our model to answer our original research question: **Predicting transportation spending in 2019 using past infrastructure data (up to 2018) in the US.**

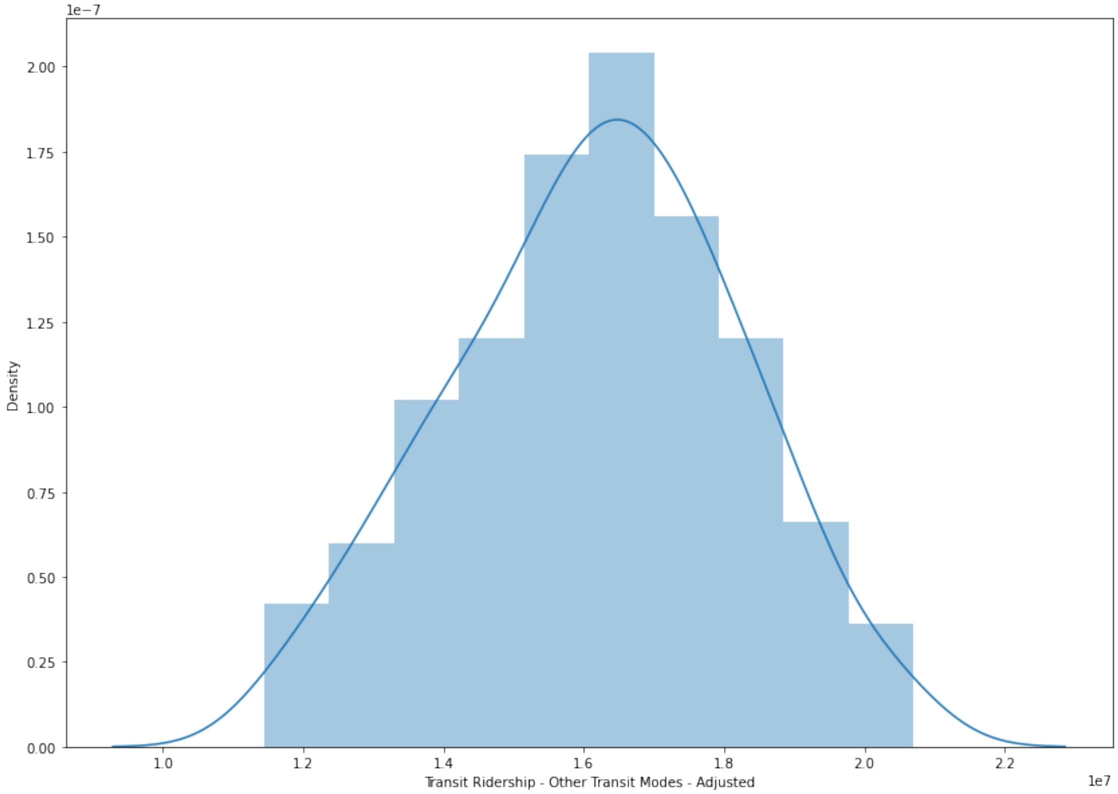
Categorical Variables

There are no qualitative variables in this dataset, so we decided to code the 3 transit ridership features into tiers of very low, low, high, very high. The reason we chose to code the transit ridership features is that they are good indicators of utilization, and the purpose of additional government investment is to meet the demand and / or encourage public transportation. In addition, while the Urban Rail and Other modes of Transit ridership are very correlated to transportation spending, the "Fixed Bus Route" has a somewhat low correlation. It would be interesting to compare the trends of variables with high and low correlation.

[22]:
```
#Other Transit Modes

plt.figure(figsize=(14, 10))
sns.distplot(subset["Transit Ridership - Other Transit Modes - Adjusted"])
print(np.std(subset["Transit Ridership - Other Transit Modes - Adjusted"]))
print(np.mean(subset["Transit Ridership - Other Transit Modes - Adjusted"]))
min(subset["Transit Ridership - Other Transit Modes - Adjusted"]),␣
↪max(subset["Transit Ridership - Other Transit Modes - Adjusted"])
```

```
2028697.6601536982
16164455.744444445
```

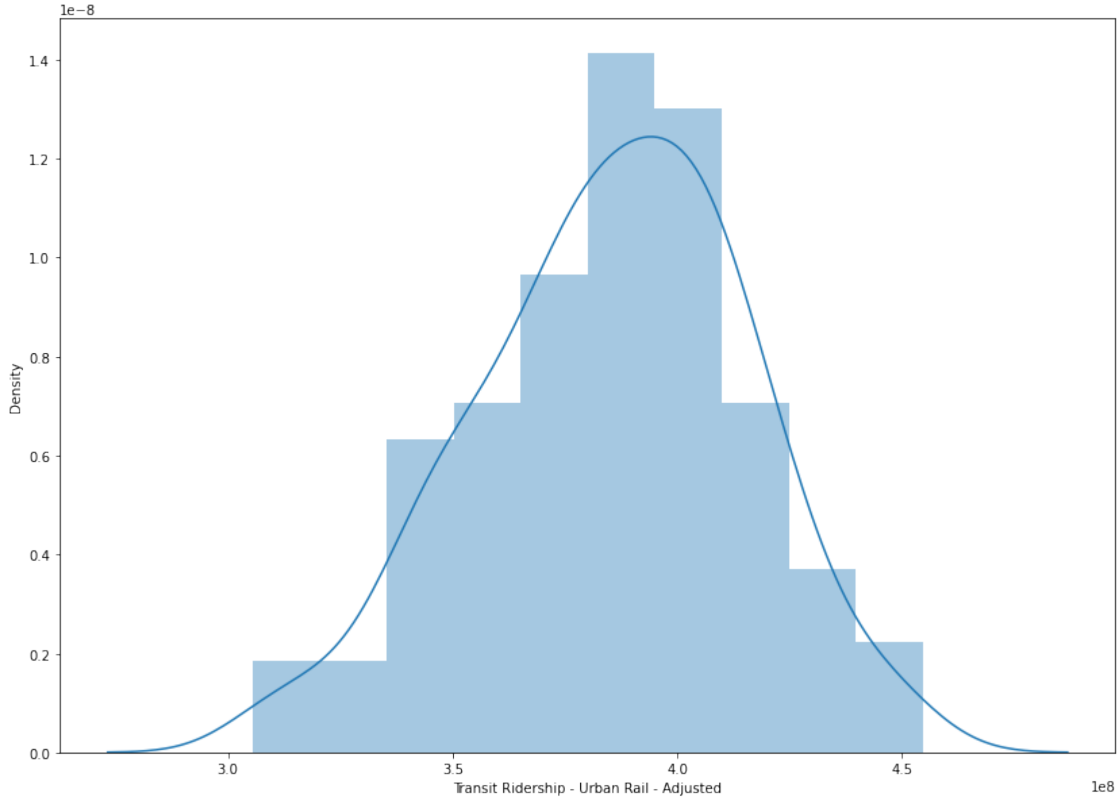
[22]:
```
(11445295.0, 20702522.0)
```



[23]:
```python
#Urban Rail

plt.figure(figsize=(14, 10))
sns.distplot(subset["Transit Ridership - Urban Rail - Adjusted"])
print(np.std(subset["Transit Ridership - Urban Rail - Adjusted"]))
print(np.mean(subset["Transit Ridership - Urban Rail - Adjusted"]))
min(subset["Transit Ridership - Urban Rail - Adjusted"]), max(subset["Transit␣
 ↪Ridership - Urban Rail - Adjusted"])
```

```
30186332.70081097
385298127.09444445
```

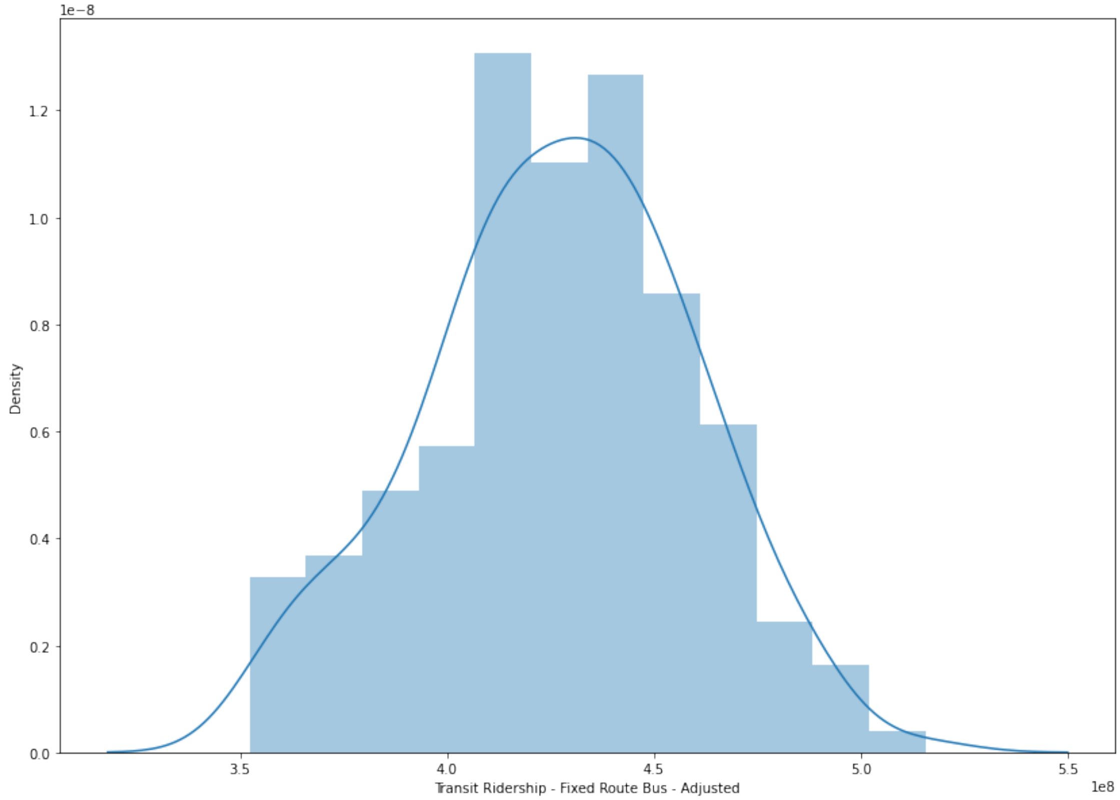
[23]: (305374953.0, 454743586.0)



[24]:
```python
#Other Fixed Route Bus

plt.figure(figsize=(14, 10))
sns.distplot(subset["Transit Ridership - Fixed Route Bus - Adjusted"])
print(np.std(subset["Transit Ridership - Fixed Route Bus - Adjusted"]))
print(np.mean(subset["Transit Ridership - Fixed Route Bus - Adjusted"]))
min(subset["Transit Ridership - Fixed Route Bus - Adjusted"]),␣
 ↪max(subset["Transit Ridership - Fixed Route Bus - Adjusted"])
```

```
32217733.02184518
426611771.1722222
```

[24]:
```
(352319744.0, 515540107.0)
```



Visualizing the distribution of the 3 transit ridership features shows that their distribution follows a somewhat normal distribution. Because of this, we will use mean +- 1 std dev as the cut-off for the tiers: very low, low, high, and very high.

Below is the code to add in the 3 categorical columns:

[25]:
```
#Other Transit Modes
vlo = np.mean(subset["Transit Ridership - Other Transit Modes - Adjusted"]) -␣
↪np.std(subset["Transit Ridership - Other Transit Modes - Adjusted"])
lo = np.mean(subset["Transit Ridership - Other Transit Modes - Adjusted"])
hi = np.mean(subset["Transit Ridership - Other Transit Modes - Adjusted"]) + np.
↪std(subset["Transit Ridership - Other Transit Modes - Adjusted"])
vlo, lo, hi
```

[25]:
```
(14135758.084290747, 16164455.744444445, 18193153.404598143)
```

[26]:
```
subset["TR_Other"] = subset["Transit Ridership - Other Transit Modes -␣
↪Adjusted"]
subset.loc[subset.TR_Other.between(0, vlo), "TR_Other"] = 50
subset.loc[subset.TR_Other.between(vlo, lo), "TR_Other"] = 15000000
subset.loc[subset.TR_Other.between(lo, hi), "TR_Other"] = 17000000
subset.loc[subset.TR_Other > hi, "TR_Other"] = 19000000
```

```
dict = {50: "very low", 15000000: "low", 17000000: "high", 19000000: "very␣
↪high"}
subset["TR_Other"] = subset.TR_Other.map(dict)
subset.TR_Other
```

[26]:
```
696     very low
697     very low
698     very low
699     very low
700     very low
          …
871    very high
872    very high
873    very high
874         high
875         high
Name: TR_Other, Length: 180, dtype: object
```

[27]:
```
#Urban Rail
vlo = np.mean(subset["Transit Ridership - Urban Rail - Adjusted"]) - np.
↪std(subset["Transit Ridership - Urban Rail - Adjusted"])
lo = np.mean(subset["Transit Ridership - Urban Rail - Adjusted"])
hi = np.mean(subset["Transit Ridership - Urban Rail - Adjusted"]) + np.
↪std(subset["Transit Ridership - Urban Rail - Adjusted"])
vlo, lo, hi
```

[27]:
```
(355111794.3936335, 385298127.09444445, 415484459.7952554)
```

[28]:
```
subset["TR_UR"] = subset["Transit Ridership - Urban Rail - Adjusted"]
subset.loc[subset.TR_UR.between(0, vlo), "TR_UR"] = 50
subset.loc[subset.TR_UR.between(vlo, lo), "TR_UR"] = 370000000
subset.loc[subset.TR_UR.between(lo, hi), "TR_UR"] = 400000000
subset.loc[subset.TR_UR > hi, "TR_UR"] = 420000000
dict = {50: "very low", 370000000: "low", 400000000: "high", 420000000: "very␣
↪high"}
subset["TR_UR"] = subset.TR_UR.map(dict)
subset.TR_UR
```

[28]:
```
696     very low
697     very low
698     very low
699     very low
700     very low
          …
871         high
872         high
873    very high
```

```
874          high
875          high
Name: TR_UR, Length: 180, dtype: object
```

[29]:
```
#Fixed Route Bus
vlo = np.mean(subset["Transit Ridership - Fixed Route Bus - Adjusted"]) - np.
 ↪std(subset["Transit Ridership - Fixed Route Bus - Adjusted"])
lo = np.mean(subset["Transit Ridership - Fixed Route Bus - Adjusted"])
hi = np.mean(subset["Transit Ridership - Fixed Route Bus - Adjusted"]) + np.
 ↪std(subset["Transit Ridership - Fixed Route Bus - Adjusted"])
vlo, lo, hi
```

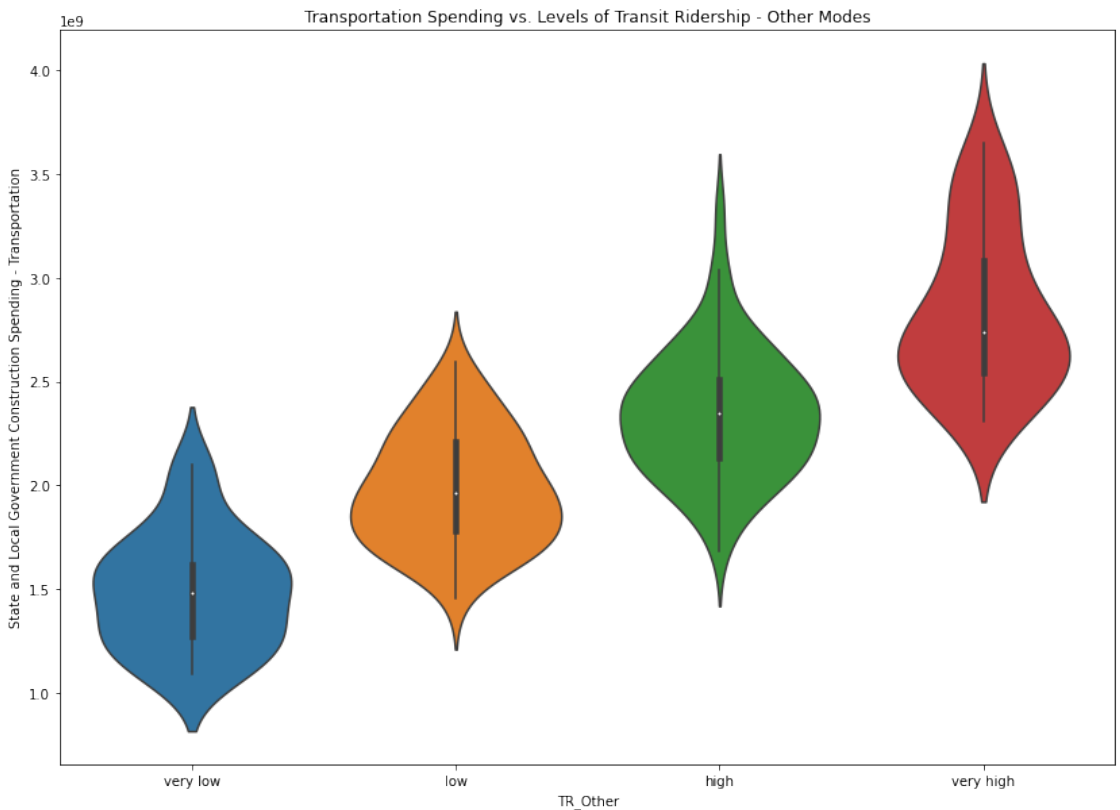
[29]:
```
(394394038.15037704, 426611771.1722222, 458829504.19406736)
```

[30]:
```
subset["TR_frb"] = subset["Transit Ridership - Fixed Route Bus - Adjusted"]
subset.loc[subset.TR_frb.between(0, vlo), "TR_frb"] = 50
subset.loc[subset.TR_frb.between(vlo, lo), "TR_frb"] = 400000000
subset.loc[subset.TR_frb.between(lo, hi), "TR_frb"] = 430000000
subset.loc[subset.TR_frb > hi, "TR_frb"] = 460000000
dict = {50: "very low", 400000000: "low", 430000000: "high", 460000000: "very␣
 ↪high"}
subset["TR_frb"] = subset.TR_frb.map(dict)
subset.TR_frb
```

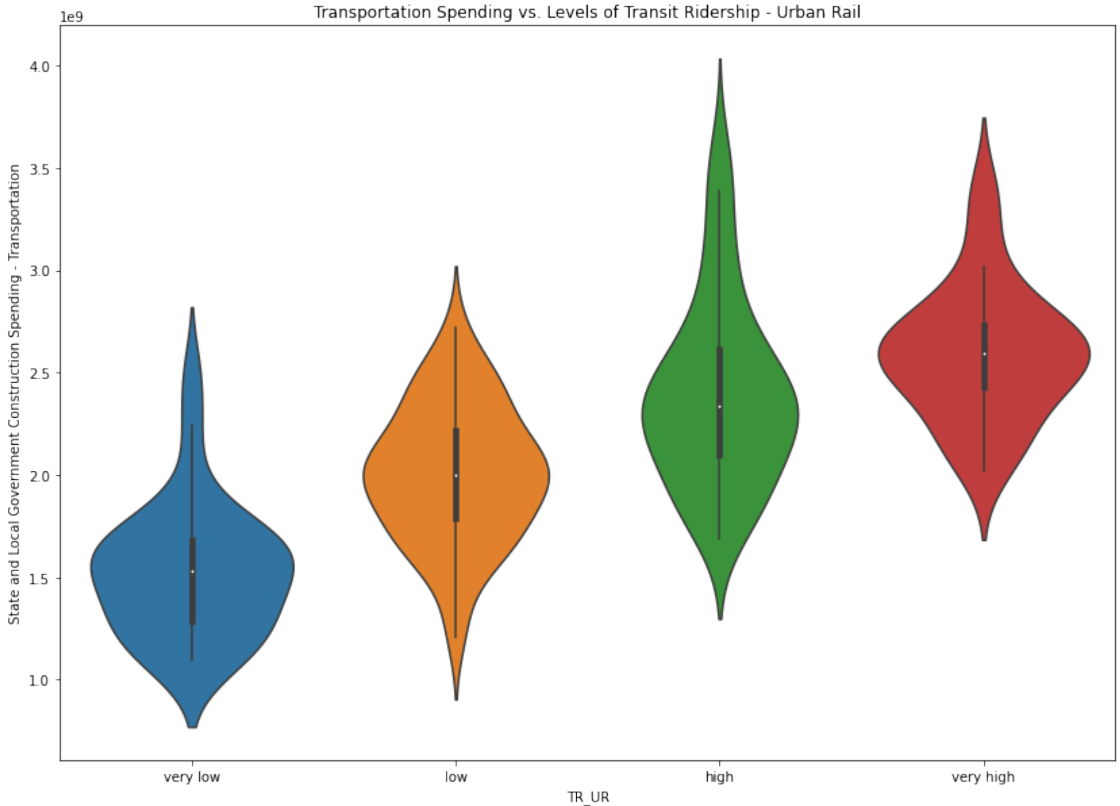
[30]:
```
696           low
697           low
698     very high
699          high
700          high
          …
871      very low
872           low
873           low
874      very low
875      very low
Name: TR_frb, Length: 180, dtype: object
```

Violinplots to Compare Transportation Spending vs. Levels of Transit Ridership

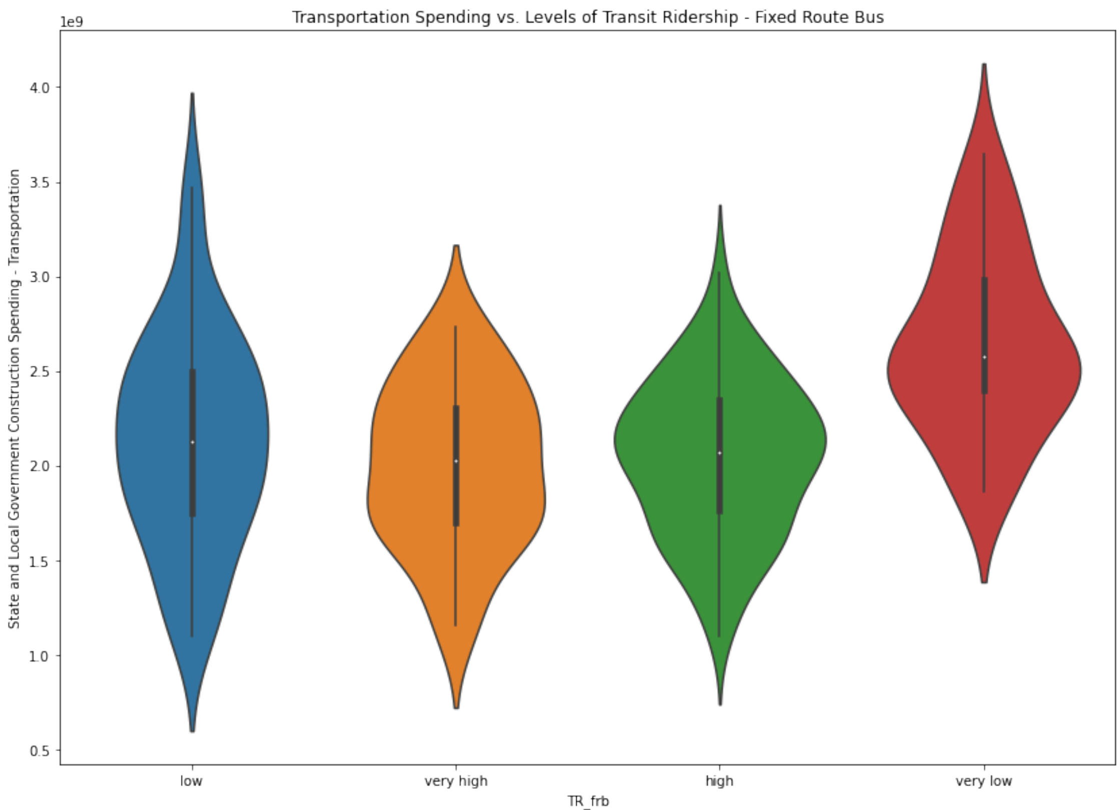
[31]:
```
#Other Transit Modes
plt.figure(figsize=(14, 10))
sns.violinplot(x="TR_Other", y="State and Local Government Construction␣
 ↪Spending - Transportation", data=subset)
plt.title("Transportation Spending vs. Levels of Transit Ridership - Other␣
 ↪Modes");
```



[32]:
```
#Urban Rail
plt.figure(figsize=(14, 10))
sns.violinplot(x="TR_UR", y="State and Local Government Construction Spending -␣
↪Transportation", data=subset);
plt.title("Transportation Spending vs. Levels of Transit Ridership - Urban␣
↪Rail");
```



[33]:
```
#Fixed Route Bus
plt.figure(figsize=(14, 10))
sns.violinplot(x="TR_frb", y="State and Local Government Construction Spending␣
↪- Transportation", data=subset);
plt.title("Transportation Spending vs. Levels of Transit Ridership - Fixed␣
↪Route Bus");
```



Observation / Reasoning

We used a violinplot to compare the categorical variables of transit ridership tiers and the spending on transportation because it is an effective way to visualize the relationship between a quantitative and qualitative variable.

As expected, the Other Modes and Urban Rail showed a much clearer positive correlation to transportation spending, and have less variance in each category. On the other hand, the level of transit ridership for fixed route bus actually showed a negative correlation to transportation spending. The fixed route bus ridership data also has the most spread, suggesting that this negative correlation may have been affected by other variables. Incorporating those other variables that are resulting in this trend would be important to ensure that our model will predict the 2019 spending on transportation more effectively.

2.2 1.2. Constructing GLM

To establish a GLM, it is important first to distinguish between **bayesian** and **frequentist** models. We recall that the main difference (among others) between the two are that bayesian models hold the unknown parameter to be random (represented by a RV with an appropriate statistical distribution) while frequentist models hold the unknown parameter to be fixed.

As a reminder, our main point of emphasis in this investigation is to use **US transportation spend metrics from 2005-2018 to model and predict transportation spend in 2019**.

With this in mind, it is important to recognize that since our outcome variable is national US spending, there are clear exogenous variables that impact this variable. Some of these include:

1. **National Debt** - the nation's debt influences the baseline of funds available for infrastructure and transportation spending.
2. **Political Atmosphere** - the political party affiliation of both the president as well as the senate and house of representatives influences the baseline willingness to contribute to infrastructure spending.

There are other variables that may similarly influence our outcome variable of US Transportation Spending. For this reason, we have chosen to proceed with a **Bayesian GLM** since the outcome variable as well as the impact on the outcome variable by other features will *not* be fixed. In reality, there are factors that are constantly influencing the outcome.

Next, to choose a certain Bayesian GLM to use. In order to evaluate this, we must first look at the distribution of the outcome variable: US Transportation Spending.

[34]:
```
#Reimport Libraries and raw data
import numpy as np
import pandas as pd
import re
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import gamma

import pymc3 as pm
from pymc3 import glm
import statsmodels.api as sm
import arviz

import warnings
warnings.filterwarnings('ignore')

cleaned = subset

# Subset to dates prior to 2019 and save 2019 for test set
cleaned_train = cleaned.iloc[:-12]
cleaned_test = cleaned.iloc[-12:]
```

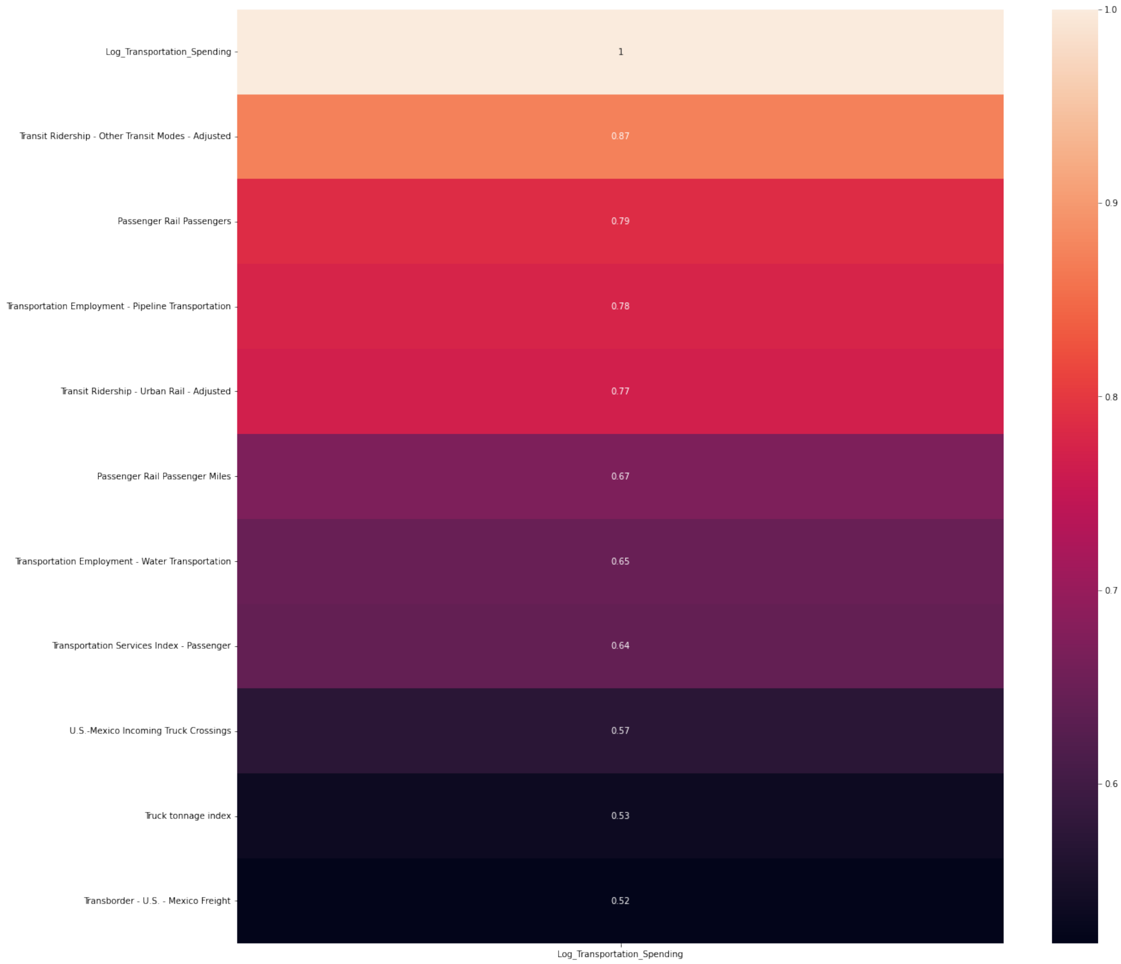
2.2.1 1.2.1. Determining Strong Features

From the cleaned data, we know that the primary variable of interest (outcome variable) is `State and Local Government Construction Spending - Transportation`. In order to determine which features to use to develop a GLM, let's first identify the historic correlation between transportation metrics (X's) and transportation spending (Y)

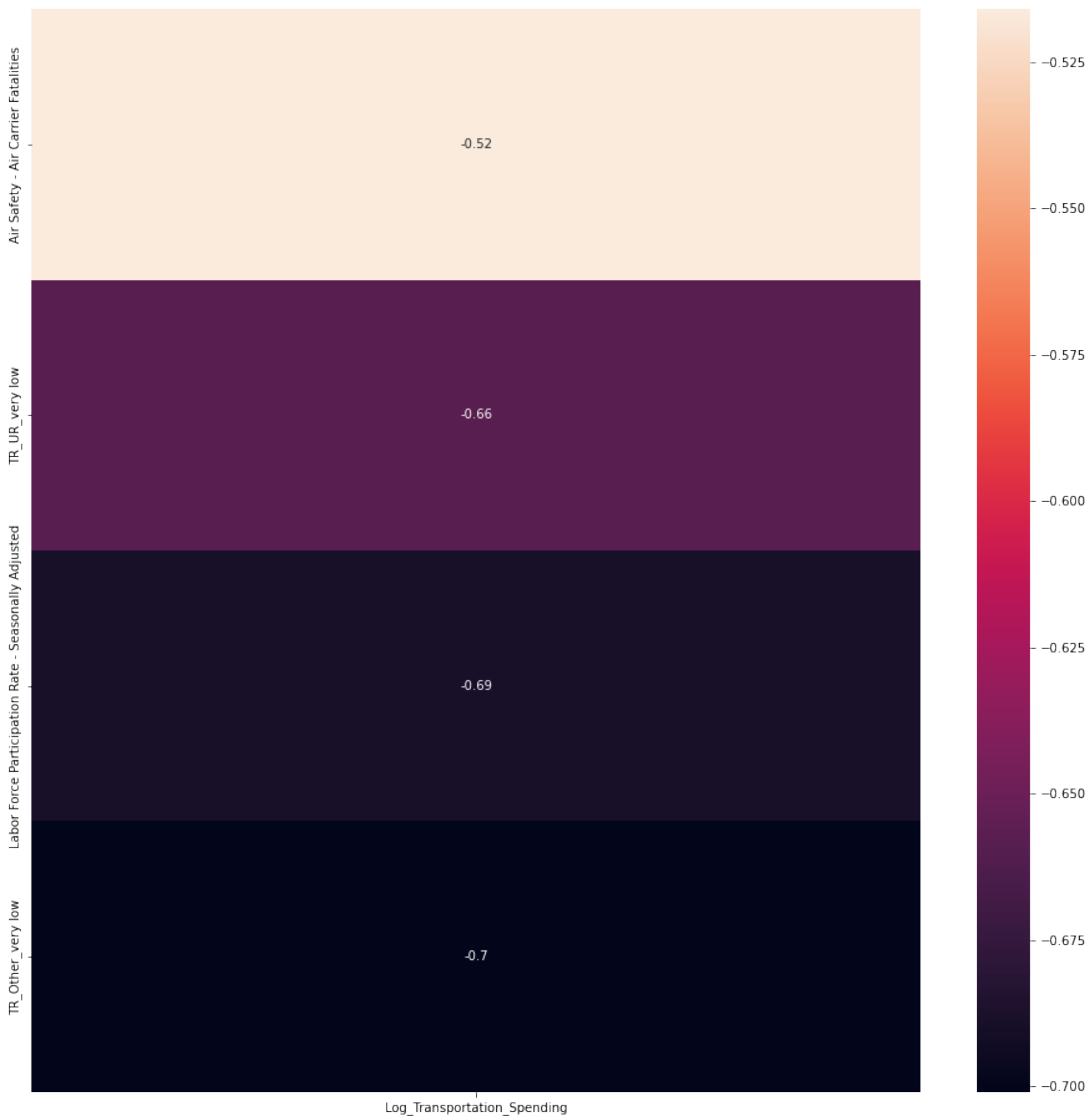
[35]:
```
# First, take the log of all spending values and one-hot the categorical␣
↪variables, adding them to the cleaned data
log_spend = for_viz[y_col]
```

```
cleaned_train["Log_Transportation_Spending"] = log_spend
temp = cleaned_train.drop(columns=["Date", "Month", "TR_Other",
                                    "TR_UR", "TR_frb", "Log_Transportation_Spending"],␣
 ↪axis=1)
log_cleaned_train = np.log(temp)
dummies = pd.get_dummies(cleaned_train[["TR_UR", "TR_Other", "TR_frb"]])
cleaned_train = log_cleaned_train.join(dummies)
```

[36]:
```
# Visualize heatmap of positive correlations between spending and non-spending␣
 ↪features

plt.figure(figsize=(20, 20))

# Subset data to cons/dev gov spending and the remaining non-spend cols
col_list = list(cleaned_train.columns)
bools = [not "Spending" in col for col in col_list]
cols_for_viz = [col_list[index] for index in np.where(bools)[0]]

y_col = "Log_Transportation_Spending"
transp_df = cleaned_train[cols_for_viz]
transp_df[y_col] = log_spend
transp_corr_df = transp_df.corr()[[y_col]]
transp_corr_df = transp_corr_df.sort_values(y_col, ascending=False)
subset_transp_positive_corr_df = transp_corr_df.loc[transp_corr_df.mean(axis=1)␣
 ↪>= .5]
sns.heatmap(subset_transp_positive_corr_df, annot=True);
```



[37]:
```
# Visualize negative correlations with y variable (transportation spending)

plt.figure(figsize=(16, 16))

subset_transp_negative_corr_df = transp_corr_df.loc[transp_corr_df.mean(axis=1)
 ↪<= -.5]
sns.heatmap(subset_transp_negative_corr_df, annot=True);
```



From the above two heatmaps, we see that with respect to `Log Transportation Spending`, we have a total of 10 moderately strong to strongly positively-correlated features and 4 strongly negatively-correlated features (Note: here, moderately strong correlation is demonstrated by an absolute pearsson value of .5 or greater.

2.2.2 1.2.2. Background of Features

In regards to building a GLM, the next step is the develop and indicate any pre-existing information regarding the distribution of the possible features. For convenience, the features have been put into a table below.

Feature ID	Feature/Column Name	Correlation
x1	Transit Ridership - Other Transit Modes - Adjusted	0.863
x2	Passenger Rail Passenger	0.775
x3	Transportation Employment - Pipeline Transportation	0.764
x4	Transit Ridership - Urban Rail - Adjusted	0.758
x5	Passenger Rail Passenger Miles	0.654
x6	Transportation Employment - Water Transportation	0.640
x7	Transportation Services Index - Passenger	0.639
x8	U.S.-Mexico Incoming Truck Crossings	0.579
x9	Truck tonnage index	0.546
x10	Transborder - U.S. - Mexico Freight	0.541
x11	Air Safety - Air Carrier Fatalities	-0.520
x12	TR_UR_very low	-0.658
x13	Labor Force Participation Rate - Seasonally Adjusted	-0.689
x14	TR_Other_very low	-0.700

Forming Likelihood and Prior Although we have found the correlation coefficients of the features above, this is not yet enough to warrant specific prior distributions for all 14 features. Additionally, after appropriate research regarding the impacts of each feature on the general spending, there were contrasting perspectives on whether or not each feature had an impact and whether or not it was positive or negative. Likely, this was due to different political perspectives as spending governed by the White House has socio-political implications - most notably demonstrated with the Republican pushback of the otherwise Democratic-backed new infrastructure deal. Thus, each prior has been assessed the un-informative/objective Normal(0, 1) distribution as contrasting sources have eliminated the presence of convicting, one-sided data regarding the prior distributions.

[38]:
```
cleaned_train["Log_Transportation_Spending"] = log_spend
cleaned_train["Air Safety - Air Carrier Fatalities"] = np.e**cleaned_train["Air␣
↪Safety - Air Carrier Fatalities"]
```

[39]:
```
# For ease of model creation, rename columns to x_is

cleaned_train = cleaned_train.rename({"Transit Ridership - Other Transit Modes␣
↪- Adjusted": "x1",
               "Transportation Employment - Pipeline Transportation": "x3",
               "Passenger Rail Passengers": "x2",
               "Transportation Services Index - Passenger": "x7",
               "Transit Ridership - Urban Rail - Adjusted": "x4",
               "Truck tonnage index": "x9",
               "U.S.-Mexico Incoming Truck Crossings": "x8",
               "Labor Force Participation Rate - Seasonally Adjusted": "x8",
               "Transborder - U.S. - Mexico Freight": "x10",
               "Transportation Employment - Water Transportation": "x6",
               "Air Safety - Air Carrier Fatalities" : "x11",
               "TR_UR_very low": "x12",
               "Passenger Rail Passenger Miles": "x5",
```

```
                 "Labor Force Participation Rate - Seasonally Adjusted": "x13",
                 "TR_Other_very low": "x14"
                }, axis=1)

cleaned_train = cleaned_train[["Log_Transportation_Spending", "x1", "x2", "x3",␣
↪"x4", "x5", "x6", "x7", "x8", "x9", "x10",
                  "x11", "x12", "x13", "x14"]]
```

[40]:

```
cleaned_train
```

[40]:

```
     Log_Transportation_Spending         x1         x2         x3         x4  \
696                    20.841049  16.267539  14.425270  10.547970  19.558339
697                    20.828526  16.253089  14.400341  10.537415  19.537051
698                    20.865633  16.404069  14.630733  10.534759  19.673103
699                    20.955964  16.373309  14.566232  10.540064  19.631491
700                    20.964642  16.362126  14.602603  10.532096  19.652670
..                           …          …          …          …          …
859                    21.856602  16.845766  14.908451  10.821776  19.803354
860                    21.815189  16.703359  14.764664  10.829729  19.787361
861                    21.828191  16.779112  14.848626  10.835652  19.910162
862                    21.750740  16.645884  14.871585  10.825760  19.788514
863                    21.631121  16.593970  14.798556  10.831707  19.727786

            x5         x6        x7         x8        x9        x10  x11  x12  \
696  19.751378  10.924138  4.680278  12.797959  4.479607  24.434803  0.0    1
697  19.677958  10.916905  4.685828  12.812117  4.457830  24.434803  0.0    1
698  19.955025  10.945529  4.685828  12.893514  4.450853  24.434803  0.0    1
699  19.880450  10.992050  4.691348  12.887855  4.461300  24.434803  0.0    1
700  19.951106  11.020267  4.690430  12.890139  4.452019  24.434803  0.0    1
..         …          …         …          …         …          …    …    …
859  20.248716  11.130200  4.877485  13.222645  4.736198  24.703953  0.0    0
860  20.021902  11.103452  4.873669  13.110406  4.746670  24.647892  0.0    0
861  20.110215  11.095894  4.884316  13.250320  4.754452  24.758936  0.0    0
862  20.146211  11.077516  4.877485  13.190801  4.762174  24.686720  0.0    0
863  20.128846  11.077516  4.881286  13.059204  4.746670  24.564564  0.0    0

          x13  x14
696 -0.418550    1
697 -0.417032    1
698 -0.417032    1
699 -0.414001    1
700 -0.414001    1
..          …    …
859 -0.466809    0
860 -0.466809    0
861 -0.465215    0
862 -0.463624    0
```

```
863 -0.462035    0

[168 rows x 15 columns]
```

Evaluating Model on Holdout Data

[41]:
```
cleaned_test
```

[41]:
```
                       Date  \
864  01/01/2019 12:00:00 AM
865  02/01/2019 12:00:00 AM
866  03/01/2019 12:00:00 AM
867  04/01/2019 12:00:00 AM
868  05/01/2019 12:00:00 AM
869  06/01/2019 12:00:00 AM
870  07/01/2019 12:00:00 AM
871  08/01/2019 12:00:00 AM
872  09/01/2019 12:00:00 AM
873  10/01/2019 12:00:00 AM
874  11/01/2019 12:00:00 AM
875  12/01/2019 12:00:00 AM

     Transit Ridership - Other Transit Modes - Adjusted  \
864                                         16515635.0
865                                         15136059.0
866                                         17796909.0
867                                         18746430.0
868                                         19596702.0
869                                         19006565.0
870                                         20378395.0
871                                         20593034.0
872                                         18338805.0
873                                         19083744.0
874                                         16328180.0
875                                         16239029.0

     Transit Ridership - Fixed Route Bus - Adjusted  \
864                                     367851089.0
865                                     354692992.0
866                                     390228157.0
867                                     397479345.0
868                                     399640786.0
869                                     362002815.0
870                                     369257081.0
871                                     384027047.0
872                                     396062247.0
873                                     426327140.0
```

874	371791492.0
875	352319744.0

	Transit Ridership - Urban Rail - Adjusted	Freight Rail Intermodal Units \
864	368022820.0	1316168.0
865	350068247.0	1094580.0
866	403221955.0	1065841.0
867	415533810.0	1322588.0
868	421141236.0	1049163.0
869	398791173.0	1075974.0
870	411609150.0	1314363.0
871	410170062.0	1089839.0
872	410903169.0	1329532.0
873	448819797.0	1063908.0
874	405041309.0	1019780.0
875	401888202.0	1189369.0

	Freight Rail Carloads \
864	1238487.0
865	1000142.0
866	956821.0
867	1310228.0
868	1023136.0
869	1023394.0
870	1264354.0
871	1055024.0
872	1239455.0
873	977406.0
874	955392.0
875	1143990.0

	State and Local Government Construction Spending - Breakwater/Jetty \
864	72000000.0
865	82000000.0
866	104000000.0
867	84000000.0
868	104000000.0
869	104000000.0
870	116000000.0
871	120000000.0
872	104000000.0
873	92000000.0
874	107000000.0
875	93000000.0

	State and Local Government Construction Spending - Dam/Levee \
864	64000000.0

```
865                                              66000000.0
866                                              67000000.0
867                                              76000000.0
868                                              80000000.0
869                                             108000000.0
870                                             105000000.0
871                                             129000000.0
872                                             125000000.0
873                                             134000000.0
874                                              97000000.0
875                                              84000000.0

     State and Local Government Construction Spending - Conservation and
Development  \
864                                             238000000.0
865                                             211000000.0
866                                             232000000.0
867                                             242000000.0
868                                             266000000.0
869                                             288000000.0
870                                             307000000.0
871                                             335000000.0
872                                             308000000.0
873                                             304000000.0
874                                             280000000.0
875                                             247000000.0

     State and Local Government Construction Spending - Pump Station  …  \
864                                              61000000.0           …
865                                              76000000.0           …
866                                              72000000.0           …
867                                              92000000.0           …
868                                              79000000.0           …
869                                              87000000.0           …
870                                              84000000.0           …
871                                              60000000.0           …
872                                              76000000.0           …
873                                             106000000.0           …
874                                             141000000.0           …
875                                             136000000.0           …

     Heavy truck sales SAAR (millions)  Light truck sales SAAR (millions)  \
864                           522000.0                          11503000.0
865                           510000.0                          11861000.0
866                           524000.0                          12210000.0
867                           570000.0                          11668000.0
868                           564000.0                          12474000.0
```

869	550000.0	12380000.0
870	565000.0	12339000.0
871	535000.0	12501000.0
872	554000.0	12564000.0
873	505000.0	12330000.0
874	456000.0	12700000.0
875	470000.0	12367000.0

	Auto sales SAAR (millions)	Transborder - Total North American Freight \
864	5241000.0	9.562308e+10
865	4814000.0	9.418898e+10
866	4922000.0	1.072299e+11
867	4760000.0	1.045488e+11
868	4802000.0	1.097959e+11
869	4902000.0	1.037658e+11
870	4692000.0	1.024414e+11
871	4609000.0	1.051030e+11
872	4596000.0	1.014349e+11
873	4395000.0	1.071120e+11
874	4401000.0	9.903155e+10
875	4502000.0	9.634248e+10

	Transborder - U.S. - Mexico Freight	Transborder - U.S. - Canada Freight \
864	4.959533e+10	4.602775e+10
865	4.782260e+10	4.636638e+10
866	5.316518e+10	5.406468e+10
867	5.259620e+10	5.195258e+10
868	5.454501e+10	5.525088e+10
869	5.116206e+10	5.260373e+10
870	5.222079e+10	5.022060e+10
871	5.310121e+10	5.200176e+10
872	5.014872e+10	5.128617e+10
873	5.335177e+10	5.376023e+10
874	5.010448e+10	4.892707e+10
875	4.668673e+10	4.965575e+10

	Month	TR_Other	TR_UR	TR_frb
864	01/2019	high	low	very low
865	02/2019	low	very low	very low
866	03/2019	high	high	very low
867	04/2019	very high	very high	low
868	05/2019	very high	very high	low
869	06/2019	very high	high	very low
870	07/2019	very high	high	very low
871	08/2019	very high	high	very low
872	09/2019	very high	high	low
873	10/2019	very high	very high	low

```
874  11/2019       high       high  very low
875  12/2019       high       high  very low

[12 rows x 112 columns]
```

[42]:

```
#Clean test data
cleaned_test["Log_Transportation_Spending"] = log_spend
temp = cleaned_test.drop(columns=["Date", "Month", "TR_Other",
                            "TR_UR", "TR_frb", "Log_Transportation_Spending"],␣
 ↪axis=1)
log_cleaned_test = np.log(temp)
dummies = pd.get_dummies(cleaned_test[["TR_UR", "TR_Other", "TR_frb"]])
cleaned_test = log_cleaned_test.join(dummies)
cleaned_test["Log_Transportation_Spending"] = log_spend
cleaned_test["TR_UR_very low"] = 0
cleaned_test["TR_Other_very low"] = 0
cleaned_test["Air Safety - Air Carrier Fatalities"] = np.e**cleaned_test["Air␣
 ↪Safety - Air Carrier Fatalities"]


cleaned_test = cleaned_test.rename({"Transit Ridership - Other Transit Modes -␣
 ↪Adjusted": "x1",
               "Transportation Employment - Pipeline Transportation": "x3",
               "Passenger Rail Passengers": "x2",
               "Transportation Services Index - Passenger": "x7",
               "Transit Ridership - Urban Rail - Adjusted": "x4",
               "Truck tonnage index": "x9",
               "U.S.-Mexico Incoming Truck Crossings": "x8",
               "Labor Force Participation Rate - Seasonally Adjusted": "x8",
               "Transborder - U.S. - Mexico Freight": "x10",
               "Transportation Employment - Water Transportation": "x6",
               "Air Safety - Air Carrier Fatalities" : "x11",
               "TR_UR_very low": "x12",
               "Passenger Rail Passenger Miles": "x5",
               "Labor Force Participation Rate - Seasonally Adjusted": "x13",
               "TR_Other_very low": "x14"
              }, axis=1)

cleaned_test = cleaned_test[["Log_Transportation_Spending", "x1", "x2", "x3",␣
 ↪"x4", "x5", "x6", "x7", "x8", "x9", "x10",
                "x11", "x12", "x13", "x14"]]
```

[43]:

```
cleaned_test
```

[43]:

```
     Log_Transportation_Spending         x1         x2         x3         x4  \
864                    21.607033  16.619818  14.643525  10.831707  19.723656
865                    21.637555  16.532590  14.587725  10.823770  19.673639
```

```
866                    21.711691  16.694535  14.806115  10.833681  19.814998
867                    21.804732  16.746514  14.819444  10.837618  19.845075
868                    21.906832  16.790872  14.879471  10.855145  19.858479
869                    21.944096  16.760295  14.910177  10.858999  19.803948
870                    21.976600  16.829986  14.949746  10.864752  19.835585
871                    22.016622  16.840463  14.932805  10.853213  19.832082
872                    21.967132  16.724530  14.826481  10.855145  19.833868
873                    21.949685  16.764347  14.865175  10.855145  19.922132
874                    21.925337  16.608403  14.840933  10.857074  19.819500
875                    21.834794  16.602928  14.842001  10.858999  19.811685

            x5         x6        x7         x8        x9        x10  x11  x12  \
864  19.910862  11.063508  4.878246  13.208363  4.750136  24.627162  0.0    0
865  19.808416  11.055641  4.884316  13.147103  4.753590  24.590764  3.0    0
866  20.063592  11.058795  4.896346  13.240244  4.753590  24.696669  0.0    0
867  20.092231  11.080603  4.896346  13.169657  4.759607  24.685910  0.0    0
868  20.172946  11.119883  4.905275  13.265119  4.763028  24.722292  0.0    0
869  20.242362  11.125791  4.902307  13.187317  4.768988  24.658264  0.0    0
870  20.303567  11.144756  4.906755  13.222194  4.775756  24.678746  0.0    0
871  20.255890  11.147642  4.912655  13.217232  4.790820  24.695466  0.0    0
872  20.085244  11.125791  4.915592  13.150478  4.768139  24.638259  0.0    0
873  20.107386  11.130200  4.907495  13.260521  4.771532  24.700173  1.0    0
874  20.077358  11.115429  4.917057  13.157893  4.764735  24.637376  0.0    0
875  20.078309  11.101945  4.921440  13.075504  4.757033  24.566726  0.0    0

          x13  x14
864 -0.460449    0
865 -0.460449    0
866 -0.460449    0
867 -0.463624    0
868 -0.463624    0
869 -0.463624    0
870 -0.460449    0
871 -0.458866    0
872 -0.460449    0
873 -0.458866    0
874 -0.458866    0
875 -0.457285    0
```

[44]:

```python
np.random.seed(1)
def model_creator(data):
    with pm.Model() as model:
        # define prior
        my_priors = {"Regressor" : pm.Normal.dist(mu=0, sd=1)}
        # formula
        glm.GLM.from_formula('Log_Transportation_Spending ~ 0 + x1 + x2 + x3 +␣
↪x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11 + x12 + x13 + x14',
```

```
                          data = data,
                          priors = my_priors,
                          family=glm.families.Normal())
    return model

with model_creator(cleaned_train):
    trace = pm.sample(500, cores=1, target_accept=0.95, return_inferencedata =
 ↪True)

with model_creator(cleaned_test):
    ppc = pm.sample_posterior_predictive(trace)
```

```
Auto-assigning NUTS sampler…
Initializing NUTS using jitter+adapt_diag…
Sequential sampling (2 chains in 1 job)
NUTS: [sd, x14, x13, x12, x11, x10, x9, x8, x7, x6, x5, x4, x3, x2, x1]
```

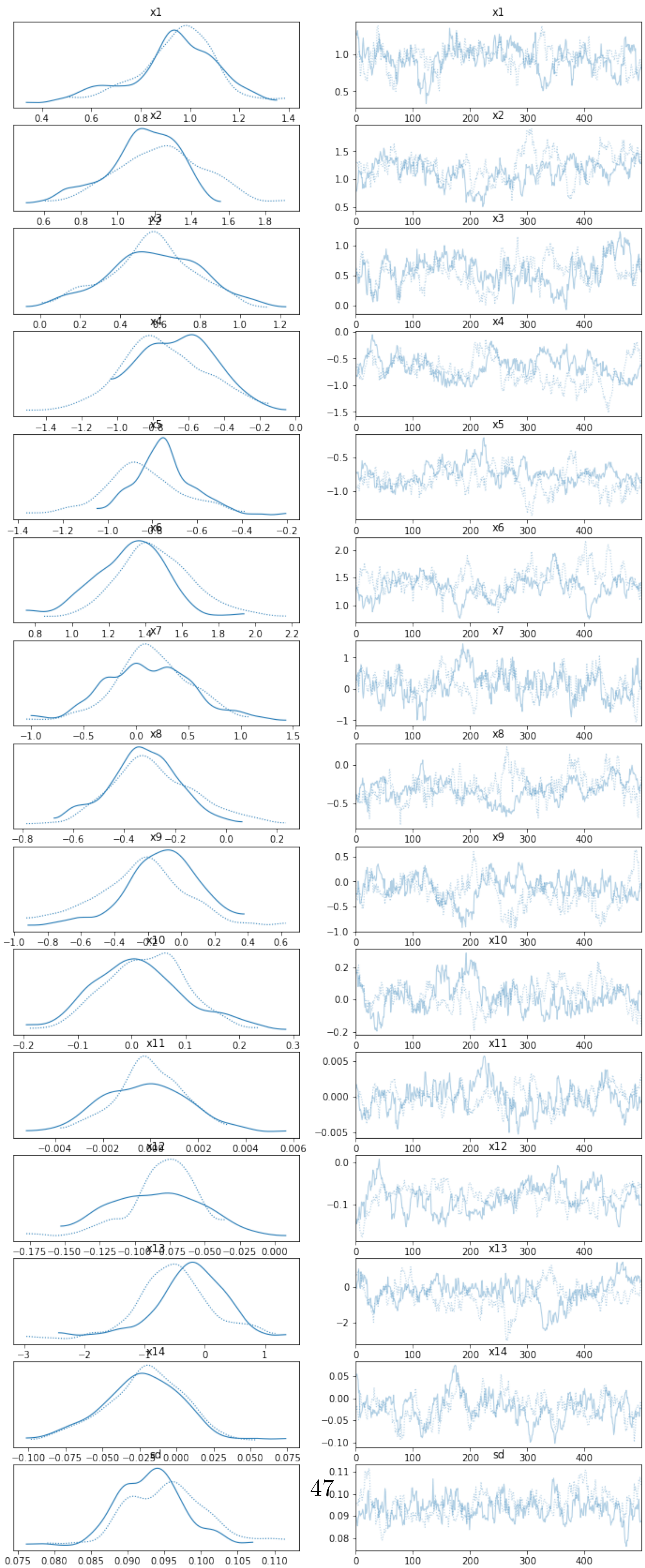
```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

```
Sampling 2 chains for 1_000 tune and 500 draw iterations (2_000 + 1_000 draws
total) took 1129 seconds.
The chain reached the maximum tree depth. Increase max_treedepth, increase
target_accept or reparameterize.
The chain reached the maximum tree depth. Increase max_treedepth, increase
target_accept or reparameterize.
The rhat statistic is larger than 1.05 for some parameters. This indicates
slight problems during sampling.
The estimated number of effective samples is smaller than 200 for some
parameters.
```

```
<IPython.core.display.HTML object>
```

[45]:
```
arviz.plot_trace(trace);
```


x1
x2
x3
x4
x5
x6
x7
x8
x9
x10
x11
x12
x13
x14
sd

[46]:
```
summary_df = pm.summary(trace)
summary_df
```

[46]:
```
       mean     sd  hdi_3%  hdi_97%  mcse_mean  mcse_sd  ess_bulk  ess_tail  \
x1    0.942  0.167   0.574    1.228      0.020    0.014      75.0     117.0
x2    1.185  0.235   0.689    1.592      0.051    0.038      22.0      28.0
x3    0.565  0.230   0.122    0.984      0.045    0.032      27.0      43.0
x4   -0.695  0.231  -1.070   -0.236      0.071    0.058      10.0      20.0
x5   -0.794  0.167  -1.087   -0.468      0.031    0.023      28.0      37.0
x6    1.392  0.222   0.961    1.825      0.058    0.043      15.0      74.0
x7    0.141  0.398  -0.623    0.872      0.048    0.034      68.0      77.0
x8   -0.304  0.155  -0.609   -0.019      0.032    0.023      27.0      89.0
x9   -0.180  0.268  -0.730    0.318      0.049    0.054      30.0      54.0
x10   0.021  0.081  -0.122    0.176      0.015    0.011      30.0      82.0
x11  -0.000  0.002  -0.003    0.003      0.000    0.000      54.0      56.0
x12  -0.083  0.029  -0.138   -0.035      0.004    0.003      44.0     102.0
x13  -0.391  0.677  -1.593    0.975      0.118    0.084      32.0      58.0
x14  -0.022  0.029  -0.086    0.022      0.004    0.003      63.0     103.0
sd    0.094  0.005   0.085    0.104      0.001    0.001      19.0      74.0

     r_hat
x1    1.00
x2    1.09
x3    1.06
x4    1.15
x5    1.10
x6    1.13
x7    1.02
x8    1.06
x9    1.11
x10   1.06
x11   1.04
x12   1.06
x13   1.03
x14   1.03
sd    1.09
```

[47]:
```
y_test = list(cleaned_test["Log_Transportation_Spending"])
y_train_df = cleaned_test.drop("Log_Transportation_Spending", axis=1).T
y_train_df["betas"] = summary_df["mean"]
```

[48]:
```
y_train_df
```

[48]:
```
            864        865        866        867        868        869  \
x1    16.619818  16.532590  16.694535  16.746514  16.790872  16.760295
x2    14.643525  14.587725  14.806115  14.819444  14.879471  14.910177
x3    10.831707  10.823770  10.833681  10.837618  10.855145  10.858999
x4    19.723656  19.673639  19.814998  19.845075  19.858479  19.803948
x5    19.910862  19.808416  20.063592  20.092231  20.172946  20.242362
x6    11.063508  11.055641  11.058795  11.080603  11.119883  11.125791
x7     4.878246   4.884316   4.896346   4.896346   4.905275   4.902307
x8    13.208363  13.147103  13.240244  13.169657  13.265119  13.187317
x9     4.750136   4.753590   4.753590   4.759607   4.763028   4.768988
x10   24.627162  24.590764  24.696669  24.685910  24.722292  24.658264
x11    0.000000   3.000000   0.000000   0.000000   0.000000   0.000000
x12    0.000000   0.000000   0.000000   0.000000   0.000000   0.000000
x13   -0.460449  -0.460449  -0.460449  -0.463624  -0.463624  -0.463624
x14    0.000000   0.000000   0.000000   0.000000   0.000000   0.000000

            870        871        872        873        874        875  betas
x1    16.829986  16.840463  16.724530  16.764347  16.608403  16.602928  0.942
x2    14.949746  14.932805  14.826481  14.865175  14.840933  14.842001  1.185
x3    10.864752  10.853213  10.855145  10.855145  10.857074  10.858999  0.565
x4    19.835585  19.832082  19.833868  19.922132  19.819500  19.811685 -0.695
x5    20.303567  20.255890  20.085244  20.107386  20.077358  20.078309 -0.794
x6    11.144756  11.147642  11.125791  11.130200  11.115429  11.101945  1.392
x7     4.906755   4.912655   4.915592   4.907495   4.917057   4.921440  0.141
x8    13.222194  13.217232  13.150478  13.260521  13.157893  13.075504 -0.304
x9     4.775756   4.790820   4.768139   4.771532   4.764735   4.757033 -0.180
x10   24.678746  24.695466  24.638259  24.700173  24.637376  24.566726  0.021
x11    0.000000   0.000000   0.000000   1.000000   0.000000   0.000000 -0.000
x12    0.000000   0.000000   0.000000   0.000000   0.000000   0.000000 -0.083
x13   -0.460449  -0.458866  -0.460449  -0.458866  -0.458866  -0.457285 -0.391
x14    0.000000   0.000000   0.000000   0.000000   0.000000   0.000000 -0.022
```

[49]:
```
from math import e
def rmse(pred, res):
    return np.sqrt(((pred - res) ** 2).mean())
```

2.2.3 1.2.3. Calculating Training Error of GLM

[50]:
```
y_train = list(cleaned_train["Log_Transportation_Spending"])
x_train_df = cleaned_train.drop("Log_Transportation_Spending", axis=1).T
x_train_df["betas"] = summary_df["mean"]

cols = list(x_train_df.columns)
y_preds = []
for col in cols:
    y_preds.append(sum(x_train_df[col] * x_train_df["betas"]))
```

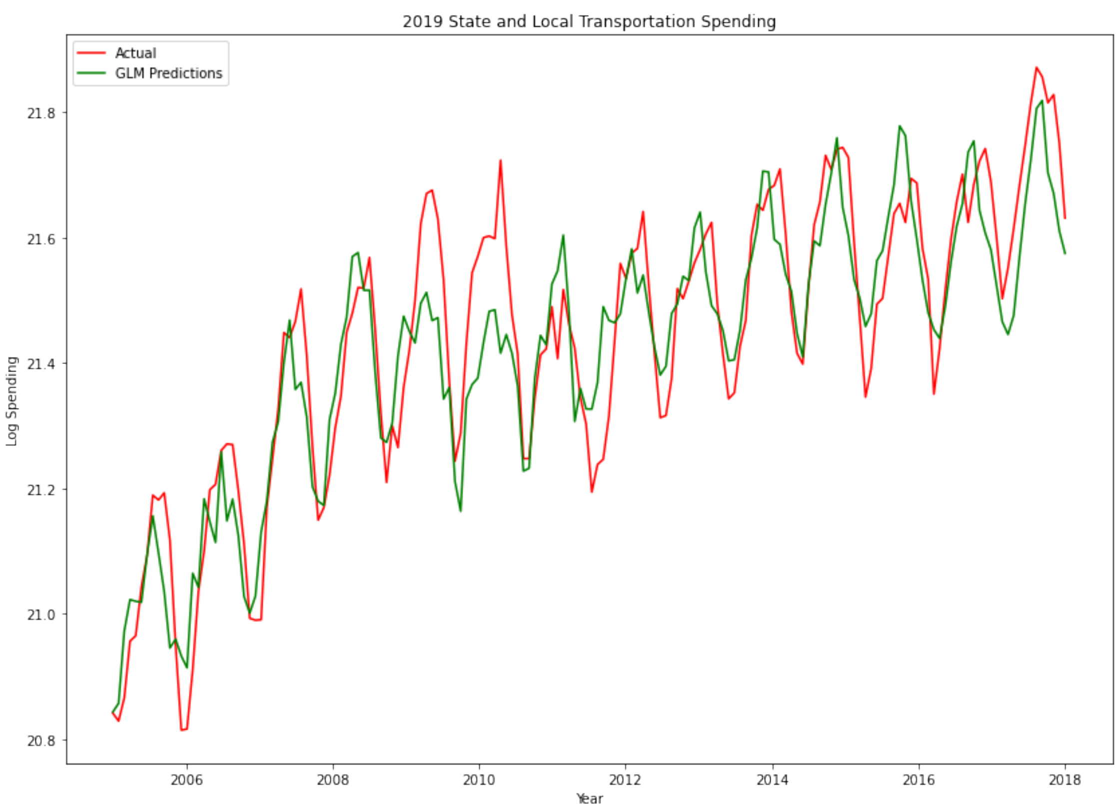
```
y_preds = y_preds[:-1]

# Train Set Error
train_rmse = rmse(np.array(y_preds), np.array(y_train))
log_train_rmse = rmse(np.array(y_preds), np.array(y_train))
train_rmse, log_train_rmse
print("Training set error for GLM (Log Dollars):    ", train_rmse)
```

```
Training set error for GLM (Log Dollars):     0.0904754014995469
```

[51]:
```
#non log rmse
rmse(np.e**np.array(y_preds), np.e**np.array(y_train))
```

[51]: 194200157.1775764

[52]:
```
plt.figure(figsize=(14, 10))
x = np.linspace(2005, 2018, 168)
plt.plot(x, y_train, color='red', label="Actual")
plt.plot(x, y_preds, color='green', label="GLM Predictions")
plt.xlabel("Year")
plt.ylabel("Log Spending")
plt.legend(loc="upper left")
plt.title("2019 State and Local Transportation Spending");
```



2.2.4 1.2.4. Calculating Test Error of GLM

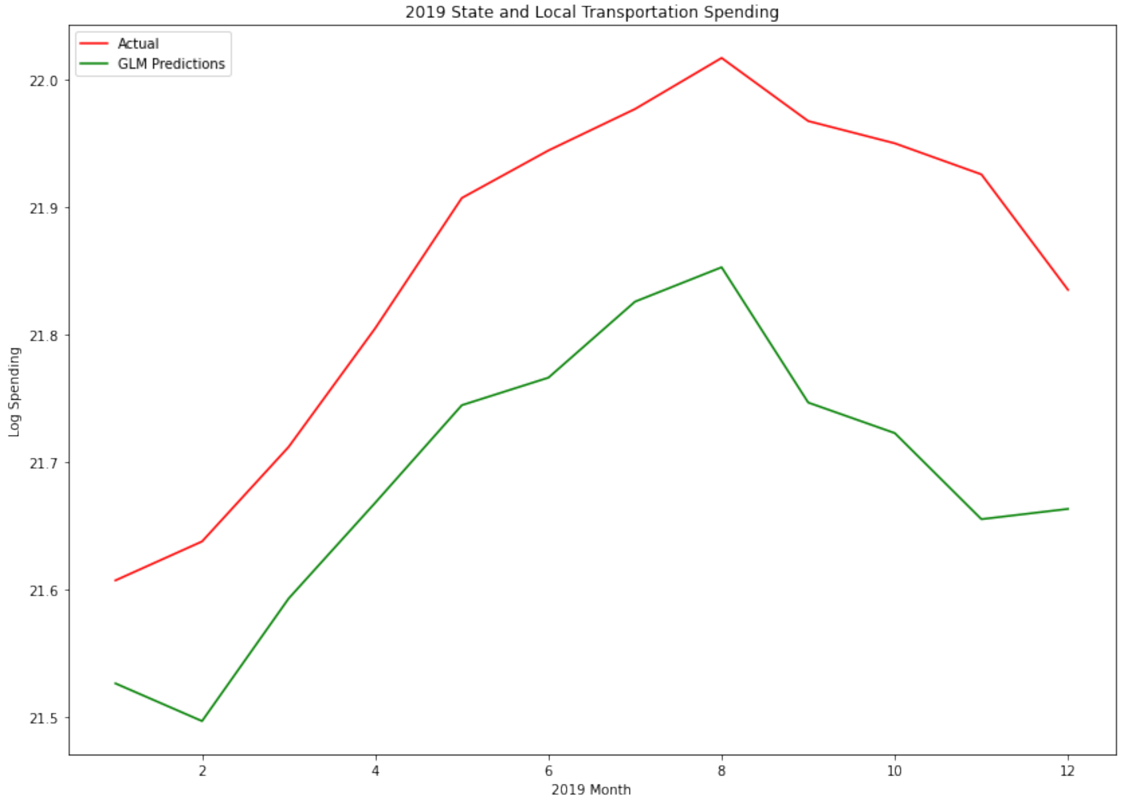
[53]:
```
# Test Set Error

y_test = list(cleaned_test["Log_Transportation_Spending"])
x_test_df = cleaned_test.drop("Log_Transportation_Spending", axis=1).T
x_test_df["betas"] = summary_df["mean"]

cols = list(x_test_df.columns)
y_preds = []
for col in cols:
    y_preds.append(sum(x_test_df[col] * x_test_df["betas"]))

y_preds = y_preds[:-1]

test_rmse = rmse(np.array(y_preds), np.array(y_test))
log_test_rmse = rmse(np.array(y_preds), np.array(y_test))
test_rmse, log_test_rmse

print("Test set error for GLM (Log Dollars):    ", test_rmse)
```

```
Test set error for GLM (Log Dollars):     0.1755747575141033
```

[54]:
```
#non log test rmse
rmse(np.e**np.array(y_preds), np.e**np.array(y_test))
```

[54]:
```
521960888.6152375
```

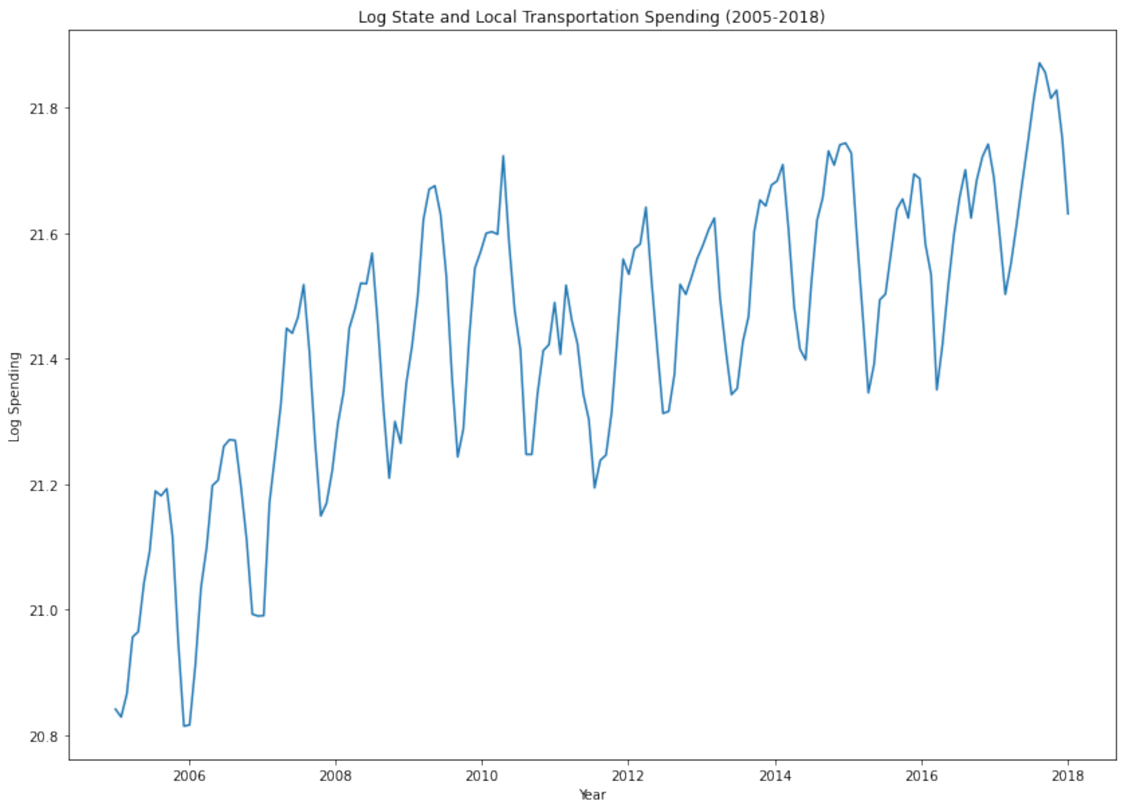
[55]:
```
plt.figure(figsize=(14, 10))
x = np.linspace(1, 12, 12)
plt.plot(x, y_test, color='red', label="Actual")
plt.plot(x, y_preds, color='green', label="GLM Predictions")
plt.xlabel("2019 Month")
plt.ylabel("Log Spending")
plt.legend(loc="upper left")
plt.title("2019 State and Local Transportation Spending");
```



2.3 1.3. Forming Non-Parametric Model

2.3.1 1.3.1. Visualize the data we have to assess which model would be most fitting

[56]:
```
plt.figure(figsize=(14, 10))
x = np.linspace(2005, 2018, 168)
y = np.log(subset["State and Local Government Construction Spending -␣
↪Transportation"])[:-12]
plt.plot(x, y)
plt.ylabel("Log Spending")
plt.xlabel("Year")
plt.title("Log State and Local Transportation Spending (2005-2018)");
```



What we're trying to predict: State and Local Government Construction Spending - Transportation in 2019. Since spending is listed in a monthly manner, we will be predicting the 12 monthly spending on transportation in 2019.

Features to Use: To build our model, we decided to use the features that have a somewhat strong correlation to our response variable. We selected 16 features that have a greater absolute correlation coefficient than 0.5.

Nonparametric method to use: Random Forest Regression.

Random forests are ensemble models that reduce the variance from decision trees. Because of the aggregation, they are not prone to overfit. Compared to a neural network, the features of a random forest are much more interpretable. In a practical setting, if the city wanted to analyze what factors contribute the most to, or are most related to spending on transportation, a neural network would not be able to provide insight, while a random forest could.

Assumptions made by modeling choice: There are no formal assumptions that are implicit to a random forest. However, as seen above, the state and local spending on transportation data shows a lot of noise though it is generally trending upwards, so the generality of a random forest is assumed to be helpful.

2.3.2 1.3.2. Creating the Random Forest Model

We are using the 14 features that are moderately-high correlated to State and Local Transportation spending.

Train / Test Data: - Train: 2005 - 2018 data on the 14 features + Transportation Spending (168 x 14) - Test: 2019 data on the 14 features + Transportation Spending (12 x 14)

Hyperparameters: - 100 trees - no limit on tree depth - 5 features per tree - ~1/3 of the 14 features

Error Metrics: RMSE

[57]:
```
def rmse(pred, res):
    return np.sqrt(((pred - res) ** 2).mean())
```

Narrowed the general dataset to only include 14 features, and set the index by date.

[58]:
```
positive_features = np.array(subset_transp_positive_corr_df.
 ↪reset_index()["index"])
negative_features = np.array(subset_transp_negative_corr_df.
 ↪reset_index()["index"])
all_feats = np.append(positive_features, negative_features)
all_feats = np.append(all_feats, "Date")
all_feats
```

[58]:
```
array(['Log_Transportation_Spending',
       'Transit Ridership - Other Transit Modes - Adjusted',
       'Passenger Rail Passengers',
       'Transportation Employment - Pipeline Transportation',
       'Transit Ridership - Urban Rail - Adjusted',
       'Passenger Rail Passenger Miles',
       'Transportation Employment - Water Transportation',
       'Transportation Services Index - Passenger',
       'U.S.-Mexico Incoming Truck Crossings', 'Truck tonnage index',
       'Transborder - U.S. - Mexico Freight',
       'Air Safety - Air Carrier Fatalities', 'TR_UR_very low',
       'Labor Force Participation Rate - Seasonally Adjusted',
       'TR_Other_very low', 'Date'], dtype=object)
```

[59]:
```
subset["Log_Transportation_Spending"] = log_spend
temp = subset.drop(columns=["Date", "Month", "TR_Other",
                            "TR_UR", "TR_frb", "Log_Transportation_Spending"],␣
 ↪axis=1)
log_cleaned = np.log(temp)
dummies = pd.get_dummies(subset[["TR_UR", "TR_Other", "TR_frb"]])
cleaned = log_cleaned.join(dummies)

col_list = list(cleaned.columns)
bools = [not "Spending" in col for col in col_list]
```

```
cols_for_viz = [col_list[index] for index in np.where(bools)[0]]

y_col = "Log_Transportation_Spending"
transp_df = cleaned[cols_for_viz]
transp_df[y_col] = log_spend
```

[60]:
```
transp_df["Date"] = subset["Date"]
#transp_df = transp_df.set_index("Date")
clean = transp_df[all_feats]
clean["Air Safety - Air Carrier Fatalities"] = np.e**clean["Air Safety - Air␣
↪Carrier Fatalities"]
clean = clean.set_index("Date")
```

[61]:
```
clean.head()
```

[61]:
```
                        Log_Transportation_Spending  \
Date
01/01/2005 12:00:00 AM                    20.841049
02/01/2005 12:00:00 AM                    20.828526
03/01/2005 12:00:00 AM                    20.865633
04/01/2005 12:00:00 AM                    20.955964
05/01/2005 12:00:00 AM                    20.964642

                        Transit Ridership - Other Transit Modes - Adjusted  \
Date
01/01/2005 12:00:00 AM                                          16.267539
02/01/2005 12:00:00 AM                                          16.253089
03/01/2005 12:00:00 AM                                          16.404069
04/01/2005 12:00:00 AM                                          16.373309
05/01/2005 12:00:00 AM                                          16.362126

                        Passenger Rail Passengers  \
Date
01/01/2005 12:00:00 AM                  14.425270
02/01/2005 12:00:00 AM                  14.400341
03/01/2005 12:00:00 AM                  14.630733
04/01/2005 12:00:00 AM                  14.566232
05/01/2005 12:00:00 AM                  14.602603

                        Transportation Employment - Pipeline Transportation  \
Date
01/01/2005 12:00:00 AM                                          10.547970
02/01/2005 12:00:00 AM                                          10.537415
03/01/2005 12:00:00 AM                                          10.534759
04/01/2005 12:00:00 AM                                          10.540064
05/01/2005 12:00:00 AM                                          10.532096
```

```
                         Transit Ridership - Urban Rail - Adjusted  \
Date
01/01/2005 12:00:00 AM                                    19.558339
02/01/2005 12:00:00 AM                                    19.537051
03/01/2005 12:00:00 AM                                    19.673103
04/01/2005 12:00:00 AM                                    19.631491
05/01/2005 12:00:00 AM                                    19.652670

                         Passenger Rail Passenger Miles  \
Date
01/01/2005 12:00:00 AM                         19.751378
02/01/2005 12:00:00 AM                         19.677958
03/01/2005 12:00:00 AM                         19.955025
04/01/2005 12:00:00 AM                         19.880450
05/01/2005 12:00:00 AM                         19.951106

                         Transportation Employment - Water Transportation  \
Date
01/01/2005 12:00:00 AM                                           10.924138
02/01/2005 12:00:00 AM                                           10.916905
03/01/2005 12:00:00 AM                                           10.945529
04/01/2005 12:00:00 AM                                           10.992050
05/01/2005 12:00:00 AM                                           11.020267

                         Transportation Services Index - Passenger  \
Date
01/01/2005 12:00:00 AM                                    4.680278
02/01/2005 12:00:00 AM                                    4.685828
03/01/2005 12:00:00 AM                                    4.685828
04/01/2005 12:00:00 AM                                    4.691348
05/01/2005 12:00:00 AM                                    4.690430

                         U.S.-Mexico Incoming Truck Crossings  \
Date
01/01/2005 12:00:00 AM                              12.797959
02/01/2005 12:00:00 AM                              12.812117
03/01/2005 12:00:00 AM                              12.893514
04/01/2005 12:00:00 AM                              12.887855
05/01/2005 12:00:00 AM                              12.890139

                         Truck tonnage index  \
Date
01/01/2005 12:00:00 AM              4.479607
02/01/2005 12:00:00 AM              4.457830
03/01/2005 12:00:00 AM              4.450853
04/01/2005 12:00:00 AM              4.461300
05/01/2005 12:00:00 AM              4.452019
```

```
                       Transborder - U.S. - Mexico Freight  \
Date
01/01/2005 12:00:00 AM                           24.434803
02/01/2005 12:00:00 AM                           24.434803
03/01/2005 12:00:00 AM                           24.434803
04/01/2005 12:00:00 AM                           24.434803
05/01/2005 12:00:00 AM                           24.434803

                       Air Safety - Air Carrier Fatalities  TR_UR_very low  \
Date
01/01/2005 12:00:00 AM                                 0.0               1
02/01/2005 12:00:00 AM                                 0.0               1
03/01/2005 12:00:00 AM                                 0.0               1
04/01/2005 12:00:00 AM                                 0.0               1
05/01/2005 12:00:00 AM                                 0.0               1

                       Labor Force Participation Rate - Seasonally Adjusted  \
Date
01/01/2005 12:00:00 AM                                          -0.418550
02/01/2005 12:00:00 AM                                          -0.417032
03/01/2005 12:00:00 AM                                          -0.417032
04/01/2005 12:00:00 AM                                          -0.414001
05/01/2005 12:00:00 AM                                          -0.414001

                       TR_Other_very low
Date
01/01/2005 12:00:00 AM                 1
02/01/2005 12:00:00 AM                 1
03/01/2005 12:00:00 AM                 1
04/01/2005 12:00:00 AM                 1
05/01/2005 12:00:00 AM                 1
```

[62]:
```
#Train-test split
X_train = clean.iloc[:168, 1:]
y_train = clean["Log_Transportation_Spending"][:168]
X_test = clean.iloc[168:, 1:]
y_test = clean["Log_Transportation_Spending"][168:]
```

Set up a train / test table to measure the accuracy of the model:

[63]:
```
train = pd.DataFrame({"Transportation Spending": y_train})
test = pd.DataFrame({"Transportation Spending": y_test})
```

[64]:
```
train
```

[64]:
```
                              Transportation Spending
Date
01/01/2005 12:00:00 AM                      20.841049
02/01/2005 12:00:00 AM                      20.828526
03/01/2005 12:00:00 AM                      20.865633
04/01/2005 12:00:00 AM                      20.955964
05/01/2005 12:00:00 AM                      20.964642
…                                                …
08/01/2018 12:00:00 AM                      21.856602
09/01/2018 12:00:00 AM                      21.815189
10/01/2018 12:00:00 AM                      21.828191
11/01/2018 12:00:00 AM                      21.750740
12/01/2018 12:00:00 AM                      21.631121

[168 rows x 1 columns]
```

[65]:
```
X_train
```

[65]:
```
                              Transit Ridership - Other Transit Modes - Adjusted  \
Date
01/01/2005 12:00:00 AM                                                16.267539
02/01/2005 12:00:00 AM                                                16.253089
03/01/2005 12:00:00 AM                                                16.404069
04/01/2005 12:00:00 AM                                                16.373309
05/01/2005 12:00:00 AM                                                16.362126
…                                                                             …
08/01/2018 12:00:00 AM                                                16.845766
09/01/2018 12:00:00 AM                                                16.703359
10/01/2018 12:00:00 AM                                                16.779112
11/01/2018 12:00:00 AM                                                16.645884
12/01/2018 12:00:00 AM                                                16.593970

                              Passenger Rail Passengers  \
Date
01/01/2005 12:00:00 AM                        14.425270
02/01/2005 12:00:00 AM                        14.400341
03/01/2005 12:00:00 AM                        14.630733
04/01/2005 12:00:00 AM                        14.566232
05/01/2005 12:00:00 AM                        14.602603
…                                                   …
08/01/2018 12:00:00 AM                        14.908451
09/01/2018 12:00:00 AM                        14.764664
10/01/2018 12:00:00 AM                        14.848626
11/01/2018 12:00:00 AM                        14.871585
12/01/2018 12:00:00 AM                        14.798556

                              Transportation Employment - Pipeline Transportation  \
```

```
Date
01/01/2005 12:00:00 AM                                            10.547970
02/01/2005 12:00:00 AM                                            10.537415
03/01/2005 12:00:00 AM                                            10.534759
04/01/2005 12:00:00 AM                                            10.540064
05/01/2005 12:00:00 AM                                            10.532096
…                                                                     …
08/01/2018 12:00:00 AM                                            10.821776
09/01/2018 12:00:00 AM                                            10.829729
10/01/2018 12:00:00 AM                                            10.835652
11/01/2018 12:00:00 AM                                            10.825760
12/01/2018 12:00:00 AM                                            10.831707

                        Transit Ridership - Urban Rail - Adjusted  \
Date
01/01/2005 12:00:00 AM                                   19.558339
02/01/2005 12:00:00 AM                                   19.537051
03/01/2005 12:00:00 AM                                   19.673103
04/01/2005 12:00:00 AM                                   19.631491
05/01/2005 12:00:00 AM                                   19.652670
…                                                            …
08/01/2018 12:00:00 AM                                   19.803354
09/01/2018 12:00:00 AM                                   19.787361
10/01/2018 12:00:00 AM                                   19.910162
11/01/2018 12:00:00 AM                                   19.788514
12/01/2018 12:00:00 AM                                   19.727786

                        Passenger Rail Passenger Miles  \
Date
01/01/2005 12:00:00 AM                       19.751378
02/01/2005 12:00:00 AM                       19.677958
03/01/2005 12:00:00 AM                       19.955025
04/01/2005 12:00:00 AM                       19.880450
05/01/2005 12:00:00 AM                       19.951106
…                                                …
08/01/2018 12:00:00 AM                       20.248716
09/01/2018 12:00:00 AM                       20.021902
10/01/2018 12:00:00 AM                       20.110215
11/01/2018 12:00:00 AM                       20.146211
12/01/2018 12:00:00 AM                       20.128846

                        Transportation Employment - Water Transportation  \
Date
01/01/2005 12:00:00 AM                                          10.924138
02/01/2005 12:00:00 AM                                          10.916905
03/01/2005 12:00:00 AM                                          10.945529
04/01/2005 12:00:00 AM                                          10.992050
```

```
05/01/2005 12:00:00 AM                                          11.020267
…                                                                       …
08/01/2018 12:00:00 AM                                          11.130200
09/01/2018 12:00:00 AM                                          11.103452
10/01/2018 12:00:00 AM                                          11.095894
11/01/2018 12:00:00 AM                                          11.077516
12/01/2018 12:00:00 AM                                          11.077516

                        Transportation Services Index - Passenger  \
Date
01/01/2005 12:00:00 AM                                   4.680278
02/01/2005 12:00:00 AM                                   4.685828
03/01/2005 12:00:00 AM                                   4.685828
04/01/2005 12:00:00 AM                                   4.691348
05/01/2005 12:00:00 AM                                   4.690430
…                                                               …
08/01/2018 12:00:00 AM                                   4.877485
09/01/2018 12:00:00 AM                                   4.873669
10/01/2018 12:00:00 AM                                   4.884316
11/01/2018 12:00:00 AM                                   4.877485
12/01/2018 12:00:00 AM                                   4.881286

                        U.S.-Mexico Incoming Truck Crossings  \
Date
01/01/2005 12:00:00 AM                             12.797959
02/01/2005 12:00:00 AM                             12.812117
03/01/2005 12:00:00 AM                             12.893514
04/01/2005 12:00:00 AM                             12.887855
05/01/2005 12:00:00 AM                             12.890139
…                                                          …
08/01/2018 12:00:00 AM                             13.222645
09/01/2018 12:00:00 AM                             13.110406
10/01/2018 12:00:00 AM                             13.250320
11/01/2018 12:00:00 AM                             13.190801
12/01/2018 12:00:00 AM                             13.059204

                        Truck tonnage index  \
Date
01/01/2005 12:00:00 AM             4.479607
02/01/2005 12:00:00 AM             4.457830
03/01/2005 12:00:00 AM             4.450853
04/01/2005 12:00:00 AM             4.461300
05/01/2005 12:00:00 AM             4.452019
…                                         …
08/01/2018 12:00:00 AM             4.736198
09/01/2018 12:00:00 AM             4.746670
10/01/2018 12:00:00 AM             4.754452
```

```
11/01/2018 12:00:00 AM            4.762174
12/01/2018 12:00:00 AM            4.746670

                        Transborder - U.S. - Mexico Freight  \
Date
01/01/2005 12:00:00 AM                             24.434803
02/01/2005 12:00:00 AM                             24.434803
03/01/2005 12:00:00 AM                             24.434803
04/01/2005 12:00:00 AM                             24.434803
05/01/2005 12:00:00 AM                             24.434803
…                                                      …
08/01/2018 12:00:00 AM                             24.703953
09/01/2018 12:00:00 AM                             24.647892
10/01/2018 12:00:00 AM                             24.758936
11/01/2018 12:00:00 AM                             24.686720
12/01/2018 12:00:00 AM                             24.564564

                        Air Safety - Air Carrier Fatalities  TR_UR_very low  \
Date
01/01/2005 12:00:00 AM                                   0.0               1
02/01/2005 12:00:00 AM                                   0.0               1
03/01/2005 12:00:00 AM                                   0.0               1
04/01/2005 12:00:00 AM                                   0.0               1
05/01/2005 12:00:00 AM                                   0.0               1
…                                                      …             …
08/01/2018 12:00:00 AM                                   0.0               0
09/01/2018 12:00:00 AM                                   0.0               0
10/01/2018 12:00:00 AM                                   0.0               0
11/01/2018 12:00:00 AM                                   0.0               0
12/01/2018 12:00:00 AM                                   0.0               0

                        Labor Force Participation Rate - Seasonally Adjusted  \
Date
01/01/2005 12:00:00 AM                                          -0.418550
02/01/2005 12:00:00 AM                                          -0.417032
03/01/2005 12:00:00 AM                                          -0.417032
04/01/2005 12:00:00 AM                                          -0.414001
05/01/2005 12:00:00 AM                                          -0.414001
…                                                                    …
08/01/2018 12:00:00 AM                                          -0.466809
09/01/2018 12:00:00 AM                                          -0.466809
10/01/2018 12:00:00 AM                                          -0.465215
11/01/2018 12:00:00 AM                                          -0.463624
12/01/2018 12:00:00 AM                                          -0.462035

                        TR_Other_very low
Date
```

```
01/01/2005 12:00:00 AM                    1
02/01/2005 12:00:00 AM                    1
03/01/2005 12:00:00 AM                    1
04/01/2005 12:00:00 AM                    1
05/01/2005 12:00:00 AM                    1
…                                     …
08/01/2018 12:00:00 AM                    0
09/01/2018 12:00:00 AM                    0
10/01/2018 12:00:00 AM                    0
11/01/2018 12:00:00 AM                    0
12/01/2018 12:00:00 AM                    0

[168 rows x 14 columns]
```

2.3.3 1.3.3. Testing Random Forest w/ RMSE

[66]:
```
from sklearn.ensemble import RandomForestRegressor


forest_model = RandomForestRegressor(n_estimators = 150, max_features = 5,␣
 ↪max_depth = 10, random_state=4)
forest_model.fit(X_train, y_train)

train["forest_pred"] = forest_model.predict(X_train)
train_rmse = rmse(train.iloc[:, 0], train.iloc[:, 1])
test["forest_pred"] = forest_model.predict(X_test)
test_rmse = rmse(test.iloc[:, 0], test.iloc[:, 1])
```

[67]:
```
print("Training set error for random forest:", train_rmse)
print("Test set error for random forest:    ", test_rmse)
```

```
Training set error for random forest: 0.031309830312467736
Test set error for random forest:     0.14847601446247302
```

[68]:
```
#remove log transformation
train_rmse = rmse(np.e**train.iloc[:, 0], np.e**train.iloc[:, 1])
test_rmse = rmse(np.e**test.iloc[:, 0], np.e**test.iloc[:, 1])
```

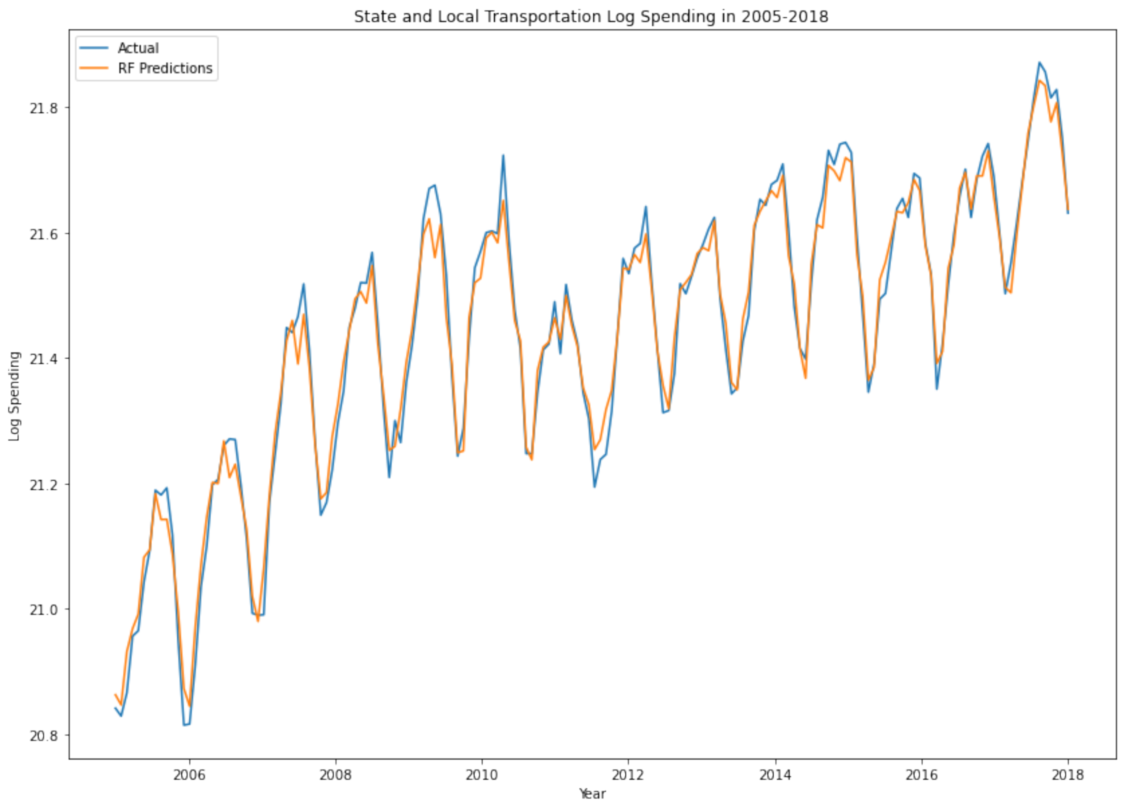
[69]:
```
train_rmse, test_rmse
```

[69]:
```
(64152531.63182865, 453046908.25875473)
```

Plot the predictions of the forest and the actual values of transportation spending from 2005 - 2018.

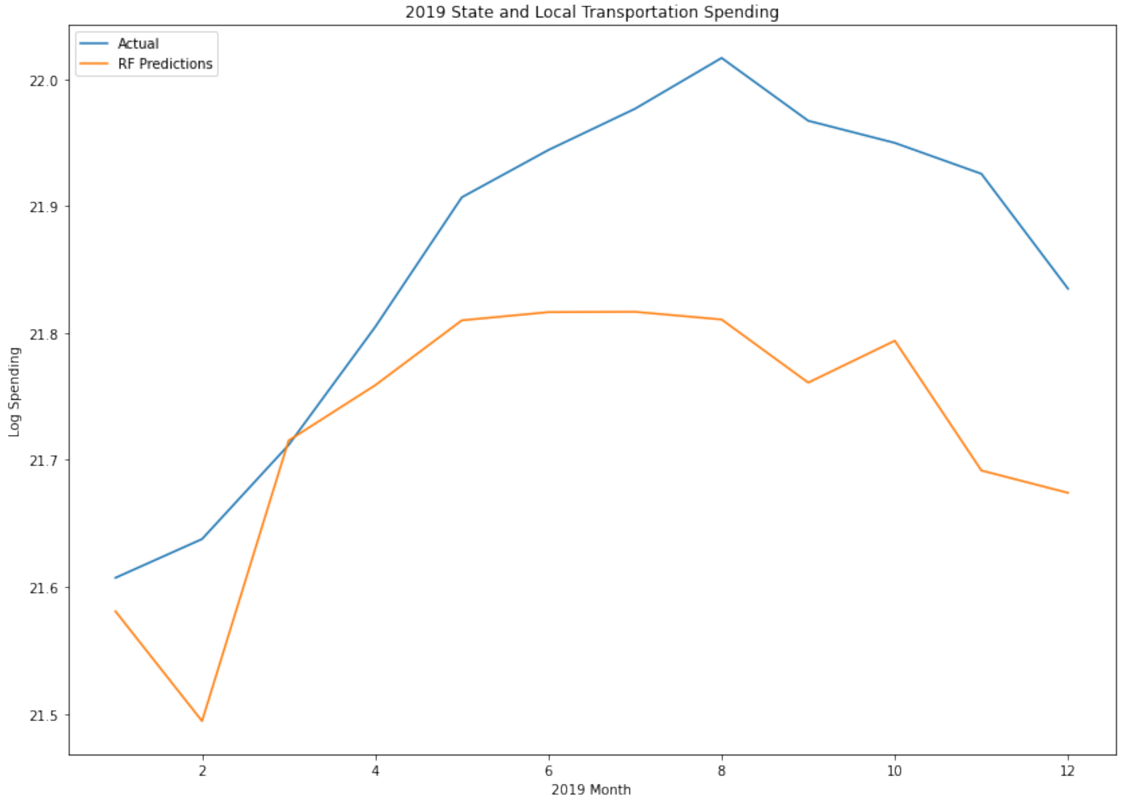
[102]:
```
plt.figure(figsize=(14, 10))
x = np.linspace(2005, 2018, 168)
```

```
y = subset["Log_Transportation_Spending"][:-12]
plt.plot(x, y, label="Actual")
plt.plot(x, train['forest_pred'], label="RF Predictions")
plt.ylabel("Log Spending")
plt.xlabel("Year")
plt.legend(loc="upper left")
plt.title("State and Local Transportation Log Spending in 2005-2018");
```



Plot the actual values of 2019 Transportation Spending Data vs. predicted values

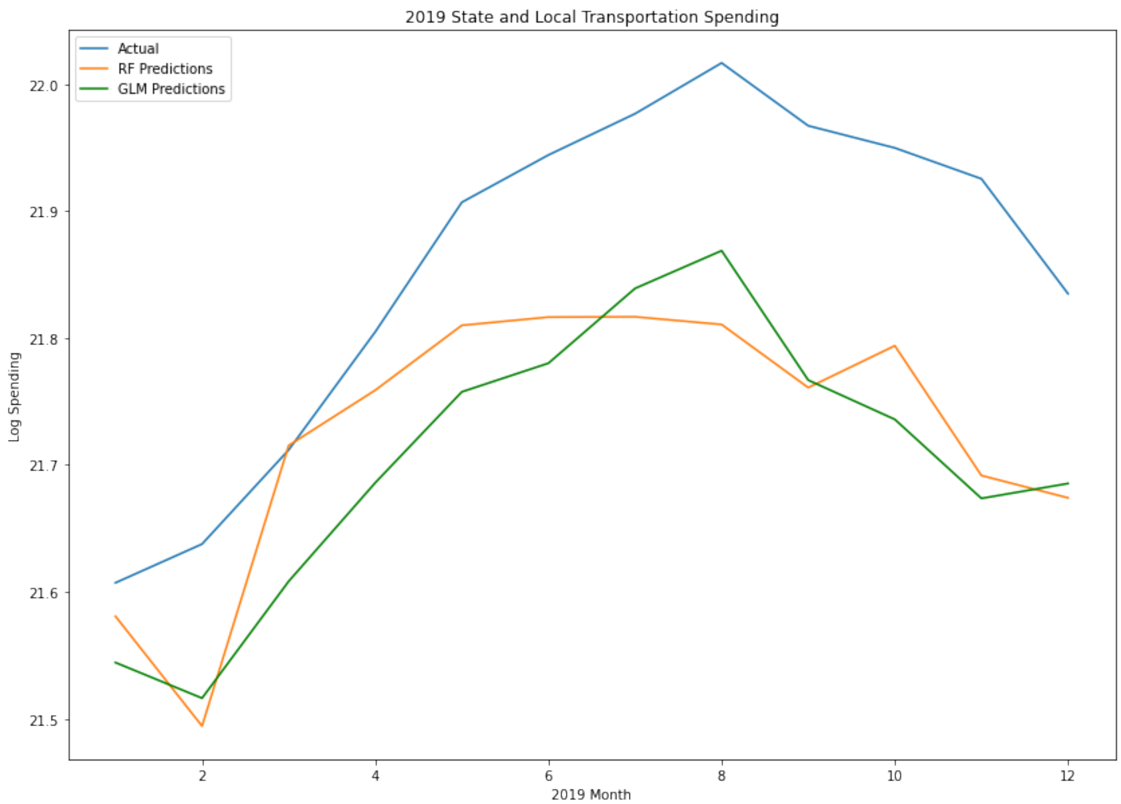
[103]:
```
plt.figure(figsize=(14, 10))
x = np.linspace(1, 12, 12)
y = subset["Log_Transportation_Spending"][168:]
plt.plot(x, y, label="Actual")
plt.plot(x, test['forest_pred'], label="RF Predictions")
plt.ylabel("Log Spending")
plt.xlabel("2019 Month")
plt.legend(loc="upper left")
plt.title("2019 State and Local Transportation Spending");
```



2.4 1.3. Comparing GLM vs. Non-Parametric Model

First, we can look at the predictions from each model and compare it to the true 2019 spending values. These can be found plotted below:

[104]:
```
plt.figure(figsize=(14, 10))
x = np.linspace(1, 12, 12)
y = subset["Log_Transportation_Spending"][168:]
plt.plot(x, y, label="Actual")
plt.plot(x, test['forest_pred'], label="RF Predictions")
plt.plot(x, y_preds, color='green', label="GLM Predictions")
plt.legend(loc="upper left")
plt.ylabel("Log Spending")
plt.xlabel("2019 Month")
plt.title("2019 State and Local Transportation Spending");
```



In order to quantify this, we look at the RSME values for the training and test set, summarized below:

Training Set Error Metrics

Model Type	RMSE in Log-Transformed Dollars	RMSE in Dollars
Non Parametric Model	0.031	64,152,531.63
GLM	0.0904	194,200,157

Testing Set Error Metrics

Model Type	RMSE in Log-Transformed Dollars	RMSE in Dollars
Non Parametric Model	0.148	453,046,908.25
GLM	0.1755	521,960,888.34

2.4.1 1.3.1. Discussion

Though expanded further in the investigation, we notice that intuitively, a RF has a very low training set error and a much higher testing set error (with respect to its training rmse) due to the nature of overfitting. Additionally, the GLM experiences a higher testing RMSE with respect to the RF testing RMSE due to its lack of utilizing subjective and informative priors. Since the prior distributions were uninformative, its broadness has resulted in the high overall degree of error.

From the plot above, it appears that each model predicts the true amount of spending with higher accuracy for different months. The RF predicts the level of 2019 spending (on a log level) better up to mid-June while the GLM predicts better for a brief period between mid-June and September. On a month by month basis, the RF tracks the amount of 2019 spending with higher degree of accuracy (hence the lower test RMSE). However, we see that in terms of overall shape, the GLM captures the cyclic pattern of transportation spending slightly better due to the relatively higher variance of the random forest (sensitivity to noise/outliers). Though, overall, we conclude that the RF was a better choice of model than the GLM (for additional reasons found in the analysis paper) when predicting future US Transportation Spending.

3 2. Causality Analysis

[70]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import math
import random
import matplotlib.image as mpimg
# Loading the instrastructure dataset as a Pandas dataframe
infra = pd.read_csv("Monthly_Transportation_Statistics.csv")
```

Research Question Does investment in infrastructure have an causal impact on the utilization of infrastructure in the US? Specifically, does the change in state and local spending on land passenger terminals have a causal effect on the number of passenger rail passenger miles, and if so is it a positive or negative effect?

3.1 2.1. Causality EDA

3.1.1 2.1.1. Initial EDA

Organizing Columns Our research question deals with the causal effect of infrastructure investment on infrastructure utilization, so a good starting move was to sort the variables at our disposal based on whether they were related to infrastructure or utilization

[71]:
```
# Keeping a list of utilization-based columns
utilization_cols = ['U.S. Airline Traffic - Total - Seasonally Adjusted',
 'U.S. Airline Traffic - International - Seasonally Adjusted',
 'U.S. Airline Traffic - Domestic - Seasonally Adjusted',
 'Transit Ridership - Other Transit Modes - Adjusted',
 'Transit Ridership - Fixed Route Bus - Adjusted',
 'Transit Ridership - Urban Rail - Adjusted',
 'Freight Rail Intermodal Units',
 'Freight Rail Carloads',
 'Highway Vehicle Miles Traveled - All Systems',
 'Highway Vehicle Miles Traveled - Total Rural',
```

```
 'Highway Vehicle Miles Traveled - Other Rural',
 'Highway Vehicle Miles Traveled - Rural Other Arterial',
 'Highway Vehicle Miles Traveled - Rural Interstate',
 'Personal Spending on Transportation - Transportation Services - Seasonally␣
 ↪Adjusted',
 'Personal Spending on Transportation - Gasoline and Other Energy Goods -␣
 ↪Seasonally Adjusted',
 'Personal Spending on Transportation - Motor Vehicles and Parts - Seasonally␣
 ↪Adjusted',
 'Passenger Rail Passengers',
 'Passenger Rail Passenger Miles',
 'Passenger Rail Total Train Miles',
 'Passenger Rail Employee Hours Worked',
 'Passenger Rail Yard Switching Miles',
 'Passenger Rail Total Reports',
 'U.S. Waterway Tonnage',
 'Transportation Services Index - Freight',
 'Transportation Services Index - Passenger',
 'Transportation Services Index - Combined',
 'U.S.-Canada Incoming Person Crossings',
 'U.S.-Canada Incoming Truck Crossings',
 'U.S.-Mexico Incoming Person Crossings',
 'U.S.-Mexico Incoming Truck Crossings',
 'U.S. Air Carrier Cargo (millions of revenue ton-miles) - International',
 'Truck tonnage index',
 'U.S. Air Carrier Cargo (millions of revenue ton-miles) - Domestic',
 'U.S. Airline Traffic - Total - Non Seasonally Adjusted',
 'U.S. Airline Traffic - Domestic - Non Seasonally Adjusted',
 'Transborder - Total North American Freight',
 'Transborder - U.S. - Mexico Freight',
 'Transborder - U.S. - Canada Freight']
```

[72]:
```
# Keeping a list of investment-based columns, which we named spending because␣
 ↪investment
# Consisted of government spending on infrastructure
spendings = ['State and Local Government Construction Spending - Breakwater/
 ↪Jetty',
 'State and Local Government Construction Spending - Dam/Levee',
 'State and Local Government Construction Spending - Conservation and␣
 ↪Development',
 'State and Local Government Construction Spending - Pump Station',
 'State and Local Government Construction Spending - Line',
 'State and Local Government Construction Spending - Water Treatment Plant',
 'State and Local Government Construction Spending - Water Supply',
 'State and Local Government Construction Spending - Line/Drain',
```

```
'State and Local Government Construction Spending - Waste Water Treatment␣
↪Plant',
'State and Local Government Construction Spending - Waste Water',
'State and Local Government Construction Spending - Line/Pump Station',
'State and Local Government Construction Spending - Sewage Treatment Plant',
'State and Local Government Construction Spending - Sewage / Dry Waste',
'State and Local Government Construction Spending - Sewage and Waste Disposal',
'State and Local Government Construction Spending - Rest Facility',
'State and Local Government Construction Spending - Bridge',
'State and Local Government Construction Spending - Lighting',
'State and Local Government Construction Spending - Pavement',
'State and Local Government Construction Spending - Highway and Street',
'State and Local Government Construction Spending - Power',
'State and Local Government Construction Spending - Dock / Marina',
'State and Local Government Construction Spending - Water',
'State and Local Government Construction Spending - Mass Transit',
'State and Local Government Construction Spending - Land Passenger Terminal',
'State and Local Government Construction Spending - Land',
'State and Local Government Construction Spending - Runway',
'State and Local Government Construction Spending - Air Passenger Terminal',
'State and Local Government Construction Spending - Air',
'State and Local Government Construction Spending - Transportation',
'State and Local Government Construction Spending - Park / Camp',
'State and Local Government Construction Spending - Neighborhood Center',
'State and Local Government Construction Spending - Social Center',
'State and Local Government Construction Spending - Convention Center',
'State and Local Government Construction Spending - Performance / Meeting␣
↪Center',
'State and Local Government Construction Spending - Sports',
'State and Local Government Construction Spending - Amusement and Recreation',
'State and Local Government Construction Spending - Fire & Rescue',
'State and Local Government Construction Spending - Other Public Safety',
'State and Local Government Construction Spending - Police & Sheriff',
'State and Local Government Construction Spending - Detention',
'State and Local Government Construction Spending - Correctional',
'State and Local Government Construction Spending - Public Safety',
'State and Local Government Construction Spending - Library / Archive',
'State and Local Government Construction Spending - Other Educational',
'State and Local Government Construction Spending - Infrastructure',
'State and Local Government Construction Spending - Sports & Recreation',
'State and Local Government Construction Spending - Dormitory',
'State and Local Government Construction Spending - Instructional',
'State and Local Government Construction Spending - Higher Education',
'State and Local Government Construction Spending - High School',
'State and Local Government Construction Spending - Middle School / Junior␣
↪High',
'State and Local Government Construction Spending - Elementary Schools',
```

```
'State and Local Government Construction Spending - Primary/Secondary Schools',
'State and Local Government Construction Spending - Educational',
'State and Local Government Construction Spending - Special Care',
'State and Local Government Construction Spending - Medical Building',
'State and Local Government Construction Spending - Hospital',
'State and Local Government Construction Spending - Health Care',
'State and Local Government Construction Spending - Parking',
'State and Local Government Construction Spending - Automotive',
'State and Local Government Construction Spending - Commercial',
'State and Local Government Construction Spending - Office',
'State and Local Government Construction Spending - Non Residential',
'State and Local Government Construction Spending - Multi Family',
'State and Local Government Construction Spending - Residential',
'State and Local Government Construction Spending - Total']
```

We decided to split the investment variables up even further based on which category of infrastructure they fell under

[73]:
```
waste_cleaning = [ 'State and Local Government Construction Spending - Waste␣
↪Water Treatment Plant',
'State and Local Government Construction Spending - Waste Water',
'State and Local Government Construction Spending - Line/Pump Station',
'State and Local Government Construction Spending - Sewage Treatment Plant',
'State and Local Government Construction Spending - Sewage / Dry Waste',
'State and Local Government Construction Spending - Sewage and Waste Disposal']
```

[74]:
```
water_drinking = ['State and Local Government Construction Spending -␣
↪Breakwater/Jetty',
'State and Local Government Construction Spending - Dam/Levee',
'State and Local Government Construction Spending - Conservation and␣
↪Development',
'State and Local Government Construction Spending - Pump Station',
'State and Local Government Construction Spending - Line',
'State and Local Government Construction Spending - Water Treatment Plant',
'State and Local Government Construction Spending - Water Supply',
'State and Local Government Construction Spending - Line/Drain']
```

[75]:
```
roads = ['State and Local Government Construction Spending - Rest Facility',
'State and Local Government Construction Spending - Bridge',
'State and Local Government Construction Spending - Lighting',
'State and Local Government Construction Spending - Pavement',
'State and Local Government Construction Spending - Highway and Street',
'State and Local Government Construction Spending - Power',
'State and Local Government Construction Spending - Mass Transit',
'State and Local Government Construction Spending - Land',
'State and Local Government Construction Spending - Parking',
'State and Local Government Construction Spending - Automotive']
```

[76]:
```
ships = ['State and Local Government Construction Spending - Dock / Marina',
 'State and Local Government Construction Spending - Water']
```

[77]:
```
air = ['State and Local Government Construction Spending - Air Passenger␣
 ↪Terminal',
 'State and Local Government Construction Spending - Air',
 'State and Local Government Construction Spending - Transportation',
 'State and Local Government Construction Spending - Runway']
```

[78]:
```
recreation = ['State and Local Government Construction Spending - Park / Camp',
 'State and Local Government Construction Spending - Neighborhood Center',
 'State and Local Government Construction Spending - Social Center',
 'State and Local Government Construction Spending - Convention Center',
 'State and Local Government Construction Spending - Performance / Meeting␣
 ↪Center',
 'State and Local Government Construction Spending - Sports',
 'State and Local Government Construction Spending - Amusement and Recreation']
```

[79]:
```
safety = ['State and Local Government Construction Spending - Fire & Rescue',
 'State and Local Government Construction Spending - Other Public Safety',
 'State and Local Government Construction Spending - Police & Sheriff',
 'State and Local Government Construction Spending - Detention',
 'State and Local Government Construction Spending - Correctional',
 'State and Local Government Construction Spending - Public Safety']
```

[80]:
```
education = ['State and Local Government Construction Spending - Library /␣
 ↪Archive',
 'State and Local Government Construction Spending - Other Educational',
 'State and Local Government Construction Spending - Infrastructure',
 'State and Local Government Construction Spending - Sports & Recreation',
 'State and Local Government Construction Spending - Dormitory',
 'State and Local Government Construction Spending - Instructional',
 'State and Local Government Construction Spending - Higher Education',
 'State and Local Government Construction Spending - High School',
 'State and Local Government Construction Spending - Middle School / Junior␣
 ↪High',
 'State and Local Government Construction Spending - Elementary Schools',
 'State and Local Government Construction Spending - Primary/Secondary Schools',
 'State and Local Government Construction Spending - Educational']
```

[81]:
```
health = ['State and Local Government Construction Spending - Special Care',
 'State and Local Government Construction Spending - Medical Building',
 'State and Local Government Construction Spending - Hospital',
 'State and Local Government Construction Spending - Health Care']
```

[82]:
```
business = [ 'State and Local Government Construction Spending - Commercial',
 'State and Local Government Construction Spending - Office',
 'State and Local Government Construction Spending - Non Residential']
```

[83]:
```
residential = [ 'State and Local Government Construction Spending - Multi␣
↪Family',
 'State and Local Government Construction Spending - Residential']
```

[84]:
```
rail = ['State and Local Government Construction Spending - Land Passenger␣
↪Terminal']
```

3.1.2 2.1.2. Handling Nulls

We noticed immediately that much of the earlier records in the dataset had mostly null values due to a lack of data recorded at the time.

[85]:
```
# Quick lookup of how many records have null values in the infrastructure␣
↪dataframe for each variable
np.array(infra.isna().sum())
```

[85]:
```
array([  0,   0, 415, 848, 849, 844, 843, 843, 662, 662, 662, 505, 505,
       854, 854, 854, 854, 854, 554, 554, 554, 554, 554, 554, 554, 554,
       554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554,
       554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554,
       554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554,
       554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554, 554,
       554, 554, 554, 554, 554, 554, 827, 568, 527, 697, 697, 697, 697,
       697, 697, 820, 820, 820, 697, 697, 697, 600, 340, 340, 340, 340,
       340, 340, 831, 844, 340, 340, 340, 638, 639, 639, 591, 591, 591,
       664, 242, 591, 242, 242, 635, 672, 638, 672, 242, 843, 242, 843,
       242, 843, 710, 710, 855, 710])
```

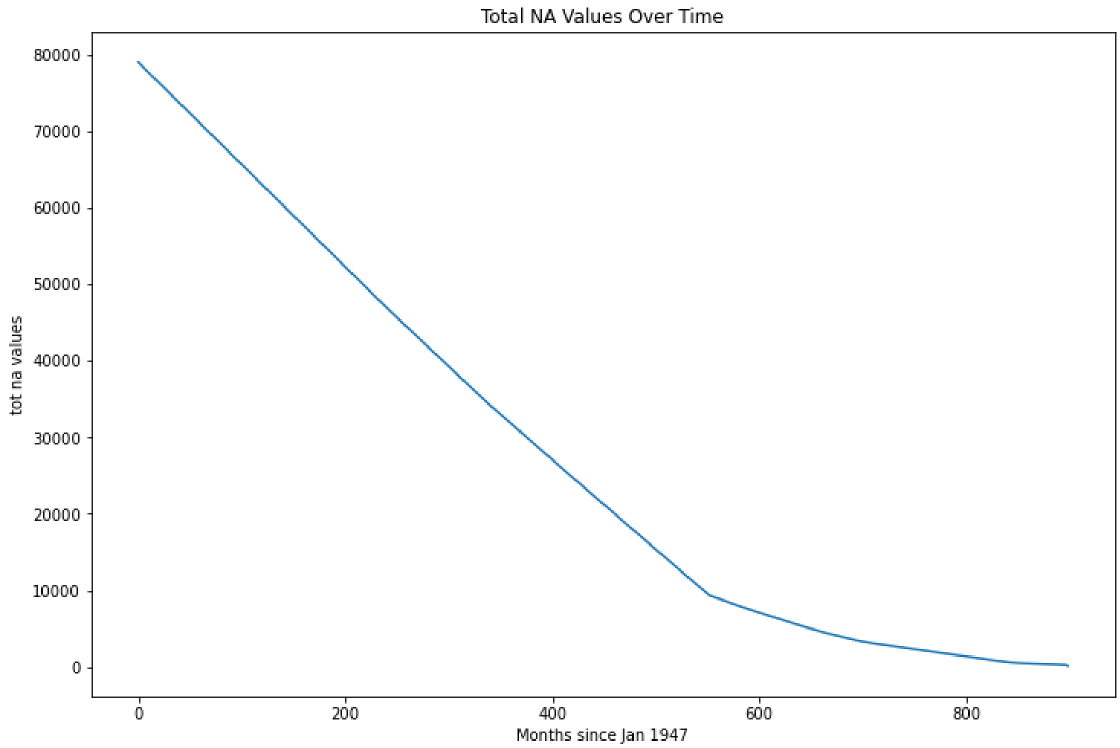
[86]:
```
infra.shape
```

[86]:
```
(899, 136)
```

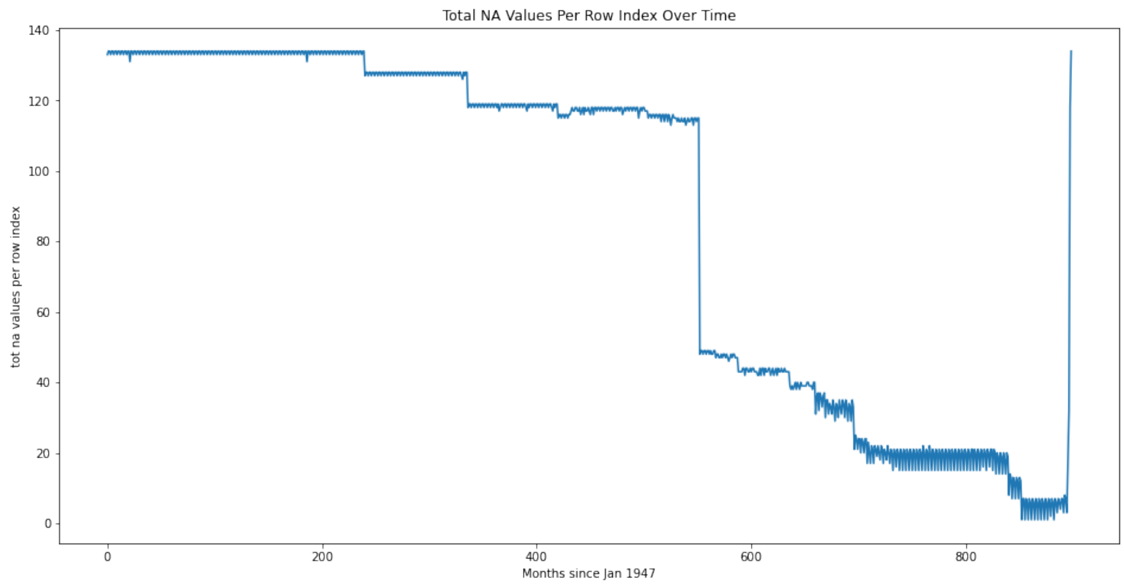
The dataframe has 899 records, so having as much as 843 records with missing values in one category is very concerning.

[87]:
```
# After which date does the number of Na values drop? Just creating an array␣
↪for now
na_values = []
na_per_row = []
for x in range(infra.shape[0]):
    na = sum(infra.iloc[x:].isna().sum())
    na_values.append(na)
    na_per_row.append(infra.loc[[x]].isna().sum().sum())
```

[88]:
```
# Plot seeing how the total number of na values differs after x amount of months
plt.figure(figsize=[12, 8]);
sns.lineplot( x=list(range(899)), y=na_values);
plt.ylabel("tot na values");
plt.xlabel("Months since Jan 1947");
plt.title("Total NA Values Over Time");
```



[89]:
```
# Number of na columns per row index
plt.figure(figsize=[16, 8]);
sns.lineplot( x=list(range(899)), y=na_per_row);
plt.ylabel("tot na values per row index");
plt.xlabel("Months since Jan 1947");
plt.title("Total NA Values Per Row Index Over Time");
```



RELEVANCE TO RESEARCH QUESTION: As can be seen from both graphs, there are an unacceptable amount of na values in our dataset further back in time towards 1947. This impacts our research question because without enough data, variance can have more of a spurious impact on our findings on the causal effect of infrastructure investment on utilization. These graphs, however, show that the number of na values in the dataset decrease significantly at around 550 months after January 1947, which provides a temporal scope from which to define our research question. So long as we stay within this temporal scope, we should have enough valid data to more accurately define the causal effect we are studying.

We handled null values by replacing them with 0. Most of the dataset's null values are from times when that information was not being recorded yet, so the presence of null data does not seem to correlated with anything other than time. The 0s and their impact on our model will be handled later.

[90]:
```
# Replacing na values with 0 in the infrastructure dataframe
infra = infra.fillna(0)
```

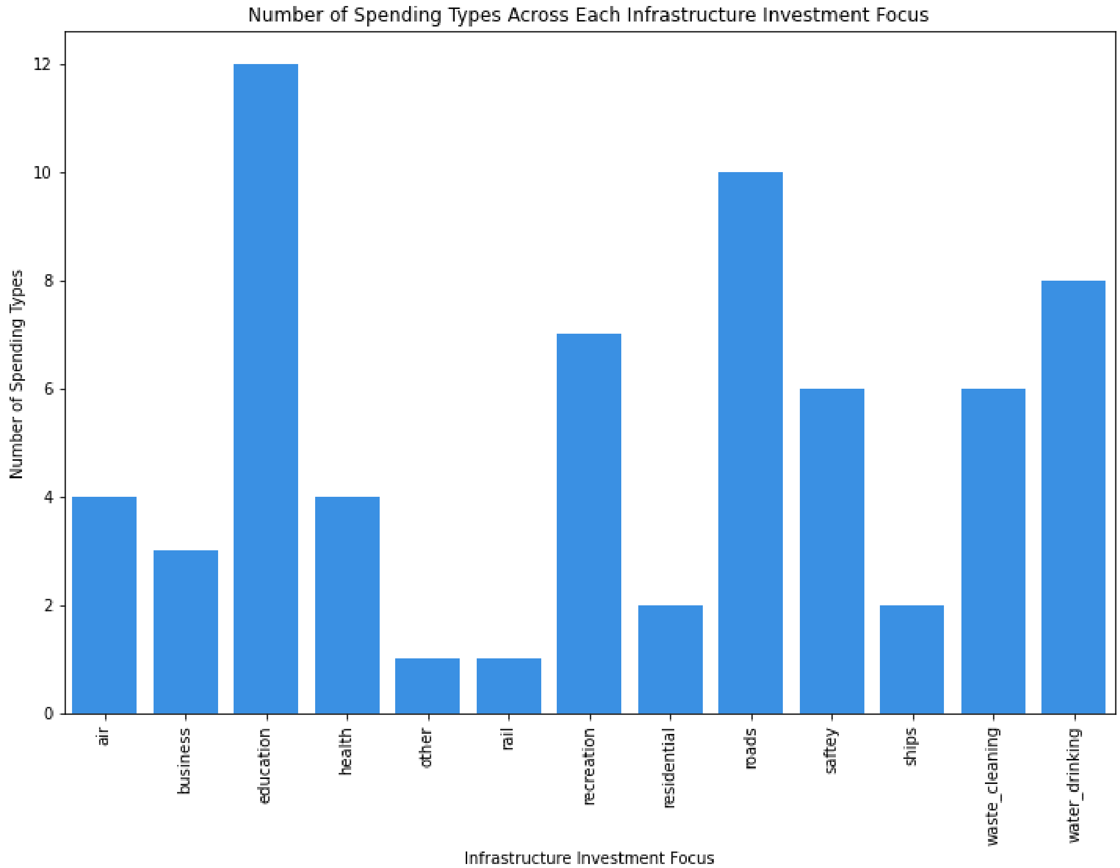
3.1.3 2.1.3. Investigating Spending Complexity Across Infrastructure Categories

From the organized variables, we created a dictionary of infrastructure categories paired with the number of spending (investment) categories that fell under them. This metric is important to our research question because it gives a rough idea of the complexity of investment behind each category of infrastructure. Since office space has relatively few forms of spending compared to automobile-related infrastructure, for example, we will know that attempting to investigate the causal impact of automobile infrastructure on utilization will necessitate a study of many forms of automobile investment first.

[91]:
```python
category = []
for spending in spendings:
    if spending in waste_cleaning:
        category.append('waste_cleaning')
    elif spending in water_drinking:
        category.append('water_drinking')
    elif spending in roads:
        category.append('roads')
    elif spending in ships:
        category.append('ships')
    elif spending in air:
        category.append('air')
    elif spending in recreation:
        category.append('recreation')
    elif spending in safety:
        category.append('saftey')
    elif spending in education:
        category.append('education')
    elif spending in health:
        category.append('health')
    elif spending in business:
        category.append('business')
    elif spending in residential:
        category.append('residential')
    elif spending in rail:
        category.append('rail')
    else:
        print(spending)
        category.append('other')
```

State and Local Government Construction Spending - Total

[92]:
```python
data = {'Number of Spending Types':spendings,
        'Infrastructure Investment Focus':category}

categories = df = pd.DataFrame(data);
categories_grouped = categories.groupby(['Infrastructure Investment Focus']).
 ↪count().reset_index();
plt.figure(figsize=[12, 8]);
sns.barplot(x="Infrastructure Investment Focus", y="Number of Spending Types",␣
 ↪data=categories_grouped, color="dodgerblue");
plt.title("Number of Spending Types Across Each Infrastructure Investment␣
 ↪Focus");
plt.xticks(rotation=90);
```



Quantitative Variable: Number of Spending Types

Categorical Variable: Infrastructure Investment Focus

TRENDS AND RELEVANCE TO RESEARCH QUESTION: In order to test if investment spending has a causal effect on utility, we need to figure out how we are measuring spending. By looking at the different columns we can see we have a lot of different columns of varying areas of spending. Since many of the spendings are very similar (ie elementary school spending and primary/secondary school spending), we decided it be best to group spendings into buckets. This also helps us since unlike spendings, there aren't nearly as many utility measuring columns that we can used. Furthermore, there are more NaN values present in the utility columns compared to the spending columns. Therefore, we thought that it might be a good idea to try to match up similar spendings with their respective utility groups and figure out which spending and utility pairs have the most amount of data that we could work with to figure out a causal effect.

By grouping into buckets we can reach the graph above. We notice that there not each bucket has varying levels spendings columns in it. We can see that education has a lot of spending related columns. While choosing education for our causal effect test might seem like a good choice, sadly there are not related utilty data that we can use. However, utility data on transportation related spendings such as air, roads and more are present in the dataset. We can see that especially for roads, we also have a good amount of spendings data related to it as well.

3.1.4 2.1.4. Investigating Investment-Utilization Correlations Across Different Categories of Infrastructure

To avoid repeating work, we establish a helper function that takes in an investment variable, a utilization variable, and a dataframe, and plots a scatterplot of the variables as well as printing the correlation coefficient.

DATA CLEANING: Because we replaced null values with 0, including these points in our scatterplots will create clusters of points along each axis at 0, so to preserve the integrity of the scatterplot our plotting function will check if the product of each point is 0 (if either x or y is 0), and will not plot the point in the scatterplot if so. This data cleaning step within our plotting function has the effect of only plotting points for which we have data on both the investment variable and the utilization variable, thus creating scatterplots and correlation coefficients that capture the actual relationship between investment and utilization.

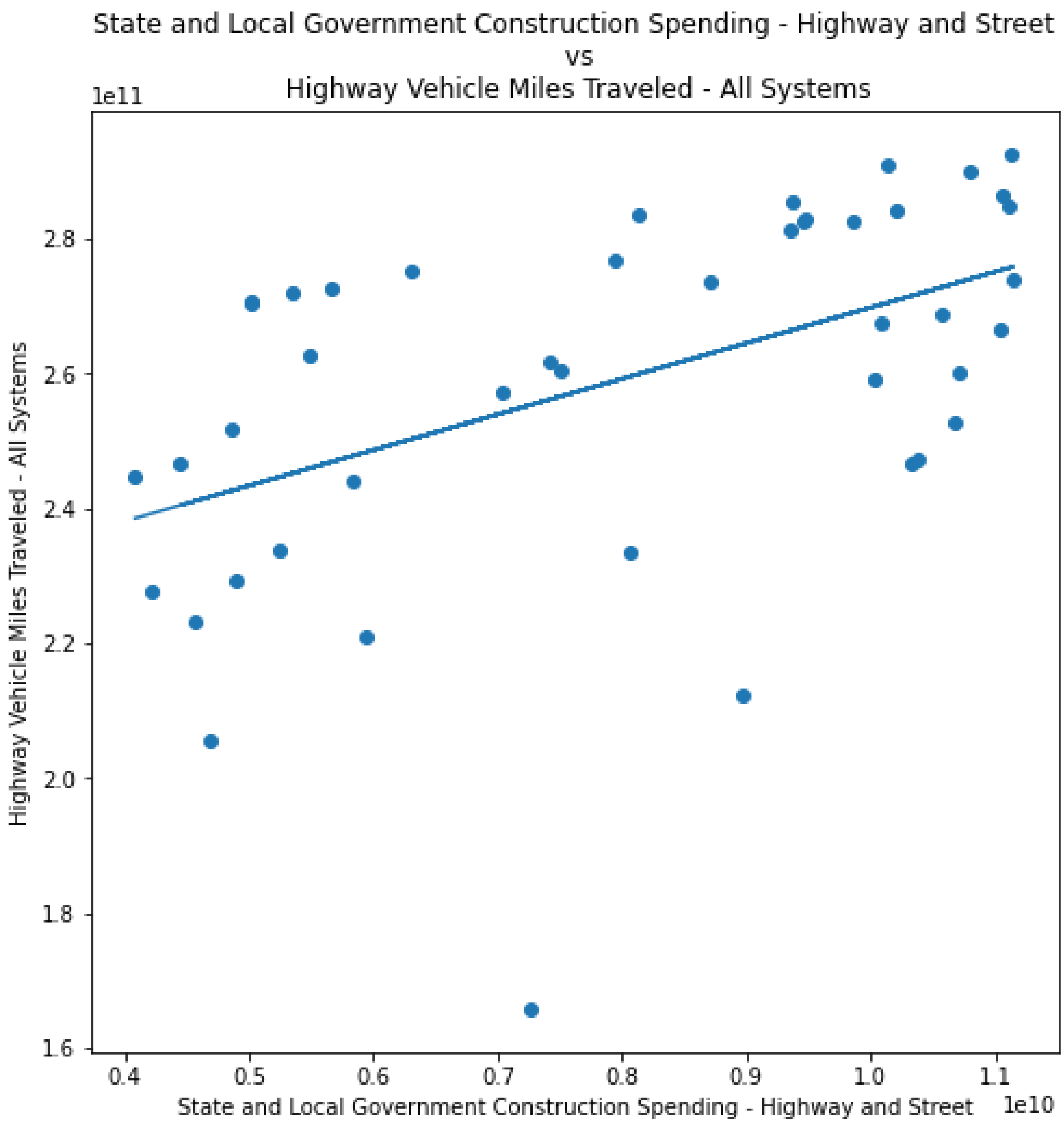
[93]:
```
# Creating a helper function to visualize the relationship between different
# investment and utilization variables
def scatter_wline(x, y, data):
    """x: name of the investment-related variable
       y: name of the utilization-realted variable
       data: dataframe to query from"""

    # Defining the data
    xs = np.array(data[x])
    ys = np.array(data[y])

    # Remove datapoints for which value is 0 (we have no data)
    bad_points = []
    for i in range(len(data)):
        if xs[i] * ys[i] == 0:
            bad_points.append(i)
    xs = np.delete(xs, bad_points)
    ys = np.delete(ys, bad_points)

    # Best fit line and correlation calculation
    m, b = np.polyfit(xs, ys, 1)
    corr = np.corrcoef(xs, ys)[0][1]
    print("Correlation: " + str(corr))

    # Plotting
    plt.figure(figsize=[8,8])
    plt.scatter(xs, ys)
    plt.plot(xs, m*xs + int(b))
    plt.title(x + "\n vs\n " + y)
    plt.xlabel(x)
```

```
    plt.ylabel(y)
```

Plotting the investment-utilization relationship for Highway Infrastructure

[94]:
```
scatter_wline("State and Local Government Construction Spending - Highway and␣
↪Street",
              "Highway Vehicle Miles Traveled - All Systems",
              infra)
```

```
Correlation: 0.48426365059771764
```

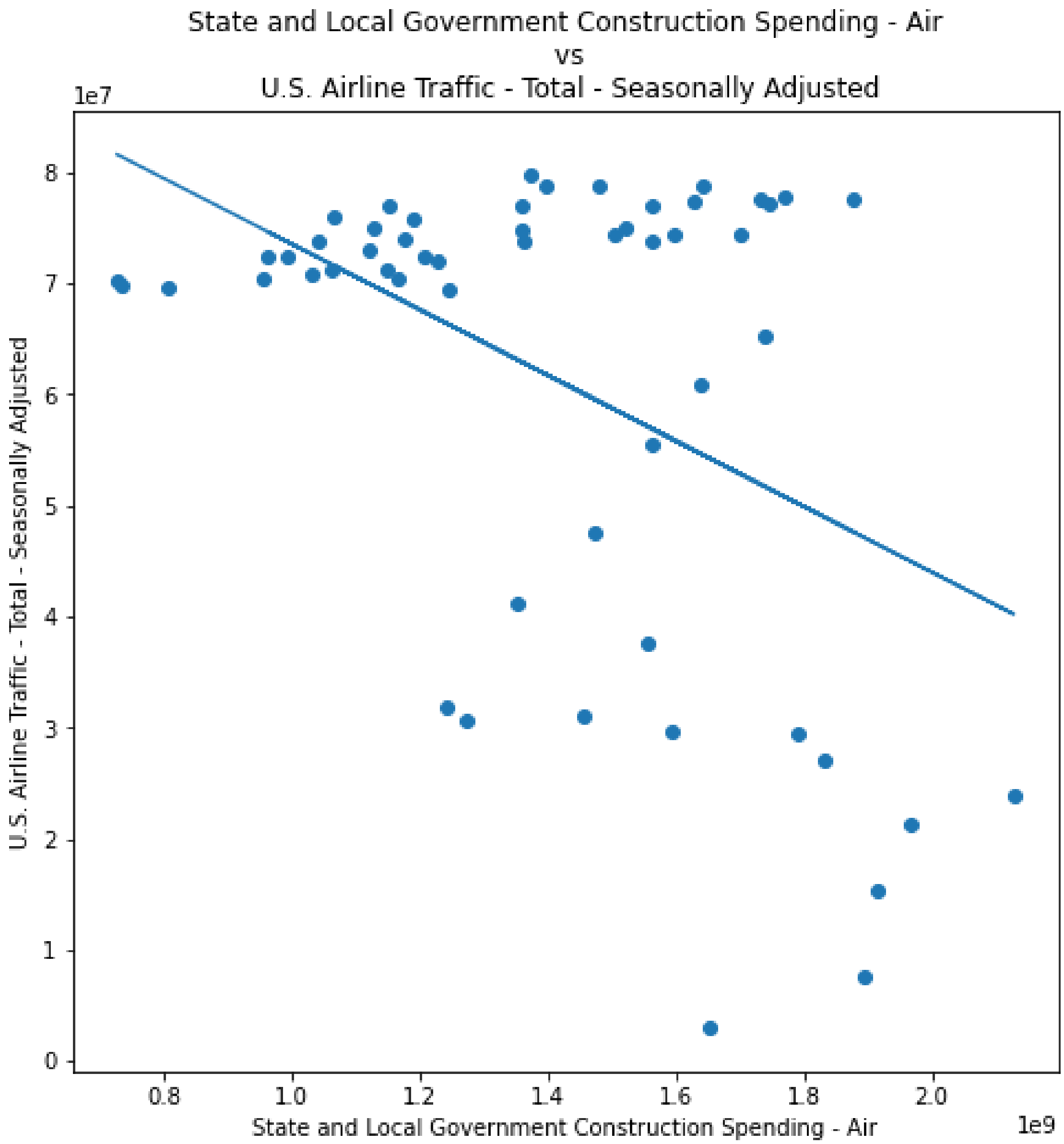


Quantitative Variable: State and Local Government Construction Spending - Highway and Street

Quantitative Variable: Highway Vehicle Miles Traveled - All Systems Plotting the investment-utilization relationship for Air Infrastructure

[95]:
```
scatter_wline('State and Local Government Construction Spending - Air',
              'U.S. Airline Traffic - Total - Seasonally Adjusted',
              infra)
```

```
Correlation: -0.4477082308908731
```

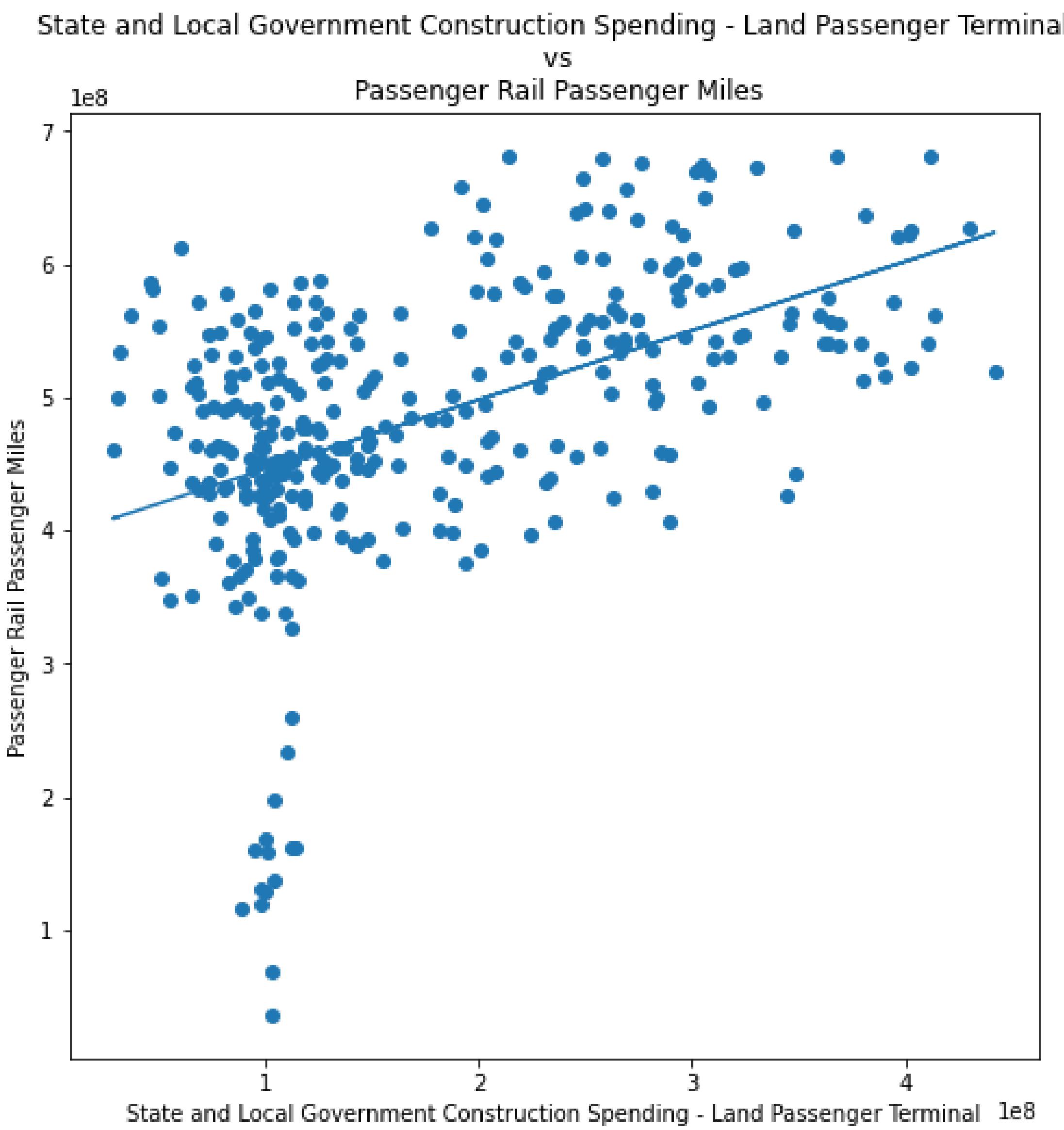


Quantitative Variable: State and Local Government Construction Spending - Air

Quantitative Variable: U.S. Airline Traffic - Total - Seasonally Adjusted Plotting the investment-utilization relationship for Land (Rail) Infrastructure

[96]:
```
scatter_wline('State and Local Government Construction Spending - Land␣
↪Passenger Terminal',
              'Passenger Rail Passenger Miles',
              infra)
```

```
Correlation: 0.48019054721057974
```

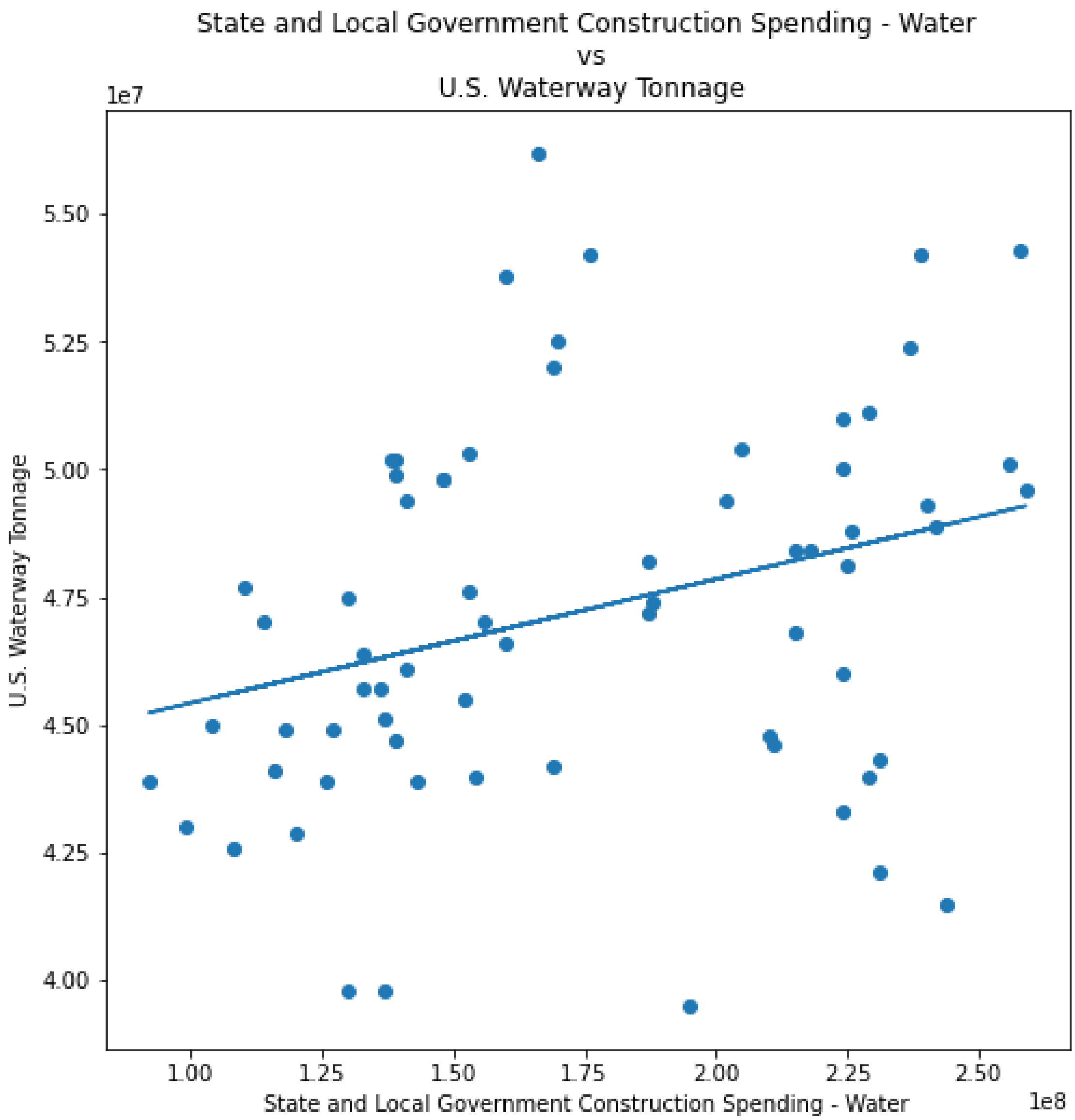


Quantitative Variable: State and Local Government Construction Spending - Land

Quantitative Variable: Passenger Rail Total Train Miles Plotting the investment-utilization relationship for Water Infrastructure

[97]:
```
scatter_wline('State and Local Government Construction Spending - Water',
              'U.S. Waterway Tonnage',
              infra)
```

```
Correlation: 0.30844874356426427
```



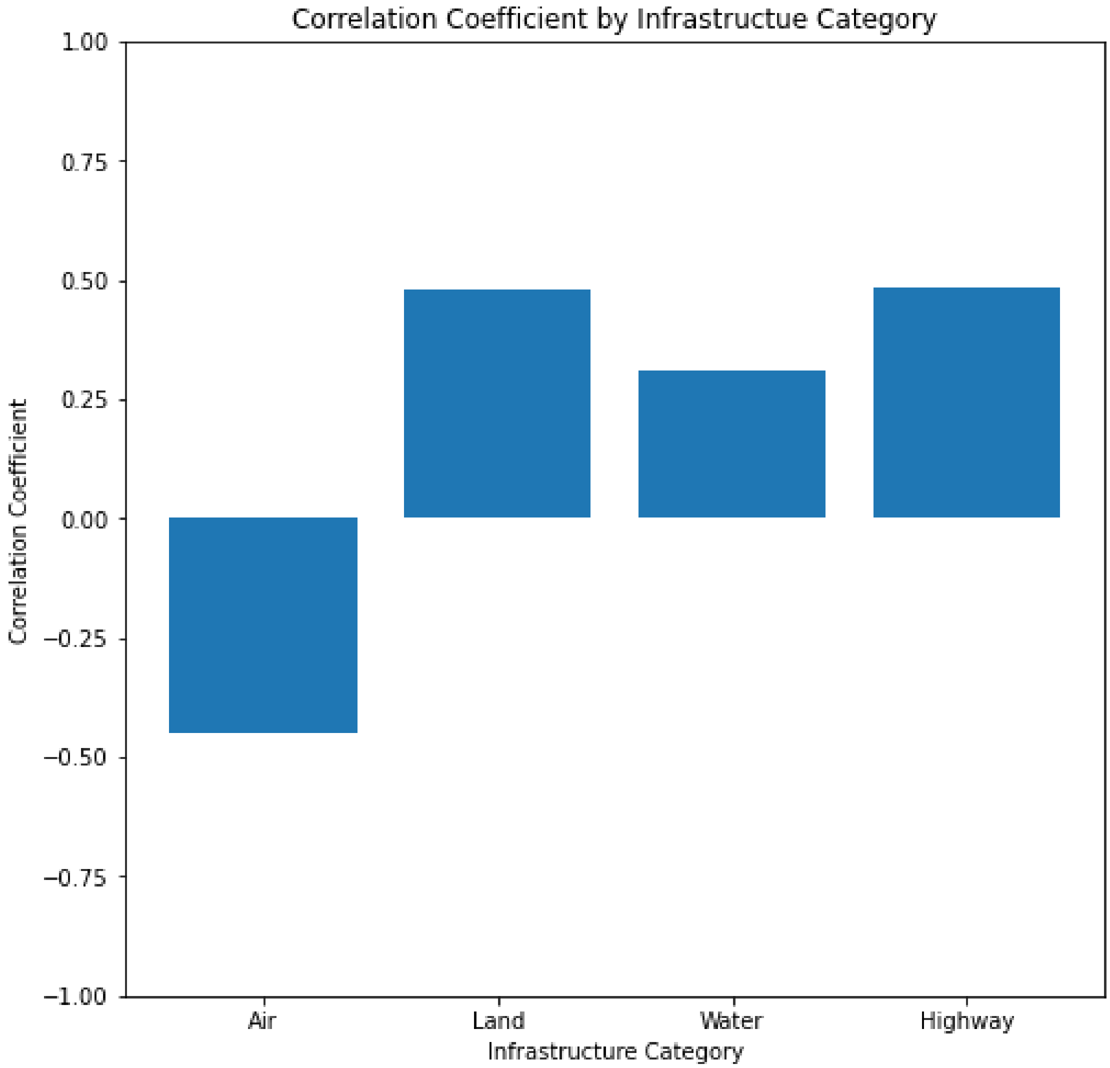
Quantitative Variable: State and Local Government Construction Spending - Water

Quantitative Variable: U.S. Waterway Tonnage Compiling these relationships from all infrastructure categories (for which we had both investment and utilization variables anyway) into a dictionary for reference.

[98]:
```
# Recording the correlation between investment and utilization for each␣
↪infrastruture type
corrs_by_infra_type = {"Air": -0.4477082308908731, "Land": 0.48019054721057974,
                       "Water": 0.30844874356426427, "Highway": 0.
↪48426365059771764}
```

Creating a bar plot of the correlations to show which categories of infrascture exhibit the strongest relationships between investment and spending.

[99]:
```
plt.figure(figsize=[8,8]);
plt.bar(corrs_by_infra_type.keys(),corrs_by_infra_type.values());
plt.ylabel("Correlation Coefficient");
plt.xlabel("Infrastructure Category");
plt.ylim(top=1, bottom=-1);
plt.title("Correlation Coefficient by Infrastructue Category");
```



Quantitative Variable: Investment-Utilization Correlation Coe

Categorical Variable: Infrastructure Category TRENDS AND RELEVANCE:

There appears to be some correlation (0.31) between water investment and utilization, with an even stronger 0.48 correlation between highway investment and utilization. Though just correlation, these relationships indicate that there could be a causal effect of investment on utilization across the infrastructure categories of water and highway, which means that for our research question we will likely focus on these particular types of infrastructure for answers beyond association.

In addition, there appears to be a noticable negative correlation (-0.45) between air infrastructure investment and utilization, which is unexpected since one would think that investing more in air infrastructure would increase its utilization. Not only does this mean there could be a causal effect of investment on utilization in air infrastructure too (and that we will study it), it also opens up a new question of why more air investment seems to be associated with less air utilization.

These contradicting correlation coefficients across several infrastructure categories mean that the causal effect of infrastructure investment on utilization is not the same for every type of infrastructure. If anything, this means the answer to our original research question is more complex than we thought, so these opposite correlations motivate the search for the true causal effect even more.

3.2 2.2. EDA After Knowing Research Question

[100]:
```
# ReLoading the instrastructure dataset as a Pandas dataframe
infra = pd.read_csv("Monthly_Transportation_Statistics.csv")
```

3.2.1 2.2.1. Dataframe Modification

Adding the treatment variable (whether State and Local Government Construction Spending - Land Passenger Terminal has increased or decreased) as an indicator (integer)

[101]:
```
# Creating a binary column in our infrastructure dataframe that specifies␣
 ↪whether
# State and Local Government Construction Spending - Land Passenger Terminal␣
 ↪has increased or decreased
# from the previous month

# Treatment Assignment:
# * current month value - last month value > 0 --> 1
# * current month value - last month value <= 0 --> 0
# * if current month value is nan --> 0
# * if current month value is not nan and last month value is nan --> 1

treatment = list(infra['State and Local Government Construction Spending - Land␣
 ↪Passenger Terminal'])
binary = [] #
first_val = 0

# 0 means no treatment, 1 means with treatment
for val in range(len(treatment)):
    if math.isnan(treatment[val]):
        binary.append(0)
    elif math.isnan(treatment[val - 1]):
        first_val = val
        binary.append(1)
    elif treatment[val] - treatment[val - 1] > 0:
        binary.append(1)
    elif treatment[val] - treatment[val - 1] <= 0:
        binary.append(0)
    else:
        binary.append(0)

# print(first_val)
```

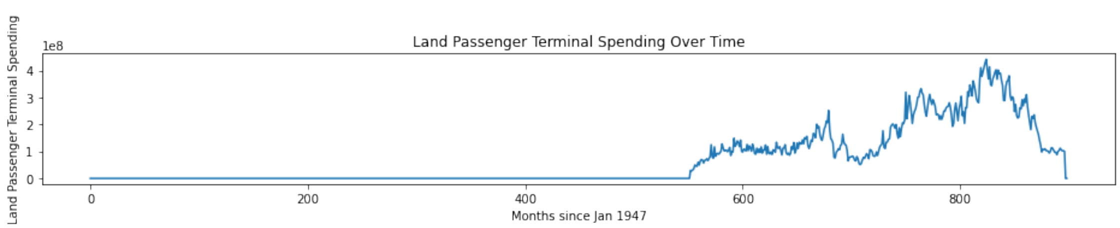
```
# print(len(binary))
infra['treatment'] = binary
```

Adding a month column

```
[102]: # Creating a month column in the infrastructure df
mod_to_month = {0: "Jan", 1: "Feb", 2: "Mar", 3: "Apr", 4:  "May", 5:  "Jun",
                6: "Jul", 7: "Aug", 8: "Sep", 9: "Oct", 10: "Nov", 11: "Dec"}

infra["month"] = [mod_to_month[idx] for idx in (np.array(range(-1, 898)) % 12)]
month = infra["month"]
```

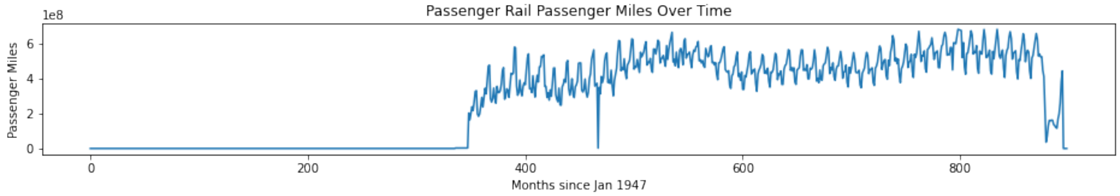
Seeing how much land passenger terminal spending (treatment) data there is to work with

```
[103]: # Initial plot of land passenger terminal spending over time
# This shows us how much data there is to work with, as we replaced null values␣
 ↪with 0

land_spending = infra["State and Local Government Construction Spending - Land␣
 ↪Passenger Terminal"].fillna(0);
plt.figure(figsize=[16, 2]);
sns.lineplot( x=list(range(899)), y=land_spending);
plt.ylabel("Land Passenger Terminal Spending");
plt.xlabel("Months since Jan 1947");
plt.title("Land Passenger Terminal Spending Over Time");
```



Seeing how much passenger rail passenger miles (outcome) data there is to work with

```
[104]: # Initial plot of passenger rail passenger miles over time
# This shows us how much data there is to work with, as we replaced null values␣
 ↪with 0

passenger_mi = infra["Passenger Rail Passenger Miles"].fillna(0);
plt.figure(figsize=[16, 2]);
sns.lineplot( x=list(range(899)), y=passenger_mi);
plt.ylabel("Passenger Miles");
plt.xlabel("Months since Jan 1947");
plt.title("Passenger Rail Passenger Miles Over Time");
```



Data Cleaning

As seen in the plots from the methods section, null values are overwhelmingly present in earlier sections of the infrastructure dataset chronologically. This suggests missing data is due to a lack of collection at the time and is not correlated with another variable that we are not accounting for.

This means for the sake of our study, it is acceptable to handle null values by simply ignoring them, narrowing down the scope of our study to time periods when both the treatment variable, outcome variable, and confounding variable are nonnull in the dataframe. This is a filtering process we execute in the code cell below.

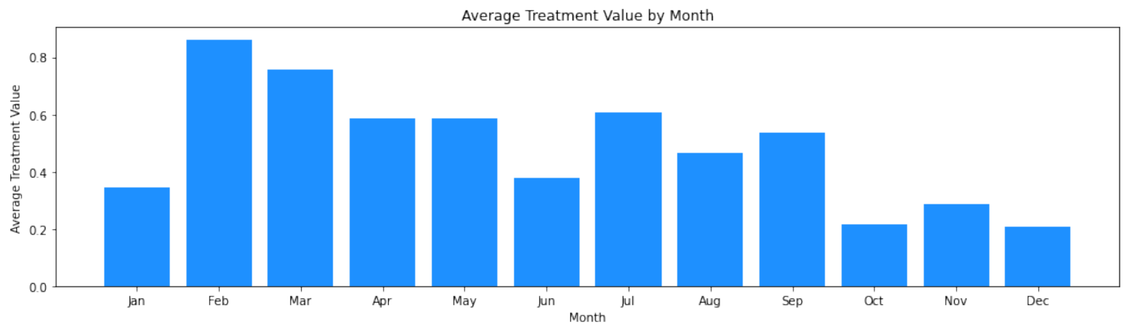
[105]:
```
# Narrowing down the dataframe to records where all variables are nonna
infra = infra[(infra["State and Local Government Construction Spending - Land␣
↪Passenger Terminal"].isna() == False) &
              (infra["Passenger Rail Passenger Miles"].isna() == False)]
```

3.3 2.3. Identifying Confounders and Colliders

3.3.1 2.3.1. Confounder 1: Month

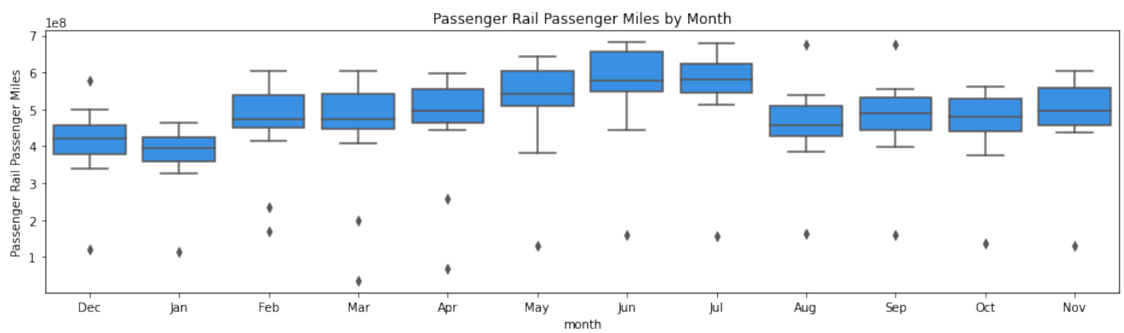
Visualizing effect of month on treatment

[106]:
```
# Visualizing the relationship between the treatment value and month
months =␣
↪["Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec"]
month_avgs = []
for month in months:
    just_month = infra[infra["month"] == month]
    just_month_nonna = just_month[just_month["treatment"].isna() == False]
    month_avg = np.mean(just_month_nonna["treatment"])
    month_avgs.append(month_avg)
plt.figure(figsize=[16, 4]);
plt.bar(x=months, height=month_avgs, color="dodgerblue");
plt.title("Average Treatment Value by Month");
plt.xlabel("Month");
plt.ylabel("Average Treatment Value");
```



Visualizing effect of month on outcome

[107]:
```
# Visualizing the relationship between passenger rail passenger miles and month
plt.figure(figsize=[16, 4]);
sns.boxplot(x="month", y="Passenger Rail Passenger Miles", data=infra,␣
↪color="dodgerblue");
plt.title("Passenger Rail Passenger Miles by Month");
```



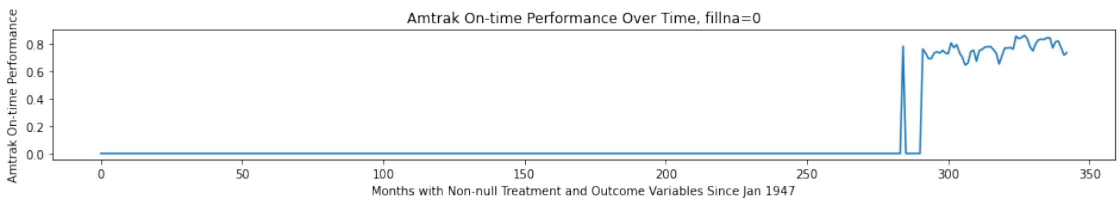
As can be seen, passenger rail passenger miles tend to be significantly greater in the Summer months from May to July compared to the Fall and Winter months from August to January. This suggests that the time of year does in fact influence railway utilization, the outcome variable

3.3.2 2.3.2. Confounder 2: Amtrak On-Time Performance

Checking how much non-null Amtrak on-time performance data there is to work with

[108]:
```
# Initial plot of passenger rail passenger miles over time
# This shows us how much data there is to work with, as we replaced null values␣
↪with 0

amtrak_ontime = infra["Amtrak On-time Performance"].fillna(0);
plt.figure(figsize=[16, 2]);
sns.lineplot( x=list(range(len(infra))), y=amtrak_ontime);
```

```
plt.ylabel("Amtrak On-time Performance");
plt.xlabel("Months with Non-null Treatment and Outcome Variables Since Jan␣
↪1947");
plt.title("Amtrak On-time Performance Over Time, fillna=0");
```



Unfortunately, there is not enough data on amtrak on-time performance to integrate it into our causal study, as there appears to be only 50 records that have nonnull values. Therefore, since month data is present in every record of our infrastructure dataframe, we will use that alone as our confounder in the study.

There exists very little Amtrak on-time performance data, so we will create a sub-dataframe with non-null Amtrak on-time performance records to peform further visualizations from.

[109]:
```
# Creating a sub-dataframe in which Amtrak On-time performance is nonnull
infra1 = infra[infra["Amtrak On-time Performance"].isna() == False]
infra1 = infra1[(infra1["State and Local Government Construction Spending -␣
↪Land Passenger Terminal"].isna() == False) &
                (infra1["Passenger Rail Passenger Miles"].isna() == False)]
```

Visualizing the effect of Amtrak on-time performance on the treatment variable

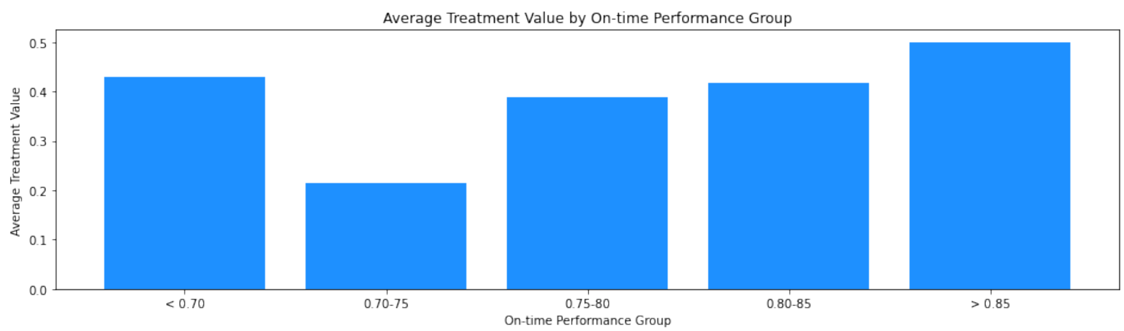
[110]:
```
# Visualizing the relationship between Amtrak on-time performance and the␣
↪treatment variable
performances = []
# Grouping Amtrak on-time performance values into discrete bins
for performance in infra1["Amtrak On-time Performance"]:
    group = ""
    if performance < 0.70:
        group = "< 0.70"
    elif performance >= 0.70 and performance < 0.75:
        group = "0.70-75"
    elif performance >= 0.75 and performance < 0.80:
        group = "0.75-80"
    elif performance >= 0.80 and performance < 0.85:
        group = "0.80-85"
    elif performance >= 0.85:
        group = "> 0.85"
    else:
        print("fixme!")
```

```
    performances.append(group)
infra1["Amtrak On-time Group"] = performances
```

[111]:
```
performance_groups = ["< 0.70","0.70-75","0.75-80","0.80-85","> 0.85"]
```

[112]:
```
# Obtaining the average treatment value for each Amtrak on-time performance bin
group_avgs = []
for group in performance_groups:
    just_group = infra1[infra1["Amtrak On-time Group"] == group]
    group_avg = np.mean(just_group["treatment"])
    group_avgs.append(group_avg)
```

[113]:
```
# Visualizing the result as a bar plot
plt.figure(figsize=[16, 4]);
plt.bar(x=performance_groups, height=group_avgs, color="dodgerblue");
plt.title("Average Treatment Value by On-time Performance Group");
plt.xlabel("On-time Performance Group");
plt.ylabel("Average Treatment Value");
```

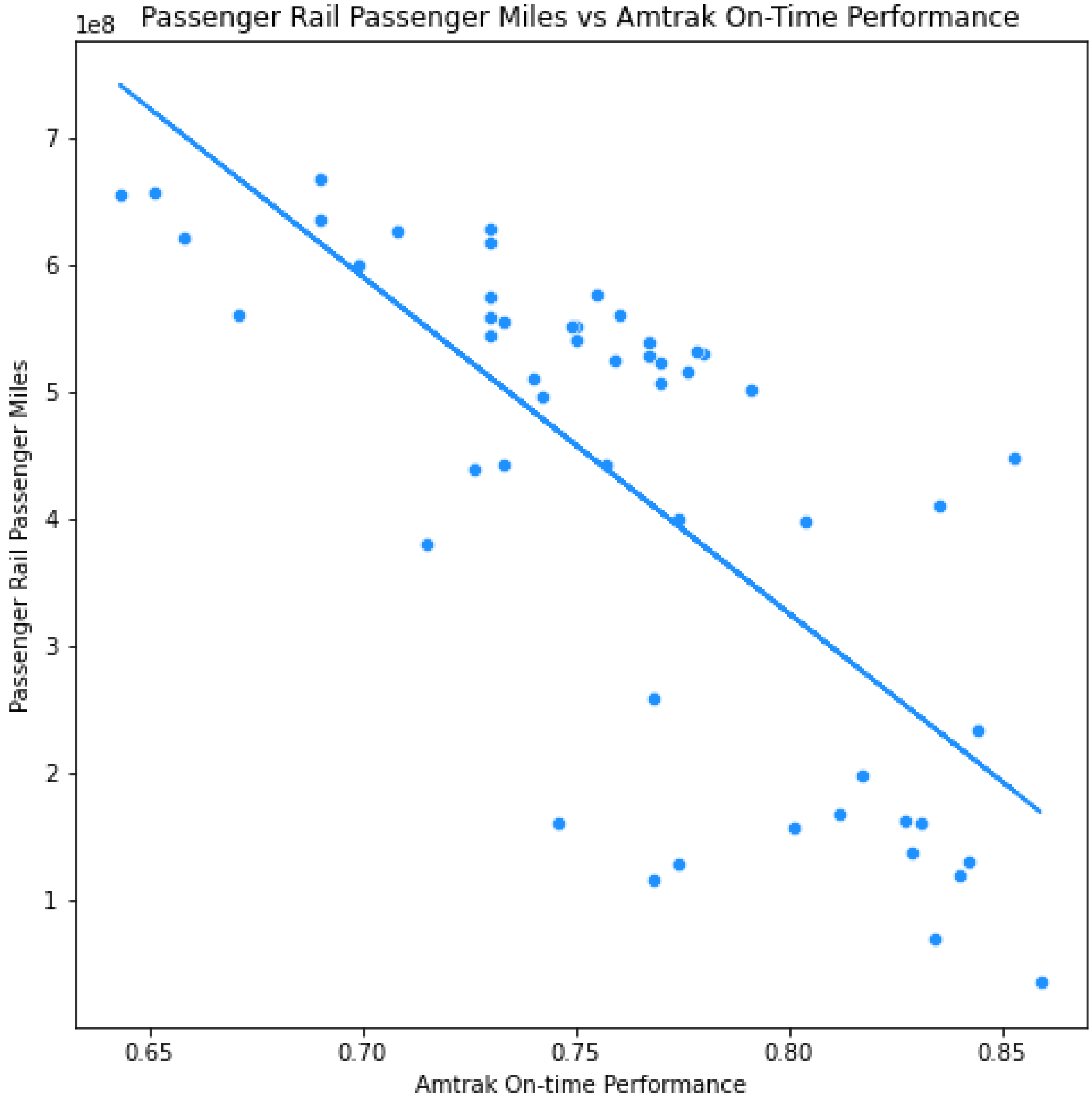


Visualizing the effect of Amtrak on-time performance on the outcome variable

[114]:
```
# Visualizing the relationship between gov spending on land passenger terminals␣
↪and amtrak on-time performance
plt.figure(figsize=[8, 8]);
xs = np.array(infra1["Amtrak On-time Performance"])
ys = np.array(infra1["Passenger Rail Passenger Miles"])
sns.scatterplot(x="Amtrak On-time Performance", y="Passenger Rail Passenger␣
↪Miles", data=infra1,
            color="dodgerblue");
# Best fit line and correlation calculation
m, b = np.polyfit(xs, ys, 1)
corr = np.corrcoef(xs, ys)[0][1]
plt.plot(xs, m*xs + int(b), color="dodgerblue")
print("Correlation: " + str(corr))
plt.ylabel("Passenger Rail Passenger Miles");
```

```
plt.title("Passenger Rail Passenger Miles vs Amtrak On-Time Performance");
```

```
Correlation: -0.742079297053696
```

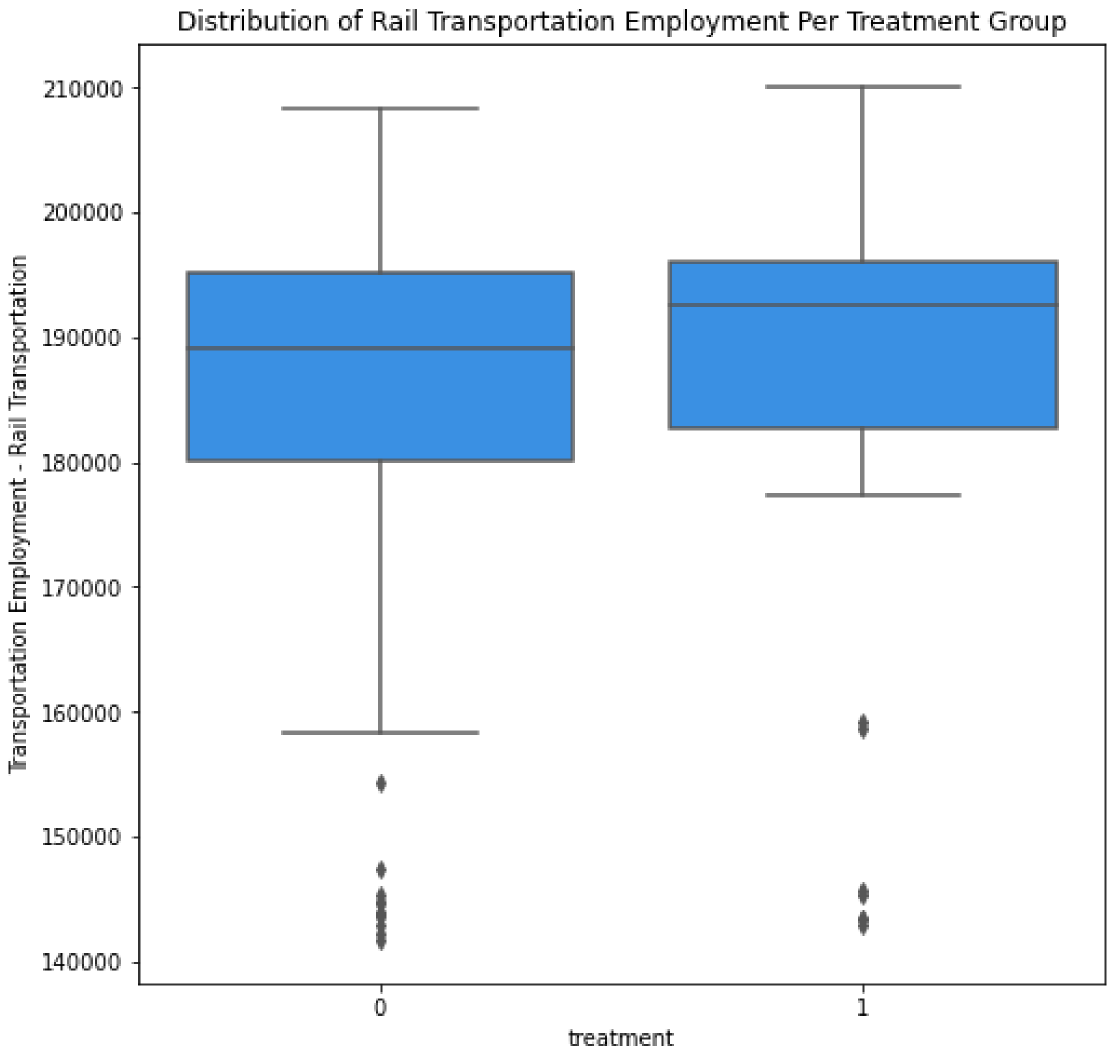


3.3.3 2.3.3. Collider 1: Rail Employment

Visualizing the effect of the treatment variable on rail employment

[115]:
```
# Visualizing the relationship between the treatment variable and rail␣
↪employment
plt.figure(figsize=[8, 8]);
sns.boxplot(x="treatment",y="Transportation Employment - Rail Transportation",␣
↪data=infra, color="dodgerblue");
```

```
plt.title("Distribution of Rail Transportation Employment Per Treatment Group");
```

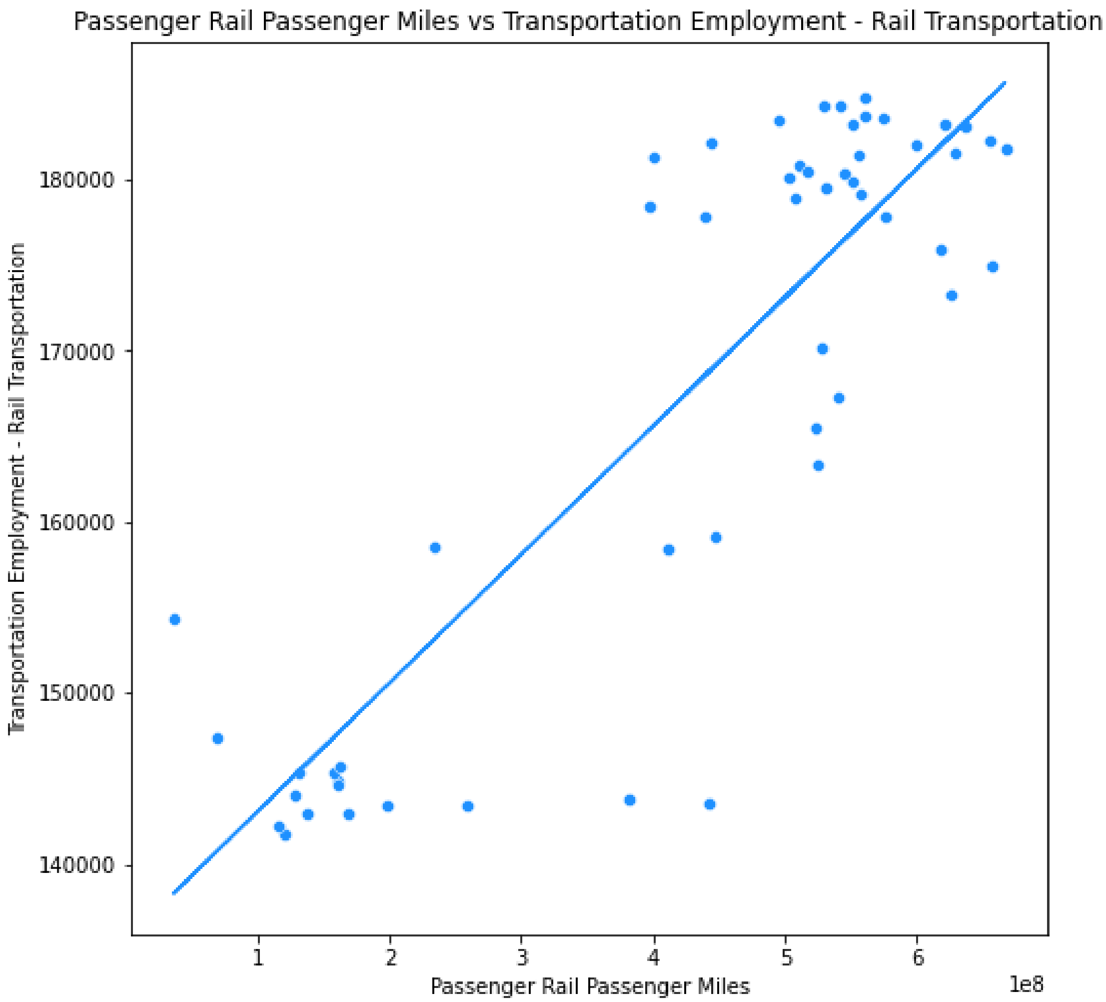


Visualizing the relationship between the outcome variable and rail employment

[116]:
```
# Visualizing the relationship between passenger rail passenger miles and rail␣
↪employment
plt.figure(figsize=[8, 8]);
xs = np.array(infra1["Passenger Rail Passenger Miles"])
ys = np.array(infra1["Transportation Employment - Rail Transportation"])
sns.scatterplot(x="Passenger Rail Passenger Miles", y="Transportation␣
↪Employment - Rail Transportation", data=infra1,
            color="dodgerblue");
# Best fit line and correlation calculation
m, b = np.polyfit(xs, ys, 1)
```

```
corr = np.corrcoef(xs, ys)[0][1]
plt.plot(xs, m*xs + int(b), color="dodgerblue")
print("Correlation: " + str(corr))
plt.ylabel("Transportation Employment - Rail Transportation");
plt.title("Passenger Rail Passenger Miles vs Transportation Employment - Rail␣
↪Transportation");
```

```
Correlation: 0.8604921782253068
```



3.4 2.4. Methods

3.4.1 2.4.1. Treatment and Outcome Variables

Describe which variables correspond to treatment and outcome.

3.4.2 Treatment: Direction of Change in State and Local Gov Construction Spending - Land Passenger Terminal from Previous Month

Explanation:

Government spending on land passenger terminals is the treatment variable because spending money on constructing land terminals constitutes an investment in the future use of said terminals by trains. This variable, therefore, is a measure of infrastructure investment.

Specifically, we wish to see if the *change* in government spending on land passenger terminals has a causal effect on railway utilization, so we take a further step to define the treatment variable as whether government spending on land passenger terminals increases from the previous month (Z=1) or decreases from the previous month (Z=0).

3.4.3 2.4.2. Outcome: Passenger Rail Passenger Miles

Explanation:

Passenger rail passenger miles represent the movement of 1 passenger for 1 mile, meaning they reflect both the volume of passengers that travel by rail as well as the cumulative distance by rail travelled. This variable, therefore, constitutes a relatively comprehensive measure of railway utilization, which is what we wish to investigate the causal effect of railway investment on.

3.5 2.5. Confounders

Describe which variables (if any) are confounders. If the unconfoundedness assumption holds, make a convincing argument for why.

3.5.1 2.5.1. Confounder 1: Month

Explanation:

Month is a confounder because seasonal travel increases rail demand, prompting the government to spend more on infrastructure in advance and driving increases in passenger mileage during holidays.

As can be seen, passenger rail passenger miles tend to be significantly greater in the Summer months from May to July compared to the Fall and Winter months from August to January. This suggests that the time of year does in fact influence railway utilization, the outcome variable

Average treatment value reflects how often the treatment was 1 relative to how often it was 0, this bar plot shows treatment tends to be true in the late Winter and early Spring months compared to other times of the year. This suggests that the time of year does in fact influence railway investment, the treatment variable. Because month affects both treatment and outcome, it is thus a confounding variable we must control for before inferring any causal effects of treatment on outcome.

3.5.2 2.5.2. Confounder 2: Amtrak On-Time Performance

Explanation:

Amtrak OTP is a confounder because deteriorating rail efficiency prompts improvement through increased government construction and disincentivizes rail travel for travellers, decreasing passenger mileage.

3.5.3 Unconfoundeness Assumption:

The unconfoundedness assumption that all confounding variables are observed and can be controlled for does not hold because we lack enough data on the confounding variable of Amtrak OTP to properly observe and control for it.

3.6 2.6. Handling Confounders

What methods will you use to adjust for confounders?

To handle the confounder of month, we will use matching since month is categorical and has only 12 possible values, creating ample opportunities to match treatment-outcome pairs on it. In addition, this is an observational study, so we have no randomization to eliminate the confounding influence of month. Matching is useful for situations like this because it eliminates the confounding influence by conditioning on it instead.

3.7 2.7. Colliders

Are there any colliders in the dataset?

Rail transportation employment is a collider in this dataset because spending more on LPT construction necessitates more rail transportation staff to maintain them, and the volume of rail passengers as measured through PRPM also necessitates a corresponding amount of rail employees to meet demand. Thus, we will avoid conditioning on this collider in the study.

3.8 2.8. Setup Summary

[134]:
```
from IPython.display import Image
from IPython.core.display import HTML
Image(url= "https://github.com/alexmcui/main-sharing/blob/master/
↪rail_causal_dag.png?raw=true")
```

[134]:
```
<IPython.core.display.Image object>
```

3.9 2.9 Supporting Work

Matching

Sorting data to aid matching later on

[118]:
```
# Splitting the cleaned infrastructure dataframe into sub-dataframes that each␣
↪share the same month
january = infra[infra["month"] == "Jan"]
february = infra[infra["month"] == "Feb"]
march = infra[infra["month"] == "Mar"]
april = infra[infra["month"] == "Apr"]
may = infra[infra["month"] == "May"]
june = infra[infra["month"] == "Jun"]
july = infra[infra["month"] == "Jul"]
august = infra[infra["month"] == "Aug"]
```

```
september = infra[infra["month"] == "Sep"]
october = infra[infra["month"] == "Oct"]
november = infra[infra["month"] == "Nov"]
december = infra[infra["month"] == "Dec"]

months =␣
↪["Jan","Feb","Mar","Apr","May","Jun","Jul","Aug","Sep","Oct","Nov","Dec"]
month_to_int = {"Jan":1,"Feb":2,"Mar":3,"Apr":4,"May":5,"Jun":6,"Jul":7,"Aug":
↪8,"Sep":9,"Oct":10,"Nov":11,"Dec":12}
month_to_df = {"Jan":january,"Feb":february,"Mar":march,"Apr":april,"May":
↪may,"Jun":june,
               "Jul":july,"Aug":august,"Sep":september,"Oct":october,"Nov":
↪november,"Dec":december}
month_dfs = [january, february, march, april, may, june, july,
             august, september, october, november, december]
```

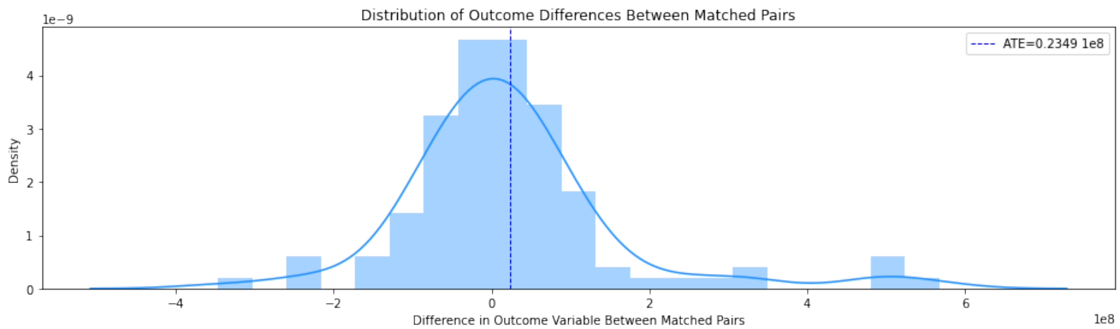
[119]:
```
# Creating a helper function that takes in a dataframe that has been␣
↪conditioned on month
# and assigns pairs between outcome variables that did have treatment and that␣
↪didn't,
# returning an array of their differences
def match(df, seed):
    """Input: df: a dataframe of infrastructure data conditioned on month
       Output: an array of differences between outcome variables
               that did have treatment and that didn't"""
    diffs = []
    outcomes_with_treatment = list(df[df["treatment"] == 1]["Passenger Rail␣
↪Passenger Miles"])
    outcomes_without_treatment = list(df[df["treatment"] == 0]["Passenger Rail␣
↪Passenger Miles"])

    # Setting shuffle seed to ensure reproducibility
    random.seed(seed)
    random.shuffle(outcomes_with_treatment)
    random.shuffle(outcomes_without_treatment)

    num_pairs = min(len(outcomes_with_treatment),␣
↪len(outcomes_without_treatment))
    for i in range(num_pairs):
        diffs.append(outcomes_with_treatment[i] - outcomes_without_treatment[i])
    return diffs
```

Having conditioned the data on month in our work section, we obtain results by randomly assigning pairs of outcome variables that did have the treatment and that did not have the treatment within each month-conditioned dataframe, combining the differences in pairs conditioned on each of the 12 months to create a total list of differences, which we average to obtain our estimate of the average treatment effect (ATE) of increasing government spending on land passenger terminals on passenger rail passenger miles.

[120]:
```python
all_diffs = []
# For each month, pair outcome variables where Z=1 and Z=0 and append their␣
↪differences to the total diff array
for month in months:
    # Random seed step to ensure reproducibility
    seed = month_to_int[month]+11
    # Obtain the month_filtered df for that month and match on it
    month_df = month_to_df[month]
    all_diffs += match(month_df, seed)
ate = np.mean(all_diffs)
print("ATE estimate: " + str(ate))
```

```
ATE estimate: 23490115.663716815
```

[121]:
```python
# Plotting the distribution of matched pair differences
plt.figure(figsize=[16, 4]);
sns.distplot(all_diffs, color="dodgerblue");
plt.axvline(ate, color='b', linestyle='dashed', linewidth=1, label=("ATE=" +␣
↪str(np.round(ate/100000000,5))+" 1e8"));
plt.legend();
plt.xlabel("Difference in Outcome Variable Between Matched Pairs");
plt.title("Distribution of Outcome Differences Between Matched Pairs");
```



[122]:
```python
# Helper function that takes any sample, matches records based on month,
# and returns the ATE of that sample
def match_and_ATE(sample, seed):
    jan_ = sample[sample["month"] == "Jan"]
    feb_ = sample[sample["month"] == "Feb"]
    mar_ = sample[sample["month"] == "Mar"]
    apr_ = sample[sample["month"] == "Apr"]
    may_ = sample[sample["month"] == "May"]
    jun_ = sample[sample["month"] == "Jun"]
    jul_ = sample[sample["month"] == "Jul"]
```

```python
    aug_ = sample[sample["month"] == "Aug"]
    sep_ = sample[sample["month"] == "Sep"]
    oct_ = sample[sample["month"] == "Oct"]
    nov_ = sample[sample["month"] == "Nov"]
    dec_ = sample[sample["month"] == "Dec"]
    month_dfs = [jan_, feb_, mar_, apr_, may_, jun_, jul_,
             aug_, sep_, oct_, nov_, dec_]
    all_diffs = []
    for month in month_dfs:
        seed += 1
        all_diffs += match(month, seed)
        ate = np.mean(all_diffs)
    return ate
```

[123]:
```python
# Bootstrapping rows of the original dataset
sample_size = 34
repetitions = 10000
ates = []
for repetition in range(repetitions):
    if repetition%1000 == 0:
        progress = (repetition/repetitions)*100
        print("Bootstrap " + str(progress)+"% done")
    sample = infra.sample(n=sample_size,replace=True,random_state=repetition)
    # Seed for reproducibility
    seed = repetition*12
    ate = match_and_ATE(sample, seed)
    ates.append(ate)
print("Bootstrap 100.0% done")
ates = np.array(ates)
ates_var_boot = np.var(ates)
```

```
Bootstrap 0.0% done
Bootstrap 10.0% done
Bootstrap 20.0% done
Bootstrap 30.0% done
Bootstrap 40.0% done
Bootstrap 50.0% done
Bootstrap 60.0% done
Bootstrap 70.0% done
Bootstrap 80.0% done
Bootstrap 90.0% done
Bootstrap 100.0% done
```

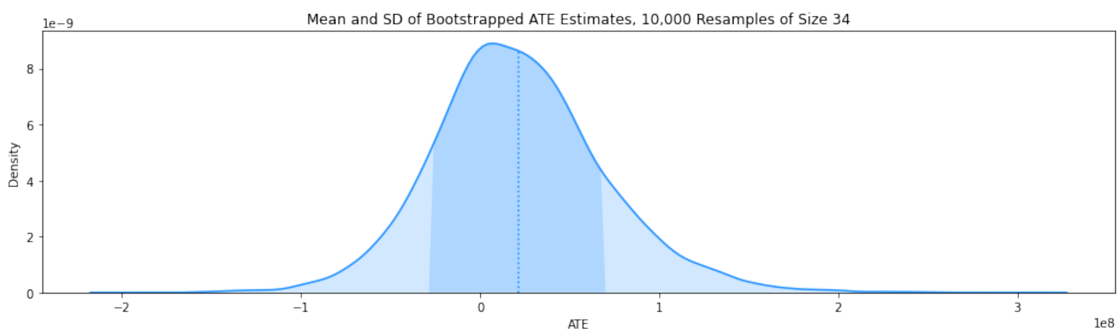
[124]:
```python
# Removing null values from the bootstrapped ATES array by replacing them with 0
ates = np.nan_to_num(ates)
ates
```

[124]:

```
array([ 1.07009759e+08,  1.06601000e+06,  2.14144884e+07, …,
        5.01165365e+07,  5.70226065e+07, -4.19010657e+07])
```

[125]:

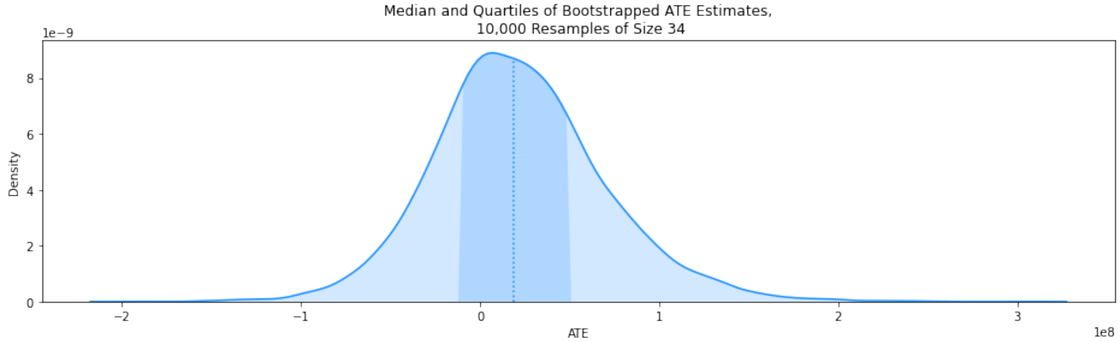
```
# Plotting the distribution of bootstrapped ATEs, focusing on mean and sd
fig, ax = plt.subplots(ncols=1, figsize=(16, 4))
sns.kdeplot(ates, shade=False, color='dodgerblue', ax=ax)
kdeline = ax.lines[0]
xs = kdeline.get_xdata()
ys = kdeline.get_ydata()
middle = ates.mean()
std = ates.std()
left = middle - std
right = middle + std
ax.set_title('Mean and SD of Bootstrapped ATE Estimates, 10,000 Resamples of␣
↪Size 34')
ax.set_xlabel("ATE")
ax.vlines(middle, 0, np.interp(middle, xs, ys), color='dodgerblue', ls=':')
ax.fill_between(xs, 0, ys, facecolor='dodgerblue', alpha=0.2)
ax.fill_between(xs, 0, ys, where=(left <= xs) & (xs <= right),␣
↪interpolate=True, facecolor='dodgerblue', alpha=0.2)
plt.show()
```



[126]:

```
# Plotting the distribution of bootstrapped ATEs, focusing on median and␣
↪quartiles
fig, ax = plt.subplots(ncols=1, figsize=(16, 4))
sns.kdeplot(ates, shade=False, color='dodgerblue', ax=ax)
kdeline = ax.lines[0]
xs = kdeline.get_xdata()
ys = kdeline.get_ydata()
left, middle, right = np.percentile(ates, [25, 50, 75])
ax.set_title('Median and Quartiles of Bootstrapped ATE Estimates,\n 10,000␣
↪Resamples of Size 34')
ax.set_xlabel("ATE")
ax.vlines(middle, 0, np.interp(middle, xs, ys), color='dodgerblue', ls=':')
```

```
ax.fill_between(xs, 0, ys, facecolor='dodgerblue', alpha=0.2)
ax.fill_between(xs, 0, ys, where=(left <= xs) & (xs <= right),␣
↪interpolate=True, facecolor='dodgerblue', alpha=0.2)
plt.show()
```



[127]:
```
# Calculating the variance of the bootstrapped ATEs
ates_var_boot = np.var(ates)
print("Bootstrapped ATE variance: " + str(ates_var_boot))
```

```
Bootstrapped ATE variance: 2319458933764664.5
```

[128]:
```
# Calculating the standard deviation of the bootstrapped ATEs
ates_sd_boot = np.sqrt(ates_var_boot)
print("Bootstrapped ATE standard deviation: " + str(ates_sd_boot))
```

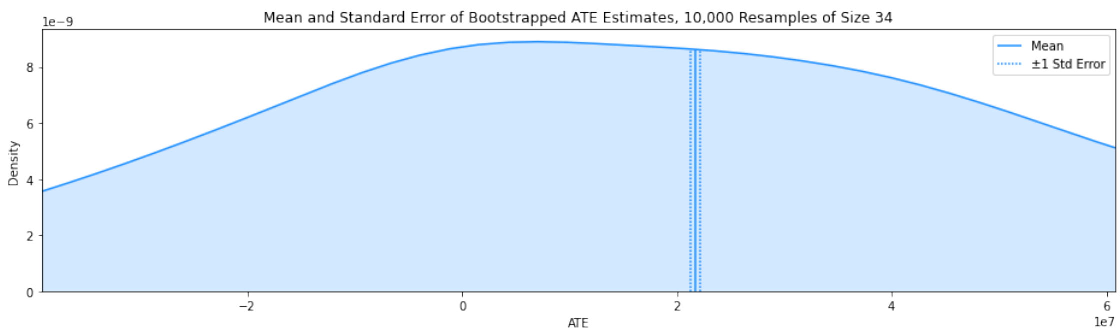
```
Bootstrapped ATE standard deviation: 48160761.34951216
```

[129]:
```
# Calculating the standard error of the bootstrapped ATEs
n = len(ates)
sme = ates_sd_boot/(np.sqrt(n))
print("Bootstrapped ATE standard error of mean: " + str(sme))
```

```
Bootstrapped ATE standard error of mean: 481607.6134951216
```

[130]:
```
# Plotting the distribution of bootstrapped ATEs, focusing on standard error
fig, ax = plt.subplots(ncols=1, figsize=(16, 4))
sns.kdeplot(ates, shade=False, color='dodgerblue', ax=ax)
kdeline = ax.lines[0]
xs = kdeline.get_xdata()
ys = kdeline.get_ydata()
middle = ates.mean()
std = ates.std()
n = len(ates)
sme = std/(np.sqrt(n))
left = middle - sme
```

```python
right = middle + sme
ax.set_title('Mean and Standard Error of Bootstrapped ATE Estimates, 10,000 Resamples of Size 34')
ax.set_xlabel("ATE")
ax.vlines(middle, 0, np.interp(middle, xs, ys), color='dodgerblue', ls='solid', label="Mean")
#
ax.vlines(left, 0, np.interp(left, xs, ys), color='dodgerblue', ls=(0,(1,1)), label="±1 Std Error")
ax.vlines(right, 0, np.interp(right, xs, ys), color='dodgerblue', ls=(0,(1,1)))
#
ax.fill_between(xs, 0, ys, facecolor='dodgerblue', alpha=0.2)
#ax.fill_between(xs, 0, ys, where=(left <= xs) & (xs <= right), interpolate=True, facecolor='dodgerblue', alpha=0.2)
sorta_middle = int(middle)/2
plt.xlim([sorta_middle-50000000, sorta_middle+50000000])
plt.legend()
plt.show()
```



Interpret your results, providing a clear statement about causality (or a lack thereof) including any assumptions necessary.

Assuming month is the only confounding variable at play (since it is the only one our results are conditioned on), we found the ATE estimate from matching is 23.4901 million. The interpretation of this estimate is that increasing state and local government construction spending on land PRPM causes an increase of 23.4901 million PRPM in a given month, on average. This effect, although subtle, is positive, meaning these results support a positive causal effect of the treatment on the outcome.

Where possible, discuss the uncertainty in your estimate and/or the evidence against the hypotheses you are investigating.

This estimate is not without flaws. We performed bootstrapping by resampling records (sample size=34) from the original data to recompute ATE 10,000 times. The bootstrap ATE variance is 2.319 1e16, meaning standard deviation is 4.816 1e7 and standard error is 4.816 1e5. This quantification means the bootstrapped ATE mean is likely very close to the true one, as visualized in figure 16, suggesting ATE is in fact positive on average. An ATE of 0, however, is within one standard deviation of the bootstrapped ATE mean, meaning the causal effect we discovered could still be negative with a non-negligible probability depending on the sample matches, making this positive effect a barely-perceptible one. Our estimate is also imperfect because our assumption that month is the only confounding variable does not hold. We could not control for the other confounding variable of Amtrak OTP because it was non-null in only 50 records, so its confounding influence on both rail investment and utilization is not reflected in our ATE estimate.

3.10 2.10 Discussion

Elaborate on the limitations of your methods.

Our method of turning rail infrastructure investment into a binary variable was a limiting choice because it does not capture the magnitude of investment but rather whether it soley increased or decreased from the previous month. For example, what if rail infrastructure increased by 100% vs 1%? Treatment would still be true either way in our study, meaning the causal effect of an increase in rail infrastructure on utilization that we found is not as descriptive as we would have hoped. While we would have performed a causal study investigating the causal effect of rail infrastructure investment itself (as a continuous variable) on railway utilization using 2SLS regression, this would have required the identification of an instrumental variable, which we did not have in our dataset.

What additional data would be useful for answering this causal question, and why?

Having Amtrak on-time performance data from further back in time would have been helpful because we would have been able to condition on it as a confounding variable in our study. This means our ATE estimate would correctly factor in the confounding influence of all confounders in the infrastructure dataset and thus produce an ATE estimate closer to the true casual effect of an increase in rail infrastructure investment on utilization.

How confident are you that there's a causal relationship between your chosen treatment and outcome? Why?

We believe there exists some relationship between whether the government increases spending on LPTs and how much passengers utilize rail transportation. EDA showed a positive correlation (0.48) between construction spending on LPTs and PRPM, for instance, and the ATE of increasing LPT spending from the previous month is an increase of 23.490 million PRPM. We are, however, uncertain about our specific ATE estimate. The ATE can also be negative within one SD as found via bootstrapping, for instance, which is only countered by the fact that our standard error for the bootstrapped ATE is so low (482K PRPM). We also did not account for the influence of Amtrak OTP, but that influence would have to be around as great as the observed ATE to negate that causal effect from the rail investment alone. Nevertheless, this means our ATE estimate is likely different from the true ATE of increasing railway spending on rail utilization.