ECON 434 Project

Uber versus public transit

In this project, we study whether Uber complements (helps) or substitutes (hurts) public transit. On the one hand, Uber can substitute public transit if riders decide to choose Uber instead of public transit. On the other hand, Uber can complement public transit if riders take Uber from home to public transit stop, which can make public transit more attractive than driving a car. The net effect is unclear and is a subject of intense policy debate.

We will expand on the original set of results presented in Hall, Palsson, and Price (2018), "Is Uber a substitute or a complement for public transit," *Journal of Urban Economics*, which is available on the class website. We will use their dataset, which is also available on the class website. In the dataset, a unit of observation is a public transit agency in a given year-month. The dataset includes information on both the transit agencies and on the Metropolitan Statistical Areas (MSA) where they operate. For each time period, the dataset contains values for the following variables:

1. UPTTotal – the number of rides for the public transit agency;
2. treatUberX - a dummy for Uber presence in the corresponding MSA;
3. treatGTNotStd - a variable measuring google search intensity for Uber in the corresponding MSA;
4. popestimate - population in the corresponding MSA;
5. employment - employment in the corresponding MSA;
6. aveFareTotal - average fare for the public transit agency;
7. VRHTTotal - vehicle hours for the public transit agency;
8. VOMSTotal - number of vehicles employed by the public transit agency;
9. VRMTotal - vehicle miles for the public transit agency;
10. gasPrice - gas price in the corresponding MSA.

In this dataset, treatUber and treatGTNotStd is qualitative and quantitative measures for the same thing: Uber presense in the MSA. We can run regressions using either of these two variables and then check whether results are robust if the other variable is used.

There are two variations in this dataset that allow us to study the effect of Uber on public transit. First, in any given time period, Uber is present in some MSAs but not in others. We can thus study the effect of Uber by comparing these MSAs. Second, for any given MSA, we have data on time periods both before and after Uber was introduced in this MSA. We can thus study the effect of Uber by comparing these time periods. By working with panel data, we are able to employ both variations at the same time.

To study the effect of Uber on public transit, we let Y_{it} be UPTTotal, D_{it} be either treatUberX or treatGTNotStd, and W_{it} be the vector including remaining variables: popestimate, employment, aveFareTotal, VRHTTotal, VOMSTotal, VRMTotal, gasPrice. We then run the following regressions:

1. OLS: $\log Y_{it} = \alpha + D_{it}\beta + W_{it}'\gamma + e_{it}$.
2. OLS: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta + W_{it}'\gamma + e_{it}$.
3. OLS: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}P_{it}\beta_2 + W_{it}'\gamma + e_{it}$, where P_{it} is a dummy that takes value 1 if the corresponding MSA has population larger than the median population in the dataset and 0 otherwise.
4. OLS: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}F_{it}\beta_2 + W_{it}'\gamma + e_{it}$, where F_{it} is a dummy that takes value 1 if the number of rides of the public travel agency is larger than the median number of rides among all public transit agencies in the dataset.
5. LASSO: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}P_{it}\beta_2 + W_{it}'\gamma + e_{it}$.
6. LASSO: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}F_{it}\beta_2 + W_{it}'\gamma + e_{it}$.
7. Double-LASSO: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}P_{it}\beta_2 + W_{it}'\gamma + e_{it}$, where coefficients of interest are β_1 and β_2.
8. Double-LASSO: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}F_{it}\beta_2 + W_{it}'\gamma + e_{it}$, where coefficients of interest are β_1 and β_2.
9. LASSO: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}P_{it}\beta_2 + \widetilde{W}_{it}'\gamma + e_{it}$, where $\widetilde{W}_{it}$ includes all interactions of order 5 of variables in the vector W_{it}.
10. LASSO: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}F_{it}\beta_2 + \widetilde{W}_{it}'\gamma + e_{it}$, where $\widetilde{W}_{it}$ includes all interactions of order 5 of variables in the vector W_{it}.
11. Double-LASSO: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}P_{it}\beta_2 + \widetilde{W}_{it}'\gamma + e_{it}$, where coefficients of interest are β_1 and β_2 and $\widetilde{W}_{it}$ includes all interactions of order 5 of variables in the vector W_{it}.
12. Double-LASSO: $\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}F_{it}\beta_2 + \widetilde{W}_{it}'\gamma + e_{it}$, where coefficients of interest are β_1 and β_2 and $\widetilde{W}_{it}$ includes all interactions of order 5 of variables in the vector W_{it}.

Regressions 2, 3, and 4 roughly correspond to regressions run in the original paper (see Table 3 there). Please refer to the original paper for motivation on including P_{it} and F_{it} in the analysis. Regressions 5–12 are new. Of particular interest to us are regressions 7, 8, 11, and 12, corresponding to Double-LASSO. The purpose of this project is to establish whether these regressions give results that are qualitatively similar to those established in the original paper.

Econ 434 Final Project

1 Econ 434 Final Project

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The scope of this project is to analyze whether Uber is a substitute or a complement for public transit. To analyze this matter, I will be running a number of regressions whose dependent variable will be the log of the number of rides for a public transit agency in a given year-month. Each of the regressions that I will be running will also include at least one independent variable related to the presence of UBER in the corresponding Metropolitan Statistical Area of the public transit agency. By interpreting the coefficients of such variables throughout multiple regressions, I will obtain a better understanding of the relation between public transit activity and UBER presence.

I begin the project by importing some of the libraries I will be using.

```
[1]: import pandas as pd
     from sklearn.impute import SimpleImputer
     import statsmodels.api as sm
     import numpy as np
     from sklearn.linear_model import LassoCV
     from sklearn.preprocessing import StandardScaler
     from sklearn.preprocessing import PolynomialFeatures
     import warnings
     warnings.filterwarnings('ignore')
```

Below I upload the dataframe I will use for this project. The columns of the dataframe are:

-UPTTotal – the number of rides for the public transit agency;
-treatUberX - a dummy for Uber presence in the corresponding MSA;
-treatGTNotStd - a variable measuring google search intensity for Uber in the corresponding MSA;
-popestimate - population in the corresponding MSA;
-employment - employment in the corresponding MSA;
-aveFareTotal - average fare for the public transit agency;
-VRHTTotal - vehicle hours for the public transit agency;
-VOMSTotal - number of vehicles employed by the public transit agency;
-VRMTotal - vehicle miles for the public transit agency;
-gasPrice - gas price in the corresponding MSA
-agency - the name of the public transit agency
--city - the city where the public transit agency is located

-state - the state where the public transit agency is located
-dateSurvey- the date when the observation was registered

```
[2]: df = pd.read_csv('/Users/sandinatatu/Desktop/uber_dataset.csv', index_col = 0)
     df.head()
```

```
[2]:    UPTTotal  treatUberX  treatGTNotStd  popestimate  employment  aveFareTotal  \
     0   8296756         0.0           0.00      3163703     1572859      0.778015
     1   7847113         0.0           1.40      3163703     1581307      0.778015
     2   9011399         0.0           3.00      3163703     1592152      0.778015
     3   8656389         0.0           2.25      3163703     1598167      0.778015
     4   8378406         0.0           2.60      3163703     1593356      0.778015

        VRHTotal  VOMSTotal   VRMTotal  gasPrice  \
     0  333329.0     2626.0  4740396.0     1.701
     1  310535.0     2626.0  4398939.0     1.862
     2  356761.0     2626.0  5176183.0     2.063
     3  341191.0     2626.0  4889387.0     2.121
     4  333418.0     2626.0  4747018.0     2.266

                                                  agency     city state  \
     0  King County Department of Transportation - Met…  Seattle    WA
     1  King County Department of Transportation - Met…  Seattle    WA
     2  King County Department of Transportation - Met…  Seattle    WA
     3  King County Department of Transportation - Met…  Seattle    WA
     4  King County Department of Transportation - Met…  Seattle    WA

        dateSurvey
     0  2004-01-01
     1  2004-02-01
     2  2004-03-01
     3  2004-04-01
     4  2004-05-01
```

```
[3]: df.shape
```

```
[3]: (76213, 14)
```

```
[4]: df.describe()
```

```
[4]:            UPTTotal    treatUberX  treatGTNotStd   popestimate    employment  \
     count  7.621300e+04  76213.000000   61824.000000  7.621300e+04  7.621300e+04
     mean   1.557973e+06      0.125017       2.711728  3.287213e+06  1.544130e+06
     std    1.247141e+07      0.329335       5.013406  5.090858e+06  2.363277e+06
     min    2.100000e+01      0.000000       0.000000  6.944200e+04  3.215000e+04
     25%    3.866000e+04      0.000000       0.000000  2.825200e+05  1.314350e+05
     50%    1.214730e+05      0.000000       1.000000  8.370360e+05  3.903810e+05
     75%    4.169980e+05      0.000000       2.250000  4.260236e+06  1.891851e+06
```

```
max    3.227260e+08      1.000000      56.024097  1.944570e+07  9.357873e+06

       aveFareTotal      VRHTotal     VOMSTotal      VRMTotal      gasPrice
count  72016.000000  7.602000e+04  76066.000000  7.603200e+04  76213.000000
mean       1.766518  4.040557e+04    185.220690  6.165114e+05      2.980399
std        4.134002  1.589262e+05    590.133284  2.326701e+06      0.653412
min        0.000026  4.000000e+01      1.000000  2.740000e+02      1.541000
25%        0.651672  4.076750e+03     22.000000  6.293075e+04      2.471000
50%        0.914369  8.701000e+03     48.000000  1.351800e+05      2.970000
75%        1.427222  2.191775e+04    125.000000  3.456725e+05      3.563000
max      135.849040  3.370515e+06  11260.000000  4.548309e+07      4.423000
```

Then, I check for the presence of missing values.

[5]:
```
df.isna().sum()
```

[5]:
```
UPTTotal            0
treatUberX          0
treatGTNotStd   14389
popestimate         0
employment          0
aveFareTotal     4197
VRHTotal          193
VOMSTotal         147
VRMTotal          181
gasPrice            0
agency              0
city                0
state               0
dateSurvey          0
dtype: int64
```

Since some of the variables contain missing values, I will impute via their mean to ensure that the dataset I will use for the regressions does not contain any missing values.

[6]:
```
imputer = SimpleImputer(strategy = 'mean')

df[['treatGTNotStd', 'aveFareTotal', 'VRHTotal', 'VOMSTotal', 'VRMTotal']] = \
imputer.fit_transform(df[['treatGTNotStd', 'aveFareTotal', 'VRHTotal',␣
 ↪'VOMSTotal', 'VRMTotal']])
```

I check to make sure that I do not have missing values anymore in the dataset.

[7]:
```
df.isna().sum()
```

[7]:
```
UPTTotal        0
treatUberX      0
treatGTNotStd   0
popestimate     0
```

```
employment       0
aveFareTotal     0
VRHTotal         0
VOMSTotal        0
VRMTotal         0
gasPrice         0
agency           0
city             0
state            0
dateSurvey       0
dtype: int64
```

Prior to running the regressions, I create two dataframes whose contents will be used as independent variables:

-agency_dummies (a dataframe containing dummy values for the public transit agency of an observation)

-date_dummies (a dataframe containing dummy values for the year-month of an observation)

[8]:
```
agency_dummies = pd.get_dummies(df['agency']).astype('int')

date_dummies = pd.get_dummies(df['dateSurvey']).astype('int')
```

1.2 Regression 1

The first regression is:

$$\log Y_{it} = \alpha + \beta D_{it} + \gamma W_{it} + \epsilon_{it}$$

Where:

-alpha is a constant
-Y is UPTTotal
-D is treatUberX
-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHTotal, VOMSTotal, VRMTotal, gasPrice

[9]:
```
df['log_UPTTotal'] = np.log(df['UPTTotal'])

y = df['log_UPTTotal'].copy()

d_uberx = df['treatUberX'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()
w = sm.add_constant(w)

x_uberx = pd.concat([d_uberx, w], axis=1)
```

```
model1 = sm.OLS(y, x_uberx).fit()

summary = model1.summary()
coef_table = summary.tables[1]
titles = coef_table.data[0]
first_variable_row = []
for row in coef_table.data:
    if 'treatUberX' in row:
        first_variable_row = row
        break

df_summary = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary)
```

```
                      coef    std err          t    P>|t|     [0.025     0.975]
0  treatUberX       0.1694      0.018      9.364    0.000      0.134      0.205
```

The coefficient of treatUberX in this regression is 0.1694 with a standard error of 0 .018. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to increase the number of rides for the public transit agency in that area by 16.94%, keeping everything else the same.

1.3 Regression 2

The second regression is:

$$\log Y_{it} = \eta_i + \delta_t + \beta D_{it} + \gamma W_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHT-Total, VOMSTotal, VRMTotal, gasPrice

[10]:
```
y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()

d_uberx = df['treatUberX'].copy()

x_uberx = pd.concat([d_uberx, w, agency_dummies, date_dummies], axis=1)

model2 = sm.OLS(y, x_uberx).fit()

summary = model2.summary()
coef_table = summary.tables[1]
```

```
titles = coef_table.data[0]
first_variable_row = []
for row in coef_table.data:
    if 'treatUberX' in row:
        first_variable_row = row
        break

df_summary = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary)
```

```
                    coef    std err          t   P>|t|     [0.025     0.975]
0  treatUberX    -0.0606      0.006     -9.829   0.000     -0.073     -0.048
```

The coefficient of treatUberX in this regression is -0.0606 with a standard error of 0.006. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to decrease the number of rides for the public transit agency in that area by 6.06%, keeping everything else the same.

1.4 Regression 3

Below I create P, a a dummy that takes value 1 if the corresponding MSA has population larger than the median population in the dataset and 0 otherwise. I also create a column I call ‘D * P’, which is the product between the newly-created P column and the ‘treatUberX’ column.

```
[11]: df['P'] = np.where(df['popestimate'] > df['popestimate'].median(),1,0)
      df['D*P'] = df['P'] * df['treatUberX']
```

The third regression is:

$$\log Y_{it} = \eta_i + \delta_t + \beta_1 D_{it} + \beta_2 D_{it} P_{it} + \gamma W_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * P is the product between the newly-created P column and the ‘treatUberX’ column.
-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHT-Total, VOMSTotal, VRMTotal, gasPrice

```
[12]: y = df['log_UPTTotal'].copy()

      w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
       ↪'VRMTotal', 'gasPrice']].copy()

      d_uberx = df['treatUberX'].copy()
      dp_uberx = df['D*P'].copy()
```

```
x_uberx = pd.concat([d_uberx, dp_uberx, w, agency_dummies, date_dummies],␣
  ↪axis=1)

model3 = sm.OLS(y, x_uberx).fit()

summary = model3.summary()
coef_table = summary.tables[1]
titles = coef_table.data[0]
first_two_rows = []
for row in coef_table.data[1:3]:
    first_two_rows.append(row)

df_summary = pd.DataFrame(first_two_rows, columns=titles)
print(df_summary)
```

```
                    coef    std err          t    P>|t|     [0.025     0.975]
0  treatUberX    -0.0303      0.009     -3.218    0.001     -0.049     -0.012
1         D*P    -0.0397      0.009     -4.249    0.000     -0.058     -0.021
```

The coefficient of treatUberX in this regression is - 0.0303 with a standard error o f 0.009. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to decrease the number of rides for the public transit agency in that area by 3.03%, keeping everything else the same.

The coefficient o f D * P in this regression i s - 0.0397 with a standard error o f 0.009. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a larger MSA is expected to decrease the number of rides for the public transit agency in that area by a further 3.97%, keeping everything else the same.

1.5 Regression 4

Below I create F, a a dummy that takes value 1 if the number of rides of the public travel agency is larger than the median number of rides among all public transit agencies in the dataset. I also create a column I call 'D * F', which is the product between the newly-created F column and the 'treatUberX' column.

[13]:
```
df['F'] = np.where(df['UPTTotal'] > df['UPTTotal'].median(),1,0)
df['D*F'] = df['F'] * df['treatUberX']
```

The fourth regression is:

$$\log Y_{it} = \eta_i + \delta_t + \beta_1 D_{it} + \beta_2 D_{it} F_{it} + \gamma W_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * F is the product between the newly-created F column and the 'treatUberX' column.

-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHT-Total, VOMSTotal, VRMTotal, gasPrice

```
[14]: y = df['log_UPTTotal'].copy()

      w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
       ↪'VRMTotal', 'gasPrice']].copy()

      d_uberx = df['treatUberX'].copy()
      df_uberx = df['D*F'].copy()

      x_uberx = pd.concat([d_uberx,df_uberx, w, date_dummies, agency_dummies], axis=1)

      model4 = sm.OLS(y, x_uberx).fit()

      summary = model4.summary()
      coef_table = summary.tables[1]
      titles = coef_table.data[0]
      first_two_rows = []
      for row in coef_table.data[1:3]:
          first_two_rows.append(row)

      df_summary = pd.DataFrame(first_two_rows, columns=titles)
      print(df_summary)
```

```
                    coef    std err          t      P>|t|      [0.025      0.975]
0  treatUberX    -0.0537      0.008     -6.742      0.000      -0.069      -0.038
1         D*F    -0.0110      0.008     -1.370      0.171      -0.027       0.005
```

The coefficeint of treatUberX in this regression is -0.0537 with a standard error of 0.008. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to decrease the number of rides for the public transit agency in that area by 5.37%, keeping everything else the same.

The coefficeint of D * F in this regression is -0.0110 with a standard error of 0.008. This result is not statistically significant at the 95% confidence level. This result indicates that the presence of UBER in an area with a high number of public transit agency rides is expected to decrease the number of rides for the public transit agency in that area by a further 1.11%, keeping everything else the same.

1.6 Regression 5

The fifth regression is:

$$\log Y_{it} = \eta_i + \delta_t + \beta_1 D_{it} + \beta_2 D_{it} P_{it} + \gamma W_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created

-D is treatUberX
-D * P is the product between the newly-created P column and the 'treatUberX' column
-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHT-Total, VOMSTotal, VRMTotal, gasPrice

It is identical to the third regression. However, I will estimate this regression this time through LASSO. Prior to running LASSO I will scale the variables using sklearn's StandardScaler. I will select the LASSO penalty parameter in this case through 5-fold cross-validation.

[15]:
```
y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()

d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

x_uberx = pd.concat([d_uberx, dp_uberx, w, agency_dummies, date_dummies],␣
 ↪axis=1)

scaler5 = StandardScaler()
x_uberx = scaler5.fit_transform(x_uberx)

lasso5 = LassoCV(cv = 5, fit_intercept = False)
model5 = lasso5.fit(x_uberx, y)

coefficients = model5.coef_
feature_names = ['treatUberX', 'D*P'] + w.columns.tolist() + agency_dummies.
 ↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

print(coef_df.head(2))
```

```
      Feature  Coefficient
0  treatUberX          0.0
1         D*P          0.0
```

The coefficient of treatUberX in this regression i s 0 , indicating that the presence o f U BER i n a MSA is not expected to impact the number of rides for the public transit agency in that area.

The coefficient of D * P is 0, indicating that the presence of UBER in a larger MSA is not expected to further impact the number of rides for the public transit agency in that area.

1.7 Regression 6

The sixth regression is:

$$\log Y_{it} = \eta_i + \delta_t + \beta_1 D_{it} + \beta_2 D_{it} F_{it} + \gamma W_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * F is the product between the newly-created F column and the 'treatUberX' column.
-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHT-Total, VOMSTotal, VRMTotal, gasPrice

It is identical to the fourth regression. However, I will estimate this regression this time through LASSO. Prior to running LASSO I will scale the independent variables using sklearn's Standard-Scaler. I will select the LASSO penalty parameter in this case through 5-fold cross-validation.

[16]:
```
y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()

d_uberx = df['treatUberX'].copy()
df_uberx = df['D*F'].copy()

x_uberx = pd.concat([d_uberx,df_uberx, w, date_dummies, agency_dummies], axis=1)

scaler6 = StandardScaler()
x_uberx = scaler6.fit_transform(x_uberx)

lasso6 = LassoCV(cv = 5, fit_intercept = False)
model6 = lasso6.fit(x_uberx, y)

coefficients = model6.coef_
feature_names = ['treatUberX', 'D*F'] + w.columns.tolist() + agency_dummies.
 ↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

print(coef_df.head(2))
```

```
      Feature  Coefficient
0  treatUberX          0.0
1         D*F          0.0
```

The coefficient of treatUberX in this regression is 0, indicating that the presence of UBER in a MSA is not expected to impact the number of rides for the public transit agency in that area.

The coefficient of D * F is 0, indicating the presence of UBER in an area with a high number of public transit agency rides is not expected to further impact the number of rides for the public transit agency in that area.

1.8 Regression 7

The seventh regression is:

$$\log Y_{it} = \eta_i + \delta_t + \beta_1 D_{it} + \beta_2 D_{it} P_{it} + \gamma W_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * P is the product between the newly-created P column and the 'treatUberX' column.
-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHT-Total, VOMSTotal, VRMTotal, gasPrice

This regression is identical to the third and fifth regressions. However, this time I will obtain estimates for beta1 and beta2 through Double Lasso. I first focus on obtaining a coefficient for beta1 through Double Lasso. To do so, I will first run Lasso of Y on the variables from above. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from LASSO are different from 0 in a list i call 'nz1'.

[17]:
```
y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()

d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

x_uberx = pd.concat([d_uberx, dp_uberx, w, agency_dummies, date_dummies],␣
 ↪axis=1)

scaler7 = StandardScaler()
x_uberx = scaler7.fit_transform(x_uberx)

lasso7 = LassoCV(cv = 5, fit_intercept = False)
model7 = lasso7.fit(x_uberx, y)

coefficients = model7.coef_

feature_names = ['treatUberX', 'D*P'] + w.columns.tolist() + agency_dummies.
 ↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

nz1 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

Then, I run LASSO of D (treatUberX)) on all of the other independent variables. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from this LASSO are different from 0 in a list i call 'nz2'.

[18]:
```
w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()
```

```
d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

temp = pd.concat([dp_uberx, w, agency_dummies, date_dummies], axis = 1)

scaler72 = StandardScaler()
temp = scaler72.fit_transform(temp)

lasso72 = LassoCV(cv = 5)
model72 = lasso72.fit(temp, d_uberx)

coefficients72 = model72.coef_

feature_names72 = ['D*P'] + w.columns.tolist() + agency_dummies.columns.
  ↪tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names72, 'Coefficient':␣
  ↪coefficients72})

nz2 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

I also run LASSO of P * D on all of the other independent variables. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from this LASSO are different from 0 in a list I call ‘nz3’.

[19]:
```
w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
  ↪'VRMTotal', 'gasPrice']].copy()

d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

temp2 = pd.concat([d_uberx, w, agency_dummies, date_dummies], axis = 1)

scaler73 = StandardScaler()
temp2 = scaler73.fit_transform(temp2)

lasso73 = LassoCV(cv = 5)
model73 = lasso73.fit(temp2, dp_uberx)

coefficients73 = model73.coef_

feature_names73 = ['treatUberX'] + w.columns.tolist() + agency_dummies.columns.
  ↪tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names73, 'Coefficient':␣
  ↪coefficients73})

nz3 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

To obtain an estimate and standard errors for 'treatUberX', I now run OLS on the unscaled 'treatUberX' and the independent variables that yielded non-zero coefficients in at least one of the first two LASSO regressions.

```
[20]: all_nz = list(set(['treatUberX'] + nz1 + nz2))

      y = df['log_UPTTotal'].copy()

      w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
       ↪'VRMTotal', 'gasPrice']].copy()

      d_uberx = df['treatUberX'].copy()
      dp_uberx = df['D*P'].copy()

      x_uberx = pd.concat([d_uberx, dp_uberx, w, agency_dummies, date_dummies],␣
       ↪axis=1)

      lhs7= x_uberx[all_nz].copy()
      lhs7 = sm.add_constant(lhs7)

      model7final = sm.OLS(y, lhs7).fit()

      summary = model7final.summary()
      coef_table = summary.tables[1]
      titles = coef_table.data[0]
      first_variable_row = []
      for row in coef_table.data:
          if 'treatUberX' in row:
              first_variable_row = row
              break

      df_summary = pd.DataFrame([first_variable_row], columns=titles)
      print(df_summary)
```

```
                       coef    std err          t    P>|t|     [0.025      0.975]
0  treatUberX       -0.0864      0.032     -2.733    0.006     -0.148      -0.024
```

The coefficient of treatUberX in this regression is -0.0864 with a standard error of 0.032. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to decrease the number of rides for the public transit agency in that area by 8.64%, keeping everything else the same.

To obtain an estimate and standard errors for 'D * P', I now run OLS on the unscaled 'treatUberX' and the unscaled independent variables that yielded non-zero coefficients in at least one of the first and third LASSO regressions.

```
[21]: all_nz3 = list(set(['D*P'] + nz1 + nz3))

      lhs72= x_uberx[all_nz3].copy()
```

```
lhs72 = sm.add_constant(lhs72)

model72final = sm.OLS(y, lhs72).fit()

summary = model72final.summary()
coef_table = summary.tables[1]
titles = coef_table.data[0]
first_variable_row = []
for row in coef_table.data:
    if 'D*P' in row:
        first_variable_row = row
        break

df_summary = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary)
```

```
               coef    std err          t    P>|t|     [0.025     0.975]
0  D*P      -0.2231      0.042     -5.346    0.000     -0.305     -0.141
```

The coefficient of D * P in this regression is -0.2231 with a standard error of 0.042. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a large MSA is expected to decrease the number of rides for the public transit agency in that area by a further 22.31%, keeping everything else the same.

1.9 Regression 8

The eighth regression is:

$$\log Y_{it} = \eta_i + \delta_t + \beta_1 D_{it} + \beta_2 D_{it} F_{it} + \gamma W_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * F is the product between the newly-created F column and the 'treatUberX' column.
-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHT-Total, VOMSTotal, VRMTotal, gasPrice

This regression is identical to the fourth and sixth regressions. However, this time I will obtain estimates for beta1 and beta2 through Double Lasso. I first focus on obtaining a coefficient for beta1 through Double Lasso. To do so, I will first run Lasso of Y on the variables from above. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from LASSO are different from 0 in a list I call 'nz4'.

```
[22]: y = df['log_UPTTotal'].copy()

      w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
       ↪'VRMTotal', 'gasPrice']].copy()
```

```
d_uberx = df['treatUberX'].copy()
df_uberx = df['D*F'].copy()

x_uberx = pd.concat([d_uberx, df_uberx, w, agency_dummies, date_dummies],␣
  ↪axis=1)

scaler8 = StandardScaler()
x_uberx = scaler8.fit_transform(x_uberx)

lasso8 = LassoCV(cv = 5, fit_intercept = False)
model8 = lasso8.fit(x_uberx, y)

coefficients2 = model8.coef_

feature_names2 = ['treatUberX', 'D*F'] + w.columns.tolist() + agency_dummies.
  ↪columns.tolist() + date_dummies.columns.tolist()
coef_df8 = pd.DataFrame({'Feature': feature_names2, 'Coefficient':␣
  ↪coefficients2})

nz4 = coef_df8[coef_df8['Coefficient'] != 0]['Feature'].tolist()
```

Then, I run LASSO of D (treatUberX) on all of the other independent variables. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from this LASSO are different from 0 in a list I call 'nz5'.

[23]:
```
w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
  ↪'VRMTotal', 'gasPrice']].copy()

d_uberx = df['treatUberX'].copy()
df_uberx = df['D*F'].copy()

temp3 = pd.concat([df_uberx, w, agency_dummies, date_dummies], axis = 1)

scaler82 = StandardScaler()
temp3 = scaler82.fit_transform(temp3)

lasso82 = LassoCV(cv = 5)
model82 = lasso82.fit(temp3, d_uberx)

coefficients82 = model82.coef_

feature_names82 = ['D*F'] + w.columns.tolist() + agency_dummies.columns.
  ↪tolist() + date_dummies.columns.tolist()
coef_df8 = pd.DataFrame({'Feature': feature_names82, 'Coefficient':␣
  ↪coefficients82})
```

```
nz5 = coef_df8[coef_df8['Coefficient'] != 0]['Feature'].tolist()
```

I also run LASSO of F * D on all of the other independent variables. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from this LASSO are different from 0 in a list I call ‘nz6’.

```
[24]: w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
       ↪'VRMTotal', 'gasPrice']].copy()

      d_uberx = df['treatUberX'].copy()
      df_uberx = df['D*F'].copy()

      temp4 = pd.concat([d_uberx, w, agency_dummies, date_dummies], axis = 1)

      scaler83 = StandardScaler()
      temp4 = scaler83.fit_transform(temp4)

      lasso83 = LassoCV(cv = 5)
      model83 = lasso83.fit(temp4, df_uberx)

      coefficients83 = model83.coef_

      feature_names83 = ['treatUberX'] + w.columns.tolist() + agency_dummies.columns.
       ↪tolist() + date_dummies.columns.tolist()
      coef_df8 = pd.DataFrame({'Feature': feature_names83, 'Coefficient':␣
       ↪coefficients83})

      nz6 = coef_df8[coef_df8['Coefficient'] != 0]['Feature'].tolist()
```

To obtain an estimate and standard errors for ‘treatUberX’, I now run OLS on the unscaled ‘treatUberX’ and the independent variables that yielded non-zero coefficients in at least one of the first two LASSO regressions (that I ran after the “Regression 8” title).

```
[25]: all_nz2 = list(set(['treatUberX'] + nz4 + nz5))

      y = df['log_UPTTotal'].copy()

      w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
       ↪'VRMTotal', 'gasPrice']].copy()

      d_uberx = df['treatUberX'].copy()
      df_uberx = df['D*F'].copy()

      x_uberx = pd.concat([d_uberx, df_uberx, w, agency_dummies, date_dummies],␣
       ↪axis=1)

      lhs8= x_uberx[all_nz2].copy()
      lhs8 = sm.add_constant(lhs8)
```

```
model8final = sm.OLS(y, lhs8).fit()

summary2 = model8final.summary()
coef_table2 = summary2.tables[1]
titles = coef_table2.data[0]
first_variable_row = []
for row in coef_table2.data:
    if 'treatUberX' in row:
        first_variable_row = row
        break

df_summary2 = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary2)
```

```
                    coef    std err          t    P>|t|     [0.025     0.975]
0  treatUberX    -0.0305      0.015     -2.044    0.041     -0.060     -0.001
```

The coefficient of treatUberX in this regression is -0.0305 with a standard error of 0.015. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to decrease the number of rides for the public transit agency in that area by 3.05%, keeping everything else the same.

[26]:
```
y = df['log_UPTTotal'].copy()

all_nz6 = list(set(['D*F'] + nz4 + nz6))

lhs82= x_uberx[all_nz6].copy()
lhs82 = sm.add_constant(lhs82)

model82final = sm.OLS(y, lhs82).fit()

summary2 = model82final.summary()
coef_table2 = summary2.tables[1]
titles = coef_table2.data[0]
first_variable_row = []
for row in coef_table2.data:
    if 'D*F' in row:
        first_variable_row = row
        break

df_summary2 = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary2)
```

```
             coef    std err          t    P>|t|     [0.025     0.975]
0  D*F     2.5126      0.034     74.436    0.000      2.446      2.579
```

The coefficient of D * F in this regression is 2.5126 with a standard error of 0.034. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in an area with a high number of public transit agency rides is expected to increase the number of rides for the public transit agency in that area by a further 251.26%, keeping everything else the same. This result is an exaggeration which occured because of the absence of several variables from this last regression, such as 'gasPrice'. Furthermore, this last regression yielded more exaggerated results, as the coefficient of "treatUberX" is -1.1798. This would mean that the presence of UBER in a MSA is expected to decrease the number of rides for the public transit agency in that area by more than 100%, keeping everything else constant.

1.10 Regression 9

The ninth regression is:

$$\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}P_{it}\beta_2 + \gamma \tilde{W}'_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * P is the product between the newly-created P column and the 'treatUberX' column.
-W~, which includes all interactions of order 5 of variables in the vector W

I will estimate this regression this through LASSO. Prior to running LASSO I will scale the variables using sklearn's StandardScaler. I will select the LASSO penalty parameter in this case through 5-fold cross-validation.

[27]:
```
y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
↪'VRMTotal', 'gasPrice']].copy()

polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

x_uberx = pd.concat([d_uberx, dp_uberx, wnew, agency_dummies, date_dummies],␣
↪axis=1)
x_uberx.columns = x_uberx.columns.astype('str')

scaler9 = StandardScaler()
x_uberx = scaler9.fit_transform(x_uberx)

lasso9 = LassoCV(cv = 5, fit_intercept = False)
model9 = lasso9.fit(x_uberx, y)

coefficients = model9.coef_
```

```
feature_names = ['treatUberX', 'D*P'] + wnew.columns.tolist() + agency_dummies.
↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

print(coef_df.head(2))
```

```
      Feature  Coefficient
0  treatUberX          0.0
1         D*P          0.0
```

The coefficient of treatUberX in this regression is 0, indicating that the presence of UBER in a MSA is not expected to impact the number of rides for the public transit agency in that area.

The coefficient of D * P is 0, indicating that the presence of UBER in a larger MSA is not expected to further impact the number of rides for the public transit agency in that area.

1.11 Regression 10

The tenth regression is:

$$\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}F_{it}\beta_2 + \gamma\tilde{W}'_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * F is the product between the newly-created F column and the 'treatUberX' column
-W includes all interactions of order 5 of variables in the vector W

I will estimate this regression through LASSO. Prior to running LASSO I will scale the variables using sklearn's StandardScaler. I will select the LASSO penalty parameter in this case through 5-fold cross-validation.

[28]:
```
y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
↪'VRMTotal', 'gasPrice']].copy()

polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
df_uberx = df['D*F'].copy()

x_uberx = pd.concat([d_uberx, df_uberx, wnew, agency_dummies, date_dummies],␣
↪axis=1)
x_uberx.columns = x_uberx.columns.astype('str')
```

```
scaler10 = StandardScaler()
x_uberx = scaler10.fit_transform(x_uberx)

lasso10 = LassoCV(cv = 5, fit_intercept = False)
model10 = lasso10.fit(x_uberx, y)

coefficients = model10.coef_
feature_names = ['treatUberX', 'D*F'] + wnew.columns.tolist() + agency_dummies.
  ↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

print(coef_df.head(2))
```

```
      Feature  Coefficient
0  treatUberX          0.0
1         D*F          0.0
```

The coefficient o f treatUberX in this regression i s 0 , indicating that the presence o f U BER i n a MSA is not expected to impact the number of rides for the public transit agency in that area.

The coefficient o f D * F is 0 , indicating that the presence o f UBER in an area with a high number of public transit agency rides is not expected to impact the number of rides for the public transit agency in that area.

1.12 Regression 11

The eleventh regression is:

$$\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}P_{it}\beta_2 + \gamma\tilde{W}'_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * P is the product between the newly-created P column and the 'treatUberX' column.
-W includes all interactions of order 5 of variables in the vector W

This regression is identical to the ninth regression. However, this time I will obtain estimates for beta1 and beta2 through Double Lasso. I first focus on obtaining a coefficient for beta 1 through Double Lasso. To do so, I will first run Lasso of Y on the variables from above. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from LASSO are different from 0 in a list I call 'nz111'.

[29]:
```
y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
  ↪'VRMTotal', 'gasPrice']].copy()
```

```
polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

x_uberx = pd.concat([d_uberx, dp_uberx, wnew, agency_dummies, date_dummies],␣
 ↪axis=1)
x_uberx.columns = x_uberx.columns.astype('str')

scaler111 = StandardScaler()
x_uberx = scaler111.fit_transform(x_uberx)

lasso111 = LassoCV(cv = 5, fit_intercept = False)
model111 = lasso111.fit(x_uberx, y)

coefficients = model111.coef_

feature_names = ['treatUberX', 'D*P'] + wnew.columns.tolist() + agency_dummies.
 ↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

nz111 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

Then, I run LASSO of D (treatUberX) on all of the other independent variables. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from this LASSO are different from 0 in a list i call 'nz112'.

[30]:
```
w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()

polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

temp = pd.concat([dp_uberx, wnew, agency_dummies, date_dummies], axis = 1)
temp.columns = temp.columns.astype('str')

scaler112 = StandardScaler()
temp = scaler112.fit_transform(temp)

lasso112 = LassoCV(cv = 5)
model112 = lasso112.fit(temp, d_uberx)

coefficients112 = model112.coef_
```

```
feature_names112 = ['D*P'] + wnew.columns.tolist() + agency_dummies.columns.
  ↪tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names112, 'Coefficient':␣
  ↪coefficients112})

nz112 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

I also run LASSO of P * D on all of the other independent variables. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from this LASSO are different from 0 in a list I call 'nz113'.

[31]:
```
w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
  ↪'VRMTotal', 'gasPrice']].copy()

polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

temp2 = pd.concat([d_uberx, wnew, agency_dummies, date_dummies], axis = 1)
temp2.columns = temp2.columns.astype('str')

scaler113 = StandardScaler()
temp2 = scaler113.fit_transform(temp2)

lasso113 = LassoCV(cv = 5)
model113 = lasso113.fit(temp2, dp_uberx)

coefficients113 = model113.coef_

feature_names113 = ['treatUberX'] + wnew.columns.tolist() + agency_dummies.
  ↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names113, 'Coefficient':␣
  ↪coefficients113})

nz113 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

To obtain an estimate and standard errors for 'treatUberX', I now run OLS on the unscaled 'treatUberX' and the independent variables that yielded non-zero coefficients in at least one of the first two LASSO regressions.

[32]:
```
all_nz = list(set(['treatUberX'] + nz111 + nz112))

y = df['log_UPTTotal'].copy()
```

```
w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()
polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
dp_uberx = df['D*P'].copy()

x_uberx = pd.concat([d_uberx, dp_uberx, wnew, agency_dummies, date_dummies],␣
 ↪axis=1)

x_uberx.columns = x_uberx.columns.map(str)

all_nz = list(map(str, all_nz))

all_nz_filtered = [col for col in all_nz if col in x_uberx.columns]

lhs111 = x_uberx[all_nz_filtered]
lhs111 = sm.add_constant(lhs111)

model111final = sm.OLS(y, lhs111).fit()

summary = model111final.summary()
coef_table = summary.tables[1]
titles = coef_table.data[0]
first_variable_row = []
for row in coef_table.data:
    if 'treatUberX' in row:
        first_variable_row = row
        break

df_summary = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary)
```

```
                      coef    std err          t   P>|t|      [0.025      0.975]
0  treatUberX   1.899e-07   3.19e-09     59.574   0.000    1.84e-07    1.96e-07
```

The coefficient of treatUberX in this regression is 1.899e-07 with a standard error of 3.19e-09. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to increase the number of rides for the public transit agency in that area by a very small amount, keeping everything else the same.

To obtain an estimate and standard errors for 'D * P', I now run OLS on the unscaled 'treatUberX' and the unscaled independent variables that yielded non-zero coefficients in at least one of the first and third LASSO regressions.

```
[33]: all_nz112 = list(set(['D*P'] + nz111 + nz113))
```

```
all_nz112 = list(map(str, all_nz112))

all_nz112_filtered = [col for col in all_nz112 if col in x_uberx.columns]

lhs112= x_uberx[all_nz112_filtered].copy()
lhs112 = sm.add_constant(lhs112)

model112final = sm.OLS(y, lhs112).fit()

summary = model112final.summary()
coef_table = summary.tables[1]
titles = coef_table.data[0]
first_variable_row = []
for row in coef_table.data:
    if 'D*P' in row:
        first_variable_row = row
        break

df_summary = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary)
```

```
              coef    std err          t    P>|t|     [0.025     0.975]
0  D*P     -0.2213      0.042     -5.308    0.000     -0.303     -0.140
```

The ceofficient of D * P in this regression is -0.2213 with a standard error of 0.042. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a large MSA is expected to decrease the number of rides for the public transit agency in that area by a further 22.13%, keeping everything else the same.

1.13 Regression 12

The twelth regression is:

$$\log Y_{it} = \eta_i + \delta_t + D_{it}\beta_1 + D_{it}F_{it}\beta_2 + \gamma\tilde{W}'_{it} + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-tau is the year-month dummy I previously created
-D is treatUberX
-D * F is the product between the newly-created F column and the 'treatUberX' column
-W includes all interactions of order 5 of variables in the vector W

This regression is identical to the tenth regression. However, this time I will obtain estimates for beta1 and beta2 through Double Lasso. I first focus on obtaining a coefficient for beta1 through Double Lasso. To do so, I will first run Lasso of Y on the variables from above. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from LASSO are different from 0 in a list I call 'nz121'

[34]:
```
y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()

polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
df_uberx = df['D*F'].copy()

x_uberx = pd.concat([d_uberx, df_uberx, wnew, agency_dummies, date_dummies],␣
 ↪axis=1)
x_uberx.columns = x_uberx.columns.astype('str')

scaler121 = StandardScaler()
x_uberx = scaler121.fit_transform(x_uberx)

lasso121 = LassoCV(cv = 5, fit_intercept = False)
model121 = lasso121.fit(x_uberx, y)

coefficients = model121.coef_

feature_names = ['treatUberX', 'D*F'] + wnew.columns.tolist() + agency_dummies.
 ↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

nz121 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

Then, I run LASSO of D (treatUberX) on all of the other independent variables. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from this LASSO are different from 0 in a list I call 'nz122'.

[35]:
```
w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()

polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
df_uberx = df['D*F'].copy()

temp = pd.concat([df_uberx, wnew, agency_dummies, date_dummies], axis = 1)
temp.columns = temp.columns.astype('str')

scaler122 = StandardScaler()
temp = scaler122.fit_transform(temp)
```

```
lasso122 = LassoCV(cv = 5)
model122 = lasso122.fit(temp, d_uberx)

coefficients122 = model122.coef_

feature_names122 = ['D*F'] + wnew.columns.tolist() + agency_dummies.columns.
  ↪tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names122, 'Coefficient':␣
  ↪coefficients122})

nz122 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

I also run LASSO of F * D on all of the other independent variables. Again, I obtain the regularization parameter for LASSO through cross-validation. Then, I store the name of variables whose coefficients from this LASSO are different from 0 in a list I call ‘nz123’

[36]:
```
w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
  ↪'VRMTotal', 'gasPrice']].copy()

polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
df_uberx = df['D*F'].copy()

temp2 = pd.concat([d_uberx, wnew, agency_dummies, date_dummies], axis = 1)
temp2.columns = temp2.columns.astype('str')

scaler123 = StandardScaler()
temp2 = scaler123.fit_transform(temp2)

lasso123 = LassoCV(cv = 5)
model123 = lasso123.fit(temp2, df_uberx)

coefficients123 = model123.coef_

feature_names123 = ['treatUberX'] + wnew.columns.tolist() + agency_dummies.
  ↪columns.tolist() + date_dummies.columns.tolist()
coef_df = pd.DataFrame({'Feature': feature_names123, 'Coefficient':␣
  ↪coefficients123})

nz123 = coef_df[coef_df['Coefficient'] != 0]['Feature'].tolist()
```

To obtain an estimate and standard errors for ‘treatUberX’, I now run OLS on the unscaled ‘treatUberX’ and the independent variables that yielded non-zero coefficients in at least one of the first two LASSO regressions.

```
[37]: all_nz = list(set(['treatUberX'] + nz121 + nz122))

y = df['log_UPTTotal'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
 ↪'VRMTotal', 'gasPrice']].copy()
polint = PolynomialFeatures(degree=5, include_bias=False)
wnew = pd.DataFrame(polint.fit_transform(w))

d_uberx = df['treatUberX'].copy()
df_uberx = df['D*F'].copy()

x_uberx = pd.concat([d_uberx, df_uberx, wnew, agency_dummies, date_dummies],␣
 ↪axis=1)

x_uberx.columns = x_uberx.columns.map(str)


all_nz_filtered = [col for col in all_nz if col in x_uberx.columns]

lhs121 = x_uberx[all_nz_filtered]
lhs121 = sm.add_constant(lhs121)

model121final = sm.OLS(y, lhs121).fit()

summary = model121final.summary()
coef_table = summary.tables[1]
titles = coef_table.data[0]
first_variable_row = []
for row in coef_table.data:
    if 'treatUberX' in row:
        first_variable_row = row
        break

df_summary = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary)
```

```
                    coef    std err          t    P>|t|     [0.025     0.975]
0  treatUberX    -0.0725      0.029     -2.498    0.013     -0.129     -0.016
```

The coefficient of treatUberX in this regression is - 0.0725 with a standard error o f 0.029. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to decrease the number of rides for the public transit agency in that area by 7.25%, keeping everything else the same.

To obtain an estimate and standard errors for ‘D * F’, I now run OLS on the unscaled ‘treatUberX’ and the unscaled independent variables that yielded non-zero coefficients in at least one of the first and third LASSO regressions.

[38]:
```
all_nz122 = list(set(['D*F'] + nz121 + nz123))

all_nz122 = list(map(str, all_nz122))

all_nz122_filtered = [col for col in all_nz122 if col in x_uberx.columns]

lhs122= x_uberx[all_nz122_filtered].copy()
lhs122 = sm.add_constant(lhs122)

model122final = sm.OLS(y, lhs122).fit()

summary = model122final.summary()
coef_table = summary.tables[1]
titles = coef_table.data[0]
first_variable_row = []
for row in coef_table.data:
    if 'D*F' in row:
        first_variable_row = row
        break

df_summary = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary)
```

```
              coef    std err          t    P>|t|     [0.025     0.975]
0  D*F      2.4669      0.034     72.994    0.000      2.401      2.533
```

The coefficient of D * F in this regression is 2.4669 with a standard error of 0.034. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in an area with a high number of public transit agency rides is expected to increase the number of rides for the public transit agency in that area by a further 246.69%, keeping everything else the same. This result is an exaggeration which occured because of the absence of several variables from this last regression, such as 'gasPrice'. Furthermore, this last regression yielded more exaggerated results, as the coefficient of "treatUberX" is - 1.1699. This is equivalent to saying that the presence of UBER in a MSA is expected to decrease the number of rides for the public transit agency in that area by more than 100%, keeping everything else constant.

1.14 Bonus Regression

The bonus regression is:

$$\log Y_{it} = \alpha + \eta_i + D_{it}\beta_1 + \gamma W_{it}' + \epsilon_{it}$$

Where:

-eta is the agency dummy that I previously created
-D is treatUberX

-W is the vector including remaining variables: popestimate, employment, aveFareTotal, VRHT-Total, VOMSTotal, VRMTotal, gasPrice

This regression does not include the year-month dummy and will be estimated through OLS.

[39]:
```
df['log_UPTTotal'] = np.log(df['UPTTotal'])y = df['log_UPTTotal'].copy()



d_uberx = df['treatUberX'].copy()

w = df[['popestimate', 'employment', 'aveFareTotal', 'VRHTotal', 'VOMSTotal',␣
  ↪'VRMTotal', 'gasPrice']].copy()
w = sm.add_constant(w)

x_uberx = pd.concat([d_uberx, w, agency_dummies], axis=1)

modelb = sm.OLS(y, x_uberx).fit()

summary = modelb.summary()
coef_table = summary.tables[1]
titles = coef_table.data[0]
first_variable_row = []
for row in coef_table.data:
  if 'treatUberX' in row:
    first_variable_row = row
    break

df_summary = pd.DataFrame([first_variable_row], columns=titles)
print(df_summary)
```

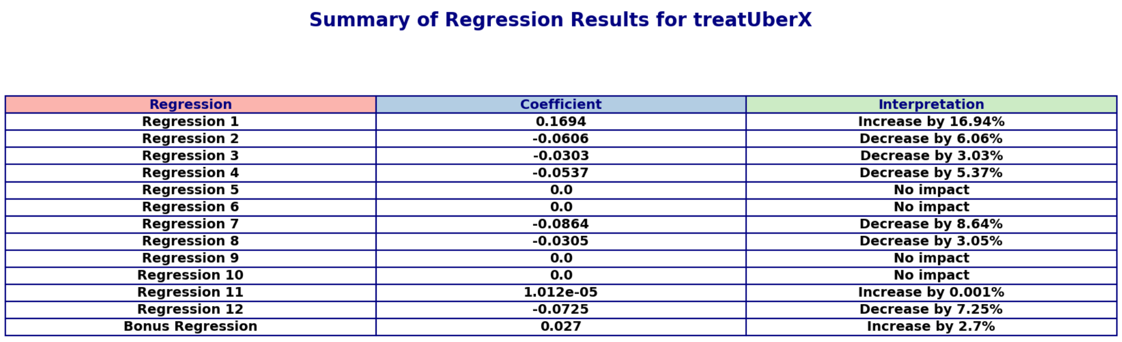
```
                   coef    std err          t    P>|t|     [0.025     0.975]
0  treatUberX    0.0270      0.004      6.326    0.000      0.019      0.035
```

The coefficient of treatUberX in this regression is 0.0270 with a standard error of 0.004. This result is statistically significant at the 95% confidence level. This result indicates that the presence of UBER in a MSA is expected to increase the number of rides for the public transit agency in that area by 2.7%, keeping everything else the same.

1.15 Summary Tables

[40]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import font_manager

# Data for treatUberX
```

```
data_treatUberX = {
    'Regression': [
        'Regression 1', 'Regression 2', 'Regression 3', 'Regression 4',
        'Regression 5', 'Regression 6', 'Regression 7', 'Regression 8',
        'Regression 9', 'Regression 10', 'Regression 11', 'Regression 12',
        'Bonus Regression'
    ],
    'Coefficient': [
        0.1694, -0.0606, -0.0303, -0.0537,
        0.0, 0.0, -0.0864, -0.0305,
        0.0, 0.0, 1.012e-05, -0.0725,
        0.0270
    ],
    'Interpretation': [
        'Increase by 16.94%', 'Decrease by 6.06%', 'Decrease by 3.03%',␣
 ↪'Decrease by 5.37%',
        'No impact', 'No impact', 'Decrease by 8.64%', 'Decrease by 3.05%',
        'No impact', 'No impact', 'Increase by 0.001%', 'Decrease by 7.25%',
        'Increase by 2.7%'
    ]
}

# Convert to DataFrame
df_treatUberX = pd.DataFrame(data_treatUberX)

# Plotting the table for treatUberX
fig, ax = plt.subplots(figsize=(14, 7))
ax.axis('off')
font_properties = font_manager.FontProperties(family='DejaVu Sans',␣
 ↪weight='bold', size=14)

colors = sns.color_palette("Pastel1", len(df_treatUberX.columns))
tbl = ax.table(
    cellText=df_treatUberX.values,
    colLabels=df_treatUberX.columns,
    cellLoc='center',
    loc='center',
    colColours=colors
)
tbl.auto_set_font_size(False)
tbl.set_fontsize(12)
tbl.scale(1.5, 1.5)
for key, cell in tbl.get_celld().items():
    cell.set_edgecolor('navy')
    cell.set_linewidth(1.5)
    if key[0] == 0:
        cell.get_text().set_fontproperties(font_properties)
        cell.get_text().set_color('navy')
    cell.get_text().set_fontproperties(font_properties)
    cell.PAD = 0.3
ax.set_title('Summary of Regression Results for treatUberX', fontsize=20,␣
 ↪fontweight='bold', color='navy', fontname='DejaVu Sans')
ax.title.set_position([0.5, 1.1])  # Adjust spacing

plt.show()
```

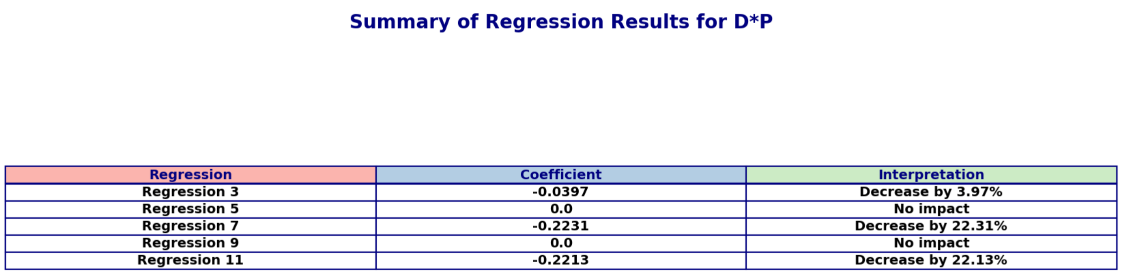


Summary of Regression Results for treatUberX

Regression	Coefficient	Interpretation
Regression 1	0.1694	Increase by 16.94%
Regression 2	-0.0606	Decrease by 6.06%
Regression 3	-0.0303	Decrease by 3.03%
Regression 4	-0.0537	Decrease by 5.37%
Regression 5	0.0	No impact
Regression 6	0.0	No impact
Regression 7	-0.0864	Decrease by 8.64%
Regression 8	-0.0305	Decrease by 3.05%
Regression 9	0.0	No impact
Regression 10	0.0	No impact
Regression 11	1.012e-05	Increase by 0.001%
Regression 12	-0.0725	Decrease by 7.25%
Bonus Regression	0.027	Increase by 2.7%

[41]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import font_manager

# Data for D*P
data_DP = {
    'Regression': [
        'Regression 3', 'Regression 5', 'Regression 7', 'Regression 9',␣
 ↪'Regression 11'
    ],
    'Coefficient': [
        -0.0397, 0.0, -0.2231, 0.0, -0.2213
    ],
    'Interpretation': [
        'Decrease by 3.97%', 'No impact', 'Decrease by 22.31%', 'No impact',␣
 ↪'Decrease by 22.13%'
    ]
}

# Convert to DataFrame
df_DP = pd.DataFrame(data_DP)
```

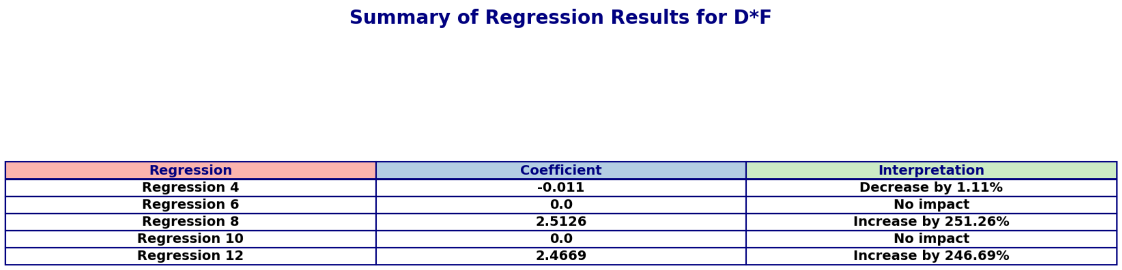
```python
# Plotting the table for D*P
fig, ax = plt.subplots(figsize=(14, 7))
ax.axis('off')
font_properties = font_manager.FontProperties(family='DejaVu Sans', weight='bold', size=14)

colors = sns.color_palette("Pastel1", len(df_DP.columns))
tbl = ax.table(
    cellText=df_DP.values,
    colLabels=df_DP.columns,
    cellLoc='center',
    loc='center',
    colColours=colors
)
tbl.auto_set_font_size(False)
tbl.set_fontsize(12)
tbl.scale(1.5, 1.5)
for key, cell in tbl.get_celld().items():
    cell.set_edgecolor('navy')
    cell.set_linewidth(1.5)
    if key[0] == 0:
        cell.get_text().set_fontproperties(font_properties)
        cell.get_text().set_color('navy')
    cell.get_text().set_fontproperties(font_properties)
    cell.PAD = 0.3
ax.set_title('Summary of Regression Results for D*P', fontsize=20, fontweight='bold', color='navy', fontname='DejaVu Sans')
ax.title.set_position([0.5, 1.05])  # Decrease the distance between title and table

plt.show()
```



Summary of Regression Results for D*P

Regression	Coefficient	Interpretation
Regression 3	-0.0397	Decrease by 3.97%
Regression 5	0.0	No impact
Regression 7	-0.2231	Decrease by 22.31%
Regression 9	0.0	No impact
Regression 11	-0.2213	Decrease by 22.13%

```
[42]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import font_manager

# Data for D*F
data_DF = {
    'Regression': [
        'Regression 4', 'Regression 6', 'Regression 8', 'Regression 10',␣
 ↪'Regression 12'
    ],
    'Coefficient': [
        -0.0110, 0.0, 2.5126, 0.0, 2.4669
    ],
    'Interpretation': [
        'Decrease by 1.11%', 'No impact', 'Increase by 251.26%', 'No impact',␣
 ↪'Increase by 246.69%'
    ]
}

# Convert to DataFrame
df_DF = pd.DataFrame(data_DF)

# Plotting the table for D*F
fig, ax = plt.subplots(figsize=(14, 7))
ax.axis('off')
font_properties = font_manager.FontProperties(family='DejaVu Sans',␣
 ↪weight='bold', size=14)

colors = sns.color_palette("Pastel1", len(df_DF.columns))
tbl = ax.table(
    cellText=df_DF.values,
    colLabels=df_DF.columns,
    cellLoc='center',
    loc='center',
    colColours=colors
)
tbl.auto_set_font_size(False)
tbl.set_fontsize(12)
tbl.scale(1.5, 1.5)
for key, cell in tbl.get_celld().items():
    cell.set_edgecolor('navy')
    cell.set_linewidth(1.5)
    if key[0] == 0:
        cell.get_text().set_fontproperties(font_properties)
        cell.get_text().set_color('navy')
    cell.get_text().set_fontproperties(font_properties)
    cell.PAD = 0.3
ax.set_title('Summary of Regression Results for D*F', fontsize=20,␣
↪fontweight='bold', color='navy', fontname='DejaVu Sans')
ax.title.set_position([0.5, 1.05])  # Decrease the distance between title and␣
↪table

plt.show()
```



Summary of Regression Results for D*F

Regression	Coefficient	Interpretation
Regression 4	-0.011	Decrease by 1.11%
Regression 6	0.0	No impact
Regression 8	2.5126	Increase by 251.26%
Regression 10	0.0	No impact
Regression 12	2.4669	Increase by 246.69%

1.16 Conclusion

While the effect of Uber on Public Transit is uncertain, most of the regressions where I employed some type of variable selection (through either LASSO or Double-LASSO) yielded negative statistically significant coefficients for the treatment variable, 'treatUberX'. This indicated that when analyzing the variables with a high predictive power for the number of rides in an MSA, the presence of Uber in that MSA will likely have a negative effect on the number of rides in the MSA.

To reach a more decisive conclusion with regard to the effect of Uber presence on the number of rides from an MSA, it would be useful to have additional covariates, such as the efficiency of the public transit in an MSA and the cleanliness of public transit vehicles in an MSA.