Global Emissions & Electric Vehicles

GREEN WAVE TEAM

KOBE PHO
Job Title

RUCHITA
Job Title

MICHAEL
Job Title

TARINI
Job Title

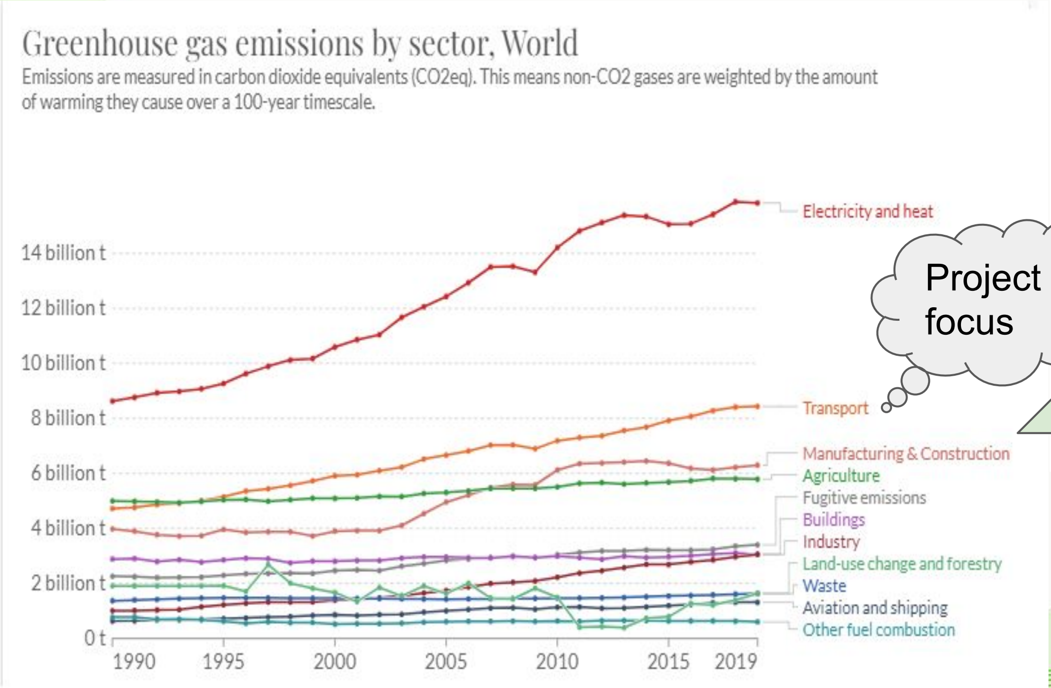
AVNEESH
Job Title

Contents:

THE CALL FOR REDUCING GREENHOUSE GAS EMISSIONS

- CO2 is the major contributor to climate change.
- Reducing carbon emissions is of extreme importance.
- In order to actually get there, it would be necessary to reduce the greenhouse emissions to zero and then fix the past damage by drawing down on past emissions.

Overall Picture for GHG emissions



Project focus

CO2

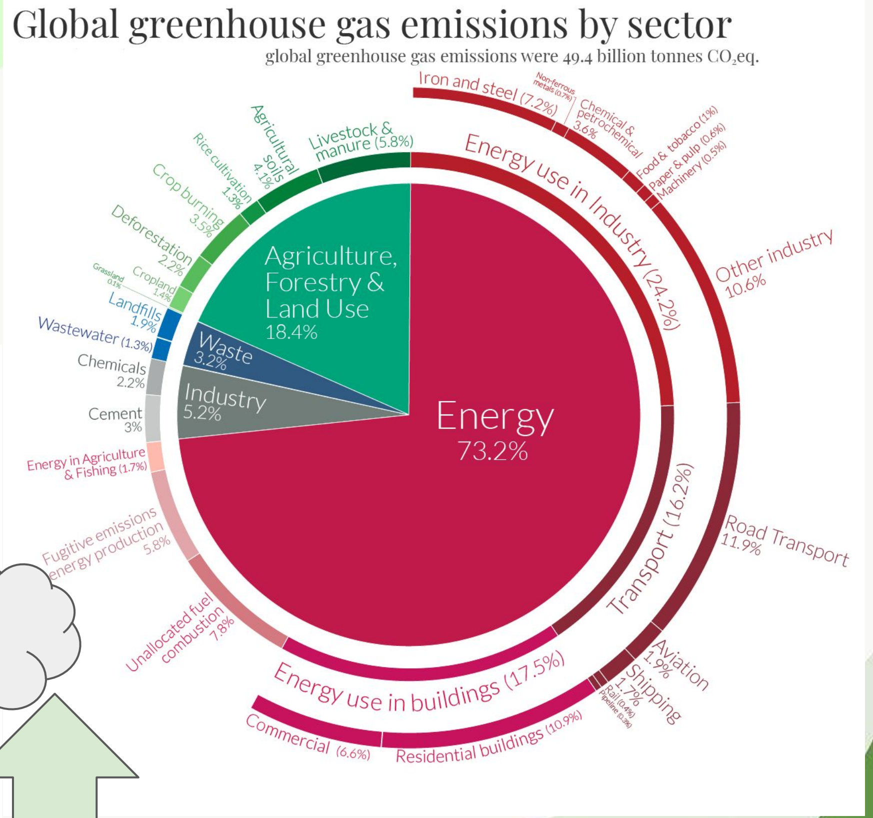
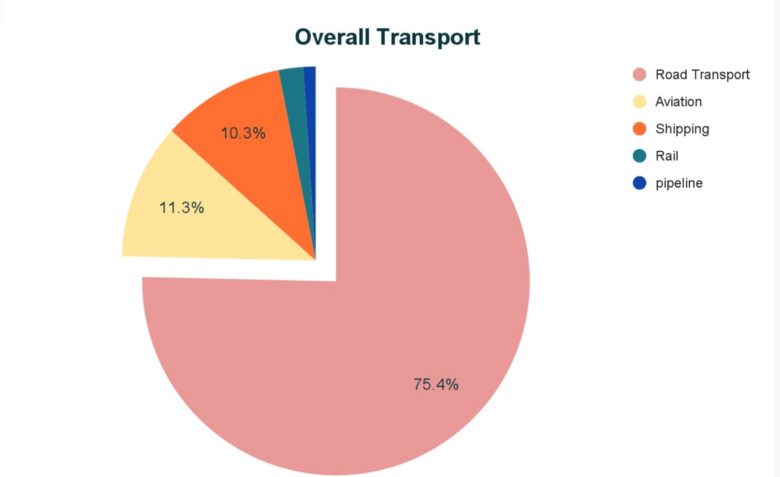
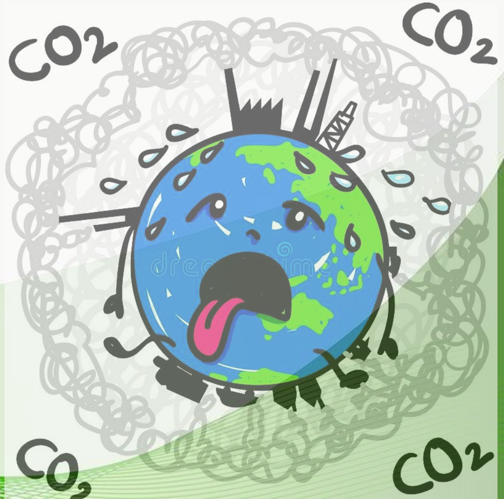


Image source: ourworlddata.org

Around the world, huge percentage of Greenhouse gases come from cars. For each gallon of gas a car burns, it releases about 19 pounds of carbon dioxide comes right out of the tailpipe emissions.





Data Collection/Sources

Data Source:

https://ourworldindata.org/

https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

https://www.iea.org/articles/global-ev-data-explorer

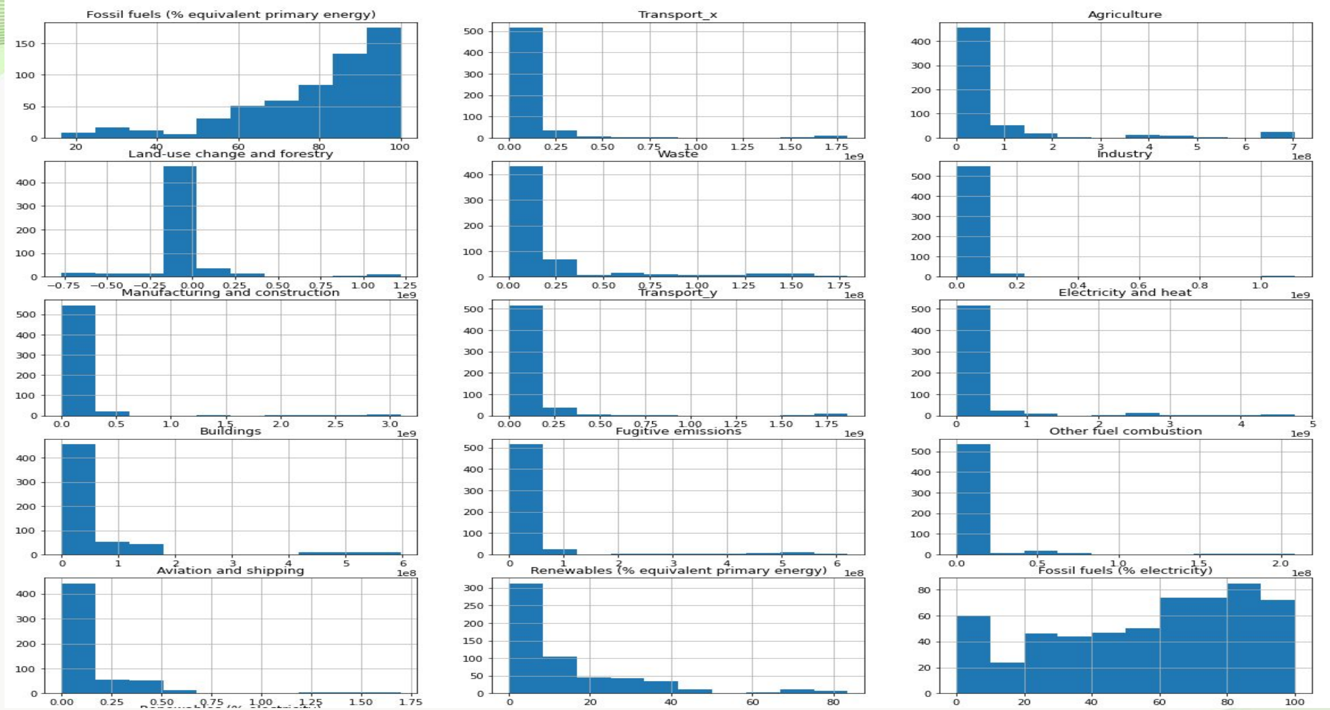
Data Description/Preparation

- Overall GHG emissions by sector.
- Market demand of all vehicles types (Diesel, Electric, Hybrid, etc.)
- Merged multiple datasets based on country and year as join keys.

Data Cleaning/Wrangling

- ➔ Dropped empty values(200 Nan values).
- ➔ Data type corrections(object to int).
- ➔ Matched mapping of country names.

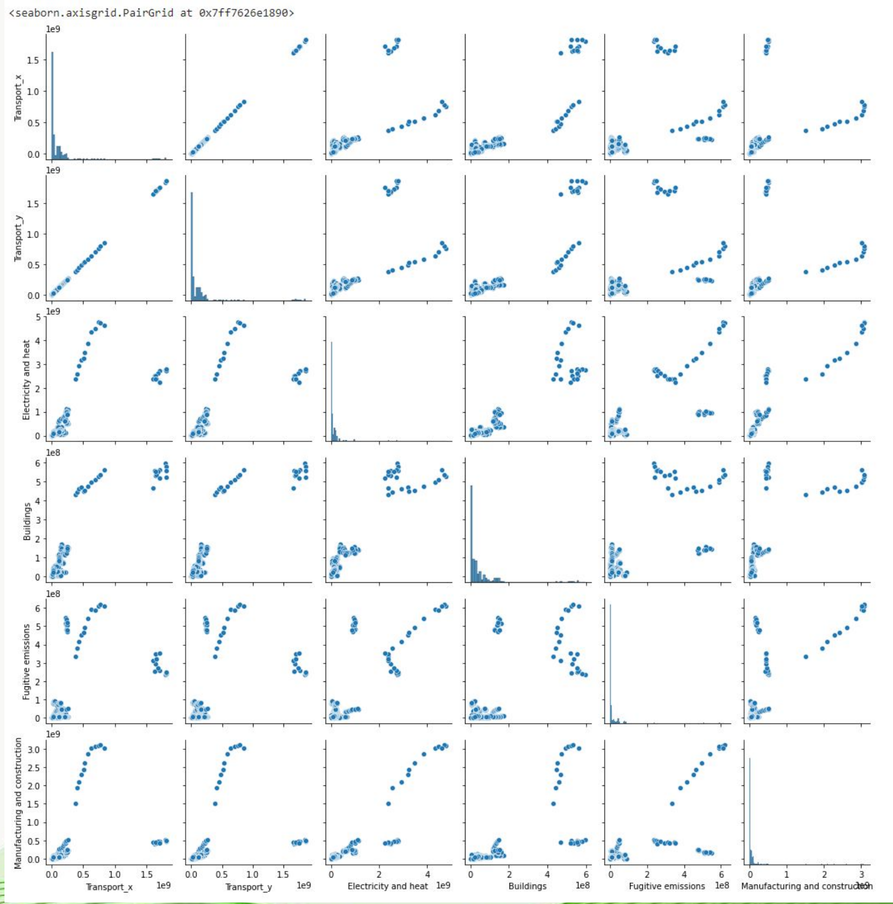
Univariate Analysis



➔ Used univariate analysis to detect and remove outliers and applied log transformation to skewed features.

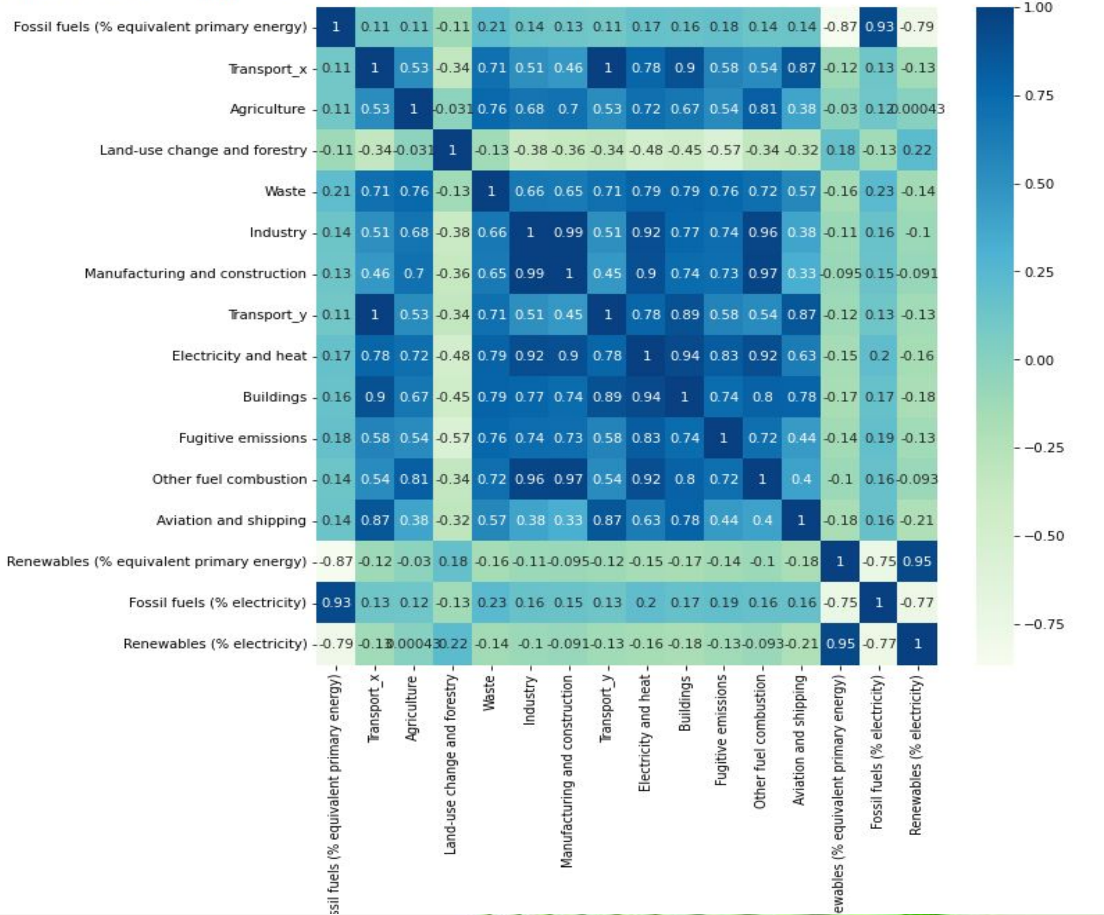
Multivariate Analysis

- ➔ Used multivariate analysis to detect feature significance and correlation across features.
- ➔ Transport_x is only CO2 emissions while Transport_y is overall GHG emissions including CO2. This is evident from the scatter plots.
- ➔ We can clearly see correlations between various sectors that emit greenhouse gases.



Correlation Matrix

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff760a393d0>
```



Machine Learning Design

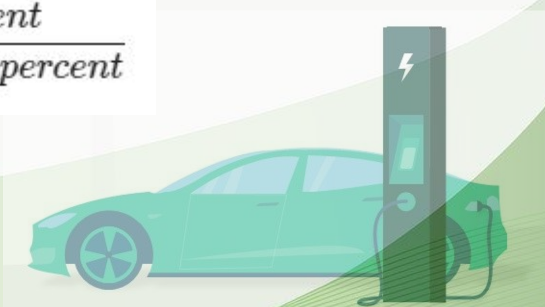
<u>Hypothesis</u>: EV vehicles lead to reduction in overall Greenhouse gases.

X: ghg emissions by sector and energy production by fuel types
Y: CO2 offset due to EV

Target Variable(Y):

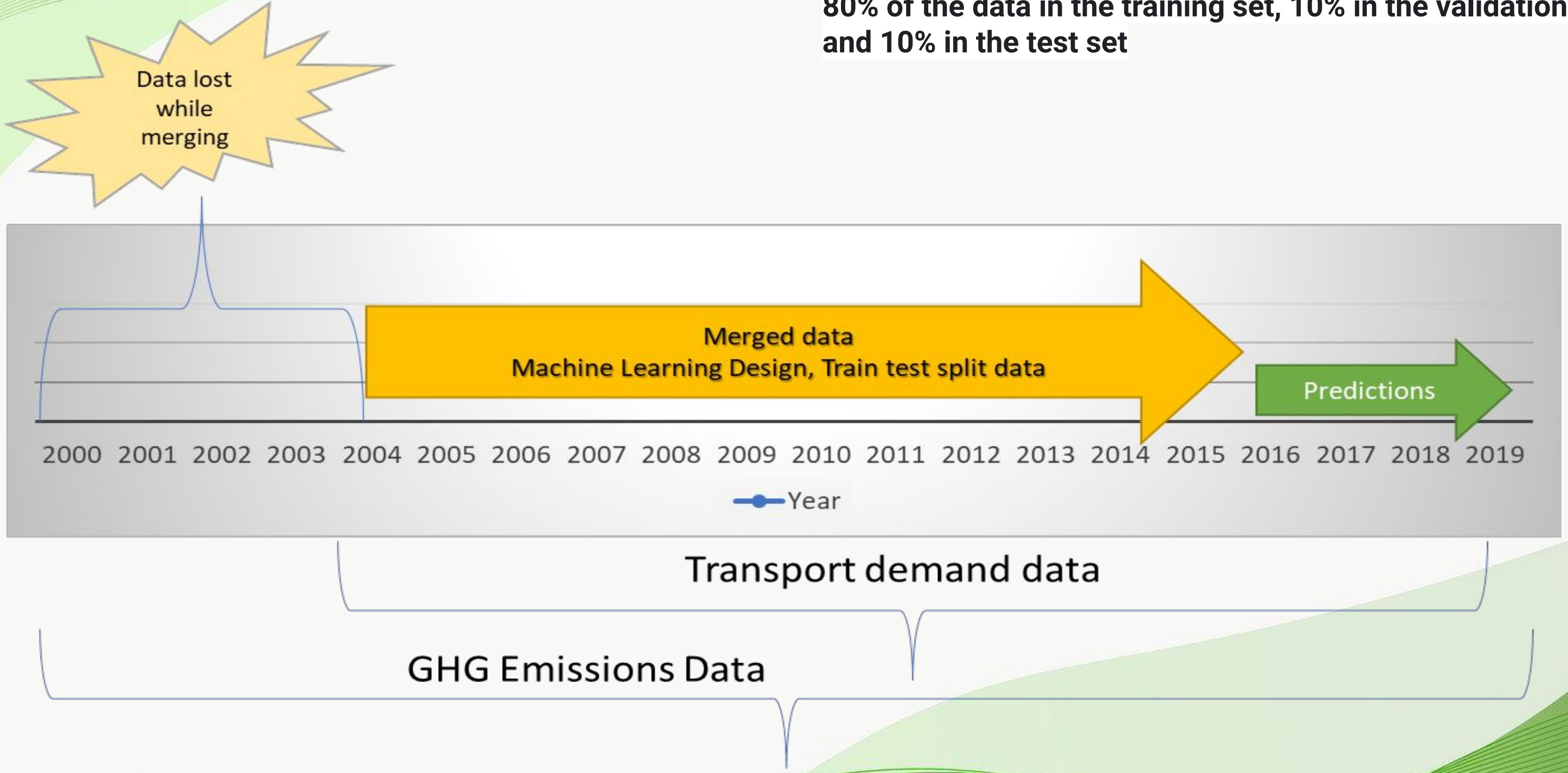
$$ev\_offset = transport\_co2eq\_emissions * \frac{ev\_demand\_percent}{gas\_vehicle\_demand\_percent}$$

<u>Problem Statement</u>:
Create a model that predicts how much CO2-eq by volume is offset by introducing EVs in a market (country+year).



Machine Learning Design

80% of the data in the training set, 10% in the validation set, and 10% in the test set



Linear Regression Model Performance

```
lm.score(X,y)
0.4954363469172296
```

Dropping Electric bike data improved performance by 10%

```
lm.score(X,y)
0.6014439142014962
```

Train-Test-Validation Splits

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1)
```

```
[383] r2_score(y_test, y_predictions)
0.7284700452410147
```

Train-Test-Validation split improved performance by further 12%

Hypothesis Testing

With a P-value threshold of 5 percent, we can see that the expected sectors are significant while predicting CO2 offset from EVs(P-value less than 5%).

- Transport
- Industry
- Manufacturing
- Electricity and Heat
- Buildings
- Fugitive Emissions

We can also see that Primary and Secondary Energy production from Renewables have some significance(P-value close to 5%)

OLS Regression Results

Dep. Variable:	ev_savings	R-squared (uncentered):	0.606
Model:	OLS	Adj. R-squared (uncentered):	0.594
Method:	Least Squares	F-statistic:	53.74
Date:	Sat, 10 Sep 2022	Prob (F-statistic):	6.63e-102
Time:	07:01:15	Log-Likelihood:	-7066.8
No. Observations:	576	AIC:	1.417e+04
Df Residuals:	560	BIC:	1.424e+04
Df Model:	16		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Fossil fuels (% equivalent primary energy)	171.3201	188.151	0.911	0.363	-198.248	540.888
Transport_x	-0.0944	0.006	-16.298	0.000	-0.106	-0.083
Agriculture	3.493e-05	4.07e-05	0.858	0.391	-4.51e-05	0.000
Land-use change and forestry	-1.824e-05	1.96e-05	-0.932	0.352	-5.67e-05	2.02e-05
Waste	-0.0002	0.000	-0.993	0.321	-0.001	0.000
Industry	0.0009	0.000	4.898	0.000	0.001	0.001
Manufacturing and construction	-0.0003	7.58e-05	-3.361	0.001	-0.000	-0.000
Transport_y	0.0915	0.006	16.380	0.000	0.081	0.103
Electricity and heat	-0.0001	4.06e-05	-3.303	0.001	-0.000	-5.44e-05
Buildings	0.0006	0.000	5.249	0.000	0.000	0.001
Fugitive emissions	0.0004	5.71e-05	7.740	0.000	0.000	0.001
Other fuel combustion	0.0004	0.001	0.765	0.444	-0.001	0.002
Aviation and shipping	-3.848e-05	0.000	-0.179	0.858	-0.000	0.000
Renewables (% equivalent primary energy)	921.3666	473.462	1.946	0.052	-8.612	1851.346
Fossil fuels (% electricity)	12.0675	205.053	0.059	0.953	-390.699	414.834
Renewables (% electricity)	-675.0721	332.980	-2.027	0.043	-1329.114	-21.030

Omnibus:	417.162	Durbin-Watson:	0.531
Prob(Omnibus):	0.000	Jarque-Bera (JB):	37756.473
Skew:	2.397	Prob(JB):	0.00
Kurtosis:	42.373	Cond. No.	2.41e+08

Forecasting/Predictions

- Although we do not have the y-values of the target variable(co2_offset/ev_savings) from 2015-19, we do have the input features(X values).
- We used the model to generate predictions and see that the CO2 offset due to EVs is predicted to be increasing year over year, as expected.