Probability Migration Matrix of Switching From

Switching To	Gas Car	Electric Car	Public Transport	Electric Bike	Regular Bike
Gas Car	**0.960797**	**0.02428**	**0.01632** [28]	**0**	**0**
Electric Car	**0.03125**	**0.89637**	**0.00068**	**0**	**0**
Public Transport	**0.0057**	**0.0057**	**0.98**	**0**	**0**
Electric Bike	**0.001523**	**0.07292**	**0.00009**	**0.9884**	**0.213**
Regular Bike	**0.00073**	**0.00073**	**0.00291**	**0.0116**	**0.787**

Table 7: Probability migration matrix for the five transportation units

3.4.2 Executing the Model

We find the number of users for each mode of transportation in 2025 and 2028 by applying the Markov chain to the initial values two and five times, respectively:

$$\mathbf{x_2 = M^2 x_0}$$
$$\mathbf{x_5 = M^5 x_0}$$

Transportation Mode	Current 2023 Users	Projected 2025 Users (x_2)	Projected 2028 Users (x_5)
Gas Car	**250,000,000**	**231,320,000**	**207,190,000**
Electric Car	**2,500,000**	**16,530,000**	**30,690,000**
Public Transport	**6,625,000**	**9,200,000**	**12,760,000**
Electric Bike	**0**	**1,280,000**	**6,520,000**
Regular Bike	**870,000**	**870,000**	**950,000**

Table 8: Projections for users of the transportation units over time

A matrix of weights for each factor that the migrations will impact is shown below. The impact weighting matrix will contain weights for carbon emissions, traffic congestion, and health. Any category with the largest possible impact will be assigned a maximum score of 1, and all other values will be proportional to that value.

From various sources, we determined the rest of these proportions. Our team found that electric vehicles release half as much greenhouse gas emissions as gas-powered cars on average [16]. For every gas car eliminated and replaced with public transportation, a saving of 30% of carbon dioxide emissions can also be realized [17]. E-bike power consumption results in an average CO_2 emissions value of 3.5 gal/mile [18], while the average car may emit 350 gal/mile in comparison [19]. Regular bikes do not produce any emissions.

Relative Effect Weighting Matrix (E)

Transportation Mode	Carbon Emissions	Traffic Congestion	Health (cal/hr)
Gas vehicles	**1**	**1**	**0.28** [23]
Electric vehicles	**0.5**	**1**	**0.28** [23]
Public transportation	**0.7**	**0.68**	**0.25** [24]
E-bikes	**0.01**	**0.96**	**0.56** [22]
Regular bikes	**0**	**0.96**	**1**

Table 9: Relative effect weighting matrix for various demand metrics

Gas and electric vehicles contribute to traffic congestion equally, whereas bikes have been reported to reduce congestion in neighborhoods by up to 4% [21]. Public transportation, including buses and trains, can reduce up to 32% of traffic in suburban and urban areas [20]. Additionally, riding bikes burn the most calories per hour, and the other values are a fraction of that. Since calories burned per hour are assumed to be representative of health benefits, changes in the distribution of primary modes of transportation will impact the health score of a given distribution.

$$\mathbf{T_2 = E'x_2}$$
$$\mathbf{T_5 = E'x_5}$$

$$\mathbf{I_2 = T_2 - T_0 = E'x_2 - E'x_0}$$
$$\mathbf{I_5 = T_5 - T_0 = E'x_5 - E'x_0}$$

The impact matrix, which shows the impacts on carbon emissions, traffic congestion, and health, is a 3x1 matrix found by multiplying the transpose of the relative effect weighting matrix (**E**) by the difference in the distributions of people's preferred mode of transportation. We then convert this difference to a percentage.

3.5 Results

Year	Carbon emission impact score	Traffic congestion impact score	Health & wellness impact score
2023 (T_0)	255,887,500	257,840,200	73,226,250
2025 (T_2)	246,040,000	256,180,000	73,290,000
2028 (T_5)	231,530,000	253,730,000	74,400,000
Change in impact in 2 years (I_2)	**-3.85%**	**-0.644%**	**+0.0891%**
Change in impact after 5 years (I_5)	**-9.52%**	**-1.60%**	**+1.60%**

Table 10: Results of matrix multiplication and predicted change in metrics

3.6 Discussion

As the usage of electric vehicles continues to grow as a whole, carbon emission impact and traffic congestion are set to decrease, while health and wellness are set to increase. In particular, after two years, carbon emissions will decrease by 3.85%, traffic congestion will decrease by 0.644%, and health and wellness will increase by 0.0891%. After five years, carbon emissions will decrease by 9.52%, traffic congestion will decrease by 1.60%, and health and wellness will increase by 1.60%.

Additionally, a decrease in overall carbon emission and traffic congestion impact from an increase in e-bikes intuitively makes sense — e-bikes would generally produce fewer emissions and ease traffic congestion in urban areas. E-bikes also help commuters burn more calories and therefore promote healthier exercise, which explains the slight increase in the health and wellness score.

3.7 Sensitivity Analysis

To test the sensitivity of our Markov chain, we changed the original migration matrix by increasing the probability of a user staying with a gas car by 1% and decreasing the probability that one switched from gas to electric cars by 1%. This ensures that our probability matrix is still column stochastic, as that column will still add up to 1. We then used this migration matrix and the same relative effective weighting matrix to determine the effect of the new migration distribution. Comparing this result to our previous result will determine if our model is adaptable and reasonable.

Altered Probability Migration Matrix for Sensitivity Analysis

Switching To	Gas Car	Electric Car	Public Transport	Electric Bike	Regular Bike
Gas Car	**0.970797 (+1%)**	0.02428	0.01632	0	0
Electric Car	**0.02125 (-1%)**	0.89637	0.00068	0	0
Public Transport	0.0057	0.0057	0.98	0	0
Electric Bike	0.001523	0.07292	0.00009	0.9884	0.213
Regular Bike	0.00073	0.00073	0.00291	0.0116	0.787

Table 11: Altered probability migration matrix with altered values for sensitivity analysis

Year	Carbon emission impact score	Traffic congestion impact score	Health & wellness impact score
Change in impact in 2 years (I_2)	**-2.88% (+0.97%)**	-0.64%	+0.018%
Change in impact after 5 years (I_5)	**-7.19% (+2.33%)**	-1.59%	+0.98%

Table 12: Assessment of sensitivity analysis

Decreasing the probability of someone's switching to an electric car by 1% results in a drastic change on the carbon emission impact score over 2 and 5 years. This is because there will be more gas cars overall, which will contribute heavily to the carbon emission impact score for each year (T_2 and T_5). In 2025, there will be a 0.97% increase in carbon emissions due to changes, and in 2028 there will be a 2.33% increase in carbon emissions.

3.8 Strengths and Weaknesses

The use of Markov chains allows us to be able to model complex relationships and changes between various modes of transportation. This also allows us to take advantage of past trends and "migrations" found between transport transitions, making our model better suited to account for different changes over time. For example, our model effectively accounts for factors such as changing environmental perceptions and restrictions, sustainability, manufacturing, and the changing urban environment.

However, by this same token, in using the Markov chain model, we assume that the initially observed trend would always be constant, making our model inflexible to more drastic changes that can be found in the long term. Additionally, the more minute relationships between the different modes of transportation, and the various factors that can influence them, may be impossible to be able to account for in our model. Other aspects of our model were also derived from past data — many of which were highly affected due to the COVID-19 pandemic — and may not be entirely accurate to the present day.

Conclusion

In the first question, we employed an ARIMA model to predict electric bike sales in two and five years. Our model predicted 1.409 million annual e-bike sales in 2025 and 1.912 million annual e-bike sales in 2028. We used the Granger causality test to analyze the significance of various factors in the growth of the e-bike market. We found that both gas prices and environmental awareness only impact e-bike sales after 1 month. On the other hand, transportation distance only impacts e-bike sales after 12 months. However, changes in median disposable income did not significantly impact e-bike sales at any time. Finally, we found that as primary transportation methods change, carbon emission will decrease by 3.85%, traffic congestion will decrease by 0.644%, and health and wellness will increase by 0.0891% after two years. After five years, carbon emissions will decrease by 9.52%, traffic congestion will decrease by 1.60%, and health and wellness will increase by 1.60%.

In summary, our findings suggest that the e-bike market is poised for an impressive growth trajectory in the coming years. Furthermore, e-bikes have the potential to create a significant positive impact on society, reducing carbon emissions and traffic congestion while simultaneously promoting health and wellness. These findings and correlations will prove to be useful for policymakers and world leaders to develop the future of transportation: electric bikes.

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Code Appendix

Question 1: The Road Ahead

```
#Imported Libraries
import numpy as np
import pmdarima as ar
import pandas as pd
import matplotlib as mp
import matplotlib.pyplot as plt
import csv
import math
# Cleaning + Prelim Graph
sales = pd.read_csv('plugin_monthly_sales.csv')
sales = sales.drop("sales_before",axis=1)
sales = sales.drop("sales_next",axis=1)
yearly_multipliers = [1.139198301,1.297546012,1.350649351,1.233552632,1.076566125]

counter = 0
for i in yearly_multipliers:
   for j in range(12):
       sales["sales"][counter] *= i
       counter+=1

for i in range(96):
   sales = sales.append({"year":2023+(i//12), "month": i%12 +
1,'sales':0},ignore_index=True)

sales['date'] = pd.to_datetime(dict(year=sales.year, month=sales.month,day=1))
sales = sales.drop("year",axis=1)
sales = sales.drop("month",axis=1)
sales = sales[["date",'sales']]
print(sales)

sales.set_index("date",inplace=True)
sales.plot()

# Train and Test Value
train = sales[:60]
test = sales[-96:]
plt.plot(train)
plt.plot(test)
```

```
# Arima Model Analysis
arima_model =
ar.auto_arima(train,start_p=0,d=1,start_q=0,max_p=5,max_d=5,max_q=5,start_P=0,D=1,star
t_Q=0,max_P=5,max_D=5,max_Q=5,m=12,
seasonal=True,error_action='warn',trace=True,suppress_warnings=True,stepwise=True,rand
om_state=20,n_fits=50)

arima_model.summary()

# Prediction Table
prediction = pd.DataFrame(arima_model.predict(n_periods=96),index=test.index)
prediction.columns = ['predicted_sales']
print(prediction)

# Values for Year
print(prediction.iloc[[24]])
print(prediction.iloc[[27]])
print(prediction.iloc[[30]])
print(prediction.iloc[[33]])
count_2025 = 0
for i in range(24,36):
   count_2025 += prediction.iloc[i]['predicted_sales']
print(count_2025)
print()
print(prediction.iloc[[60]])
print(prediction.iloc[[63]])
print(prediction.iloc[[66]])
print(prediction.iloc[[69]])
count_2028 = 0
for i in range(60,72):
   count_2028 += prediction.iloc[i]['predicted_sales']
print(count_2028)

# Sensitivity
actualJan2023 = 86000
predictedJan2023 = 82374.740980

percentError = (predictedJan2023-actualJan2023)/actualJan2023 * 100
print(percentError)
```

Question 2: Shifting Gears

```
# Imported Libraries
import statsmodels.api as sm
from statsmodels.tsa.stattools import grangercausalitytests
import numpy as np
import pandas as pd
import matplotlib as mp
import matplotlib.pyplot as plt
import csv
import math

# Sales - Cleaning
sales = pd.read_csv('plugin_monthly_sales.csv')
sales = sales.drop("sales_before",axis=1)
sales = sales.drop("sales_next",axis=1)
yearly_multipliers = [1.139198301,1.297546012,1.350649351,1.233552632,1.076566125]

counter = 0
for i in yearly_multipliers:
   for j in range(12):
       sales["sales"][counter] *= i
       counter+=1

sales['date'] = pd.to_datetime(dict(year=sales.year, month=sales.month,day=1))
sales = sales.drop("year",axis=1)
sales = sales.drop("month",axis=1)
sales = sales[["date",'sales']]
print(sales)

sales.set_index("date",inplace=True)
sales.plot()

# Gas Prices - Cleaning
gas = pd.read_csv('gas_prices.csv')

gas['date'] = pd.to_datetime(dict(year=gas.year, month=gas.month,day=1))
gas = gas.drop("year",axis=1)
gas = gas.drop("month",axis=1)
gas = gas[["date",'price']]
print(gas)

gas.set_index("date",inplace=True)
```

```
gas.plot()

# Gas Prices - Granger causality
test = 'ssr_chi2test'
gasCombine = pd.concat([sales, gas], axis=1)
gasCombine.columns = ['sales', 'prices']
gas_test = grangercausalitytests(gasCombine, 12)

# Disposable Income - Cleaning
income = pd.read_csv('income.csv')

income['date'] = pd.to_datetime(dict(year=income.year, month=income.month,day=1))
income = income.drop("year",axis=1)
income = income.drop("month",axis=1)
income = income[["date",'disp_income']]
print(income)

income.set_index("date",inplace=True)
income.plot()

# Disposable Income - Granger causality
test = 'ssr_chi2test'
incomeCombine = pd.concat([sales, income], axis=1)
incomeCombine.columns = ['sales', 'disp_income']
income_test = grangercausalitytests(incomeCombine, 12)

# Travel - Cleaning
travel = pd.read_csv('travel.csv')

travel['date'] = pd.to_datetime(dict(year=travel.year, month=travel.month,day=1))
travel = travel.drop("year",axis=1)
travel = travel.drop("month",axis=1)
travel = travel[["date",'dist_traveled']]
travel["dist_traveled"] = travel["dist_traveled"].str.replace(",","")
travel["dist_traveled"] = travel["dist_traveled"].astype(float)
print(travel)

travel.set_index("date",inplace=True)
travel.plot()

# Travel - Granger causality
test = 'ssr_chi2test'
```

```python
travelCombine = pd.concat([sales, travel], axis=1)
travelCombine.columns = ['sales', 'dist_traveled']
travel_test = grangercausalitytests(travelCombine, 16)

# Environment - Cleaning
env = pd.read_csv('environment.csv')

env['date'] = pd.to_datetime(dict(year=env.year, month=env.month,day=1))
env = env.drop("year",axis=1)
env = env.drop("month",axis=1)
env = env[["date",'env_sent']]
print(env)

env.set_index("date",inplace=True)
env.plot()

# Environment - Granger causality
test = 'ssr_chi2test'
envCombine = pd.concat([sales, env], axis=1)
envCombine.columns = ['sales', 'env_sent']
env_test = grangercausalitytests(envCombine, 12)
```

Question 3: Off the Chain: (MATLAB)

```matlab
%% Statistics/Probability Matrix M and Current distribution matrix xo
% Migration Matrix to change
M = [.960797 .02428 .01632 0 0; .03125 .8964 .00068 0 0; .0057 .0057 .98 0 0;
.0 .07292 .000009 .9884 .213; .00073 .00073 0.000291 0.0116 .787]
% Effect Matrix for CE, TC, and Health/Exercise
E = [1 1 .28; 0.5 1 .28; 0.7 .68, .25; .01 .96 .56; 0 .96 1]
W = E' % Transpose to multiply
% Mode of Transportation Distributions
x0 = [250000000; 2500000; 6625000; 0; 870000] % Current: 2023
x2 = M*M*x0 % 2025
x5 = M*M*M*M*M*x0 % 2028
% Total effect using effect matrix on transportation distribution
T0 = W*x0 % 2023
T2 = W*x2 % 2025
T5 = W*x5 % 2028
% Impact Matrix as percent change in total effect
I0 = T0./T0 .* 100 - 100 % 2023
I2 = T2./T0 .* 100 - 100 % 2025
I5 = T5./T0 .* 100 - 100 % 2028
%% Sensitivity Analysis
```

```
Ms = [.970797 .02428 .01632 0 0; .02125 .8964 .00068 0 0; .0057 .0057 .98 0 0;
.0 .07292 .000009 .9884 .213; .00073 .00073 0.000291 0.0116 .787]
M = Ms
% Effect Matrix for CE, TC, and Health/Exercise
E = [1 1 .28; 0.5 1 .28; 0.7 .68, .25; .01 .96 .56; 0 .96 1]
W = E' % Transpose to multiply
% Mode of Transportation Distributions
x0 = [250000000; 2500000; 6625000; 0; 870000] % Current: 2023
x2 = M*M*x0 % 2025
x5 = M*M*M*M*M*x0 % 2028
% Total effect using effect matrix on transportation distribution
T0 = W*x0 % 2023
T2 = W*x2 % 2025
T5 = W*x5 % 2028
% Impact Matrix as percent change in total effect
I0 = T0./T0 .* 100 - 100 % 2023
I2 = T2./T0 .* 100 - 100 % 2025
I5 = T5./T0 .* 100 - 100 % 2028
```