Executive Summary

E-bikes have the potential to play an important role in improving American commutes and reducing traffic congestion and air pollution in cities. With the increasing popularity of e-bikes, more people may choose to use them as an alternative to cars for short trips, reducing the number of vehicles on the road and freeing up space on highways and in urban areas. E-bikes can also help address the "last-mile" problem for commuters who use public transportation, making it easier and more convenient for them to reach their final destination. Furthermore, as e-bikes emit fewer pollutants than cars, they can help improve air quality in cities, contributing to better health outcomes for residents. To fully realize the potential of e-bikes, it will be important for cities to invest in bike-friendly infrastructure, including bike lanes and charging stations, and to promote safe and responsible e-bike use among riders.

We predict that e-bike sales will rapidly increase over the coming years, with over 3 million sales occurring in 2028. To determine this, we used a linear regression on the year and the logarithm of e-bike sales. Such a growth will have many effects and it is important that cities determine how best to accommodate e-bikes to maximize their efficiency and limit the risks to pedestrians. The Department of Transportation should consider creating model regulations to help cities and localities best regulate e-bikes.

The first part of our report determined the projected number of electric bikes in the United States 2 years and 5 years from now (1,611,000 and 3,157,000 respectively). We did so by collecting and cleaning data regarding the number of bike sales in previous years, linearizing the data so that a one-order relationship could be determined, and analyzing the data to determine its robustness and sensitivity against other factors of the data.

In the second part of our report, we determined a variety of factors that may play a role in the growth of electric bicycles. We determined that the average disposable income and the battery cost were the two factors in electric bicycles that played the largest roles in the number of new adopters of e-bikes.

In the third part of our report, we observe the impacts of the projected increase in e-bikes on both the environment and society. It was found that carpoolers have very little incentive to switch as they are already able to reduce their carbon footprint. Other groups, however, may switch and the probabilities are given in a 10x10 transition matrix.

Contents

1 Introduction

Electric Bicycles, commonly known as E-Bikes, have become more prevalent in the modern world. Apart from being environmentally friendly, the relatively small power draw and the smaller size of bicycles means that users are able to travel in cities and around heavily trafficked areas with much more ease. The ability for bikers to weave between traffic while also consciously understanding their impact on reducing the carbon footprint has made electric bikes an increasingly popular choice amongst a global population. [9]

In Question 1, we propose a method for modeling the number of electric bikes in the United States through the coming years.

In Question 2, we will consider a variety of possible factors that have caused the bike industry to grow and draw conclusions about each factor's impact on the growth of electric bicycles.

In Question 3, the impacts of the shift to E-Bikes will be examined, and quantitative analysis will be assessed and presented to determine how E-Bikes will transform the global landscape in terms of health, environmental recovery, and individual benefits.

2 Q1: The Road Ahead

2.1 Problem Restatement

This question asked us to predict future sales of e-bikes. Because of the recently fast-growing e-bike market in the United States, our team decided to limit the scope of our investigation to the United States. This in turn allowed for more refined investigation into the trends, impacts, and other characteristics of e-bike use present throughout the paper.

2.2 Assumptions

- **Assumption 1:** Trends in electric bike growth will continue through 2028.
- **Justification:** Trends in electric bike growth are caused by increasing affordability and an increasing desire for better methods of urban transportation. We assume that the trend in affordability will continue and that the incentives given to individuals that seek new methods of transportation will continue to draw more e-bike purchases year-over-year. In recent years, a large number of travel was done in short distances (over 60% of vehicle trips were under 6 miles), which means that there is still space in the market for growth of vehicles suited for shorter travel distances, such as electric bikes. [1]
- **Assumption 2:** There will not be any significant technological advances that greatly impact the cost or performance of e-bikes
- **Justification:** While a gradual technological improvement is anticipated (e.g. batteries become more efficient, bike materials become cheaper, or bike wheels become more robust against damage), the model assumes there is no ground-breaking progress that would significantly alter or revolutionize the cost effectiveness of materials that

comprise e-bikes. This is because implementations of new technology have historically taken decades to adopt, so such changes would not manifest on the 2-5 year time frame of the model. [8]

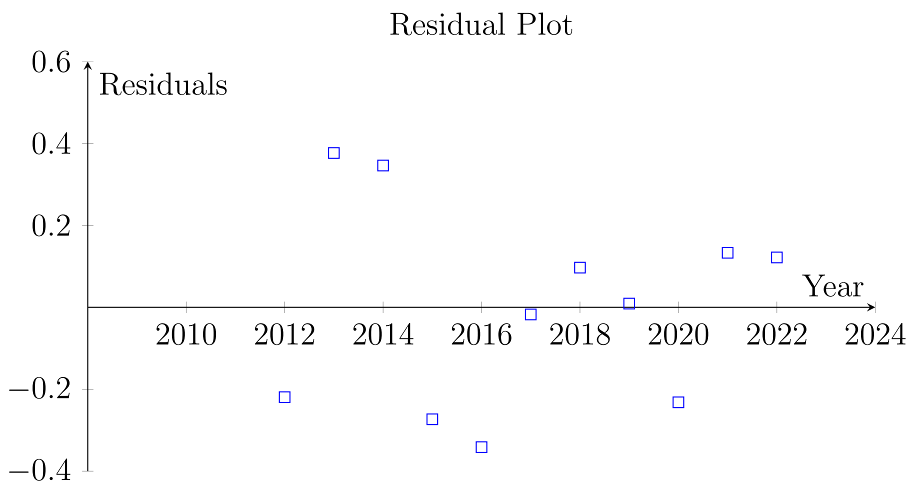

Figure 1: Residual plot for the regression model

2.3 Model

Using the given data and data from Statista for United States e-bike sales, we noted that e-bike sales appeared to be growing exponentially over the given time interval (Figure 2) Consequently, we ran a regression of the year against the natural logarithm of the e-bike sales. (Figure 3) The results of the regression are presented in Table 1.

2.4 Results

This model anticipates a sharp rise in electric bike sales, which has the potential to strain the supply chain to meet demand. In addition, cities will have to work to establish traffic laws that ensure the safety of e-bikers, cyclists, and pedestrians. They might also consider establishing more dedicated bike lanes for manual bicycles, e-bikes, and electric scooters.

Equation	$\ln(\text{sales}) = -447 + 0.224(\text{years})$
R Square	0.903
Adjusted R Square	0.892
2025 Prediction	1,611 thousand
2028 Prediction	3,157 thousand

Table 1: Results of the regression

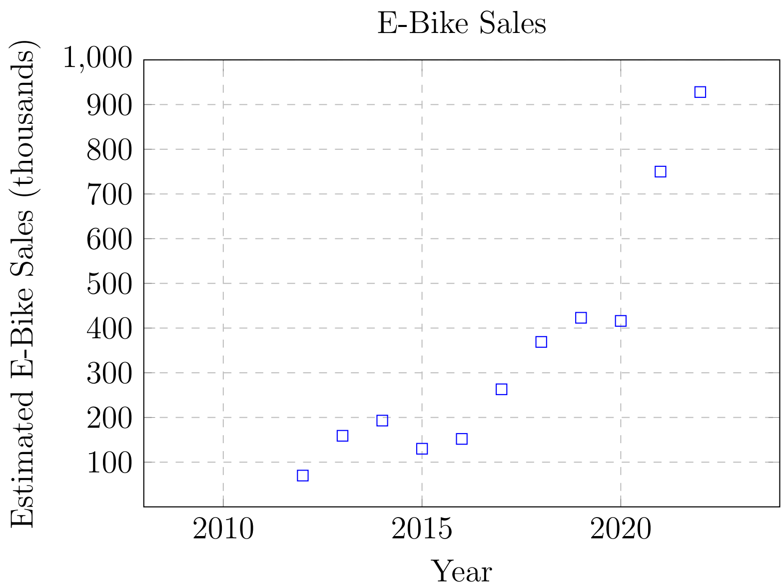

Figure 2: Sales of E-Bikes

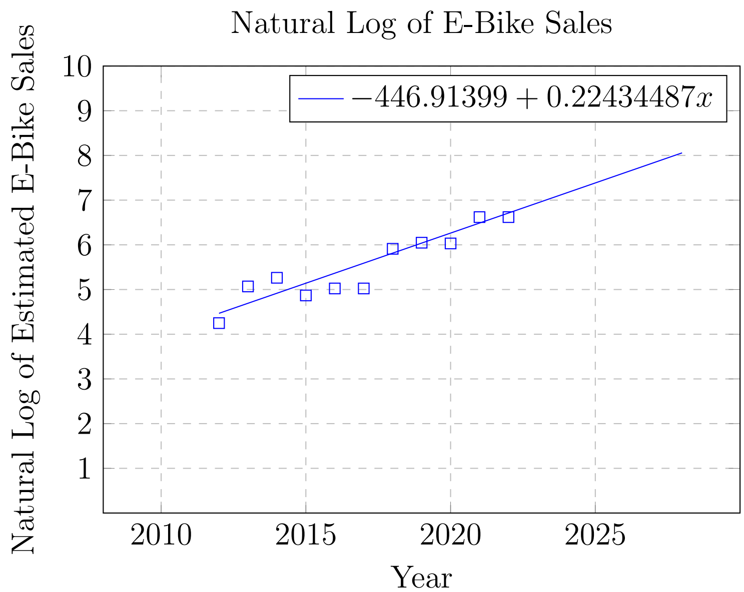

Figure 3: The natural logarithm of e-bike sales, in thousands over time. Note that this graph is roughly linear.

2.5 Sensitivity Analysis

If the historical e-bike sales were higher by a constant percentage than predicted, then the model's outputs would be higher by that same percentage based on the nature of logarithms.

2.6 Strengths and Weaknesses

A strength of this model is that its simple design avoids over-fitting and is easily understandable. While it does not directly consider the various factors influencing electric bike sales, it simply evaluates the trends over time based on previous datapoints of sales.

A weakness of this model is that its use for extrapolation is limited. Electric bike sales will reach a peak when the market becomes saturated, and then they will lower to a constant rate reflecting bike replacement rather than market expansion. This model fails to account for such changes and is consequently only useful for short-term predictions.

3 Q2: Shifting Gears

3.1 Problem Restatement

In order to get to the bottom of why the purchases of e-bikes are on the rise, we need to investigate all of the factors that may effect the sales of e-bikes throughout the United States

3.2 Assumptions

1. **Assumptions 1:** The individual points in the factors ie. gas prices in 2002 and 2022 have no correlation. **Justification 1:** as in each point of time, aside from small amounts of inflation, there is virtually little correlation between the two points
2. **Assumption 2:** The sale of e bikes are normally distributed **Justification 2:** The relatively small amount of data points makes this hard to prove, but when looking at individual sales accross the nation it can be seen that the purchases per month under similar conditions remain normally distributed. However, even if it wasn't normally distributed, ANOVA is generally robust to non-normalcy

3.3 Analysis

Given that there are many different factors that affect the sales of bikes, multiple regressions are necessary in order to find the significance of each of the different factors. These factors also experience changes over time, which allows them to predict e-bike sales over time. In contrast, factors such as commute distance and availability of public transportation affect e-bike sales but do not significantly change over short time scales.

The list of factors we will consider include:

1. Electric Bike Prices
2. Average Disposable Income
3. Environmental Awareness
4. Battery Cost
5. Batter Efficiency

6. Petrol Prices

3.3.1 Electric Bike Prices

There is very little data on e-bike prices in the US so there is little we can do to directly account for the e-bike prices in the US. However, the cost of batteries and other electrical components usually correspond fairly well with the price of the e-bike, so we can consider battery prices as a proxy. [4].

3.3.2 Average Disposable Income

Disposable income is a measure of how much money a household/individual has to spend on non-essential goods such as e-bikes. If one has more money to spend, then they are more likely to spend it on non-essential goods. This means that average disposable income may be a good indicator on how much e-bikes are being purchased.

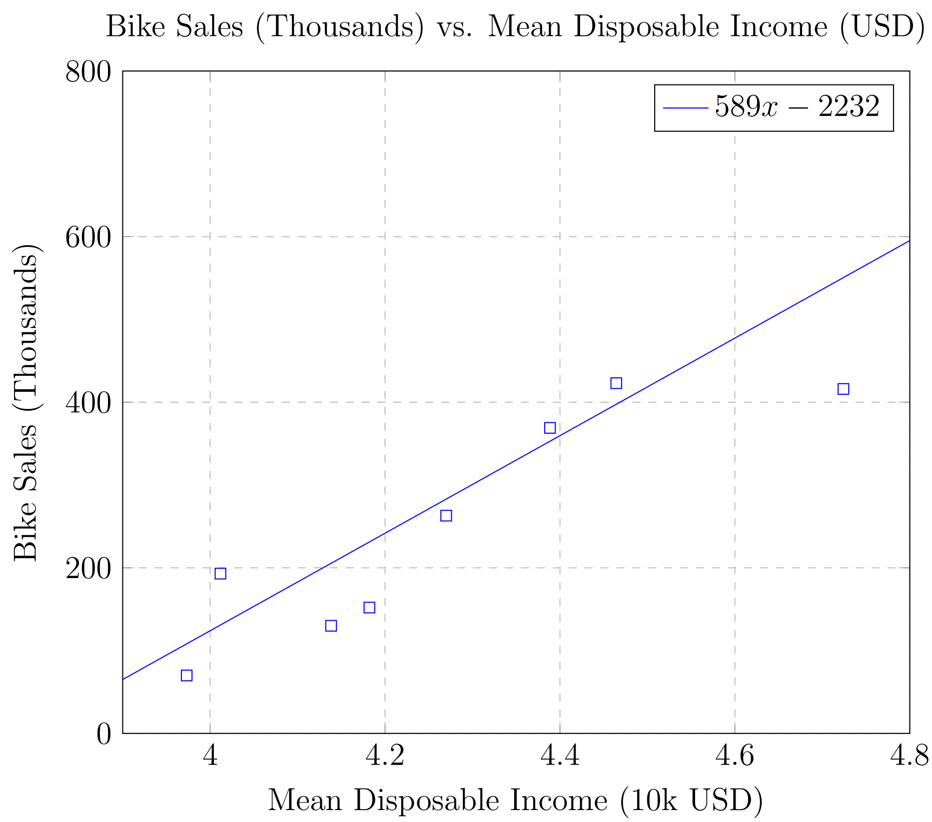

Figure 4: The Strong Linear Relationship Between Bike Sales and Mean Disposable Income ($R^2 > 0.8$)

with an R^2 of 0.822 giving a fairly strong correlation and when doing an ANOVA analysis on the data set we get

Source	DF	SS	MS	F-stat	P Value
Between Groups	1	9063791761.25	9063791761.25	1845.1564	<<0.0001
Within Groups	18	88419741.222	4912207.8457		
Total:	19	9152211502.472			

3.3.3 Environmental Awareness

Environmental awareness is a measure of how environmentally conscious a population is. To measure this, we used the data from a Gallup poll that measures what percentage of Americans are concerned with the environment. By plotting this with the e-bike sales we may be able to see a correlation between a population's environmental consciousness and e-bike sales. However, there is a problem in the fact that the Gallop pole only provides data in the format of percentage of responses in 4 categories: very concerned, concerned, a little concerned, and not concerned. In order to counter this, we need to enumerate it giving values to the 4 categories and summing the product of these values and the percentages giving us an overall environmental consciousness score.

Very Concerned	3
Concerned	2
A Little Concerned	1
Not Concerned	0

Table 2: Enumeration Values

Using this to plot gives us the following plot
ANOVA Table:

Source	DF	SS	MS	F-stat	P Value
Between Groups	1	666980.3111	666980.3111	18.055	0.0004
Within Groups	20	738832.3911	36941.6196		
Total:	21	1405812.7022			

As seen by the ANOVA table, although significant at $\alpha = 0.05$, there seems to be little to no correlation with an R^2 value of 0.135 showing that there seems to be very little correlation between the consciousness of the population and the amount of e-bikes sold.

3.3.4 Battery Cost

Due to the fact that Bikes and E-Bikes are fairly costly to the average American (upwards of 1% of the average income of a US citizen), the amount of money that people have may be an important factor in how many e-bike sales are made as in times of recession or troubles, people are less likely to have what they perceive as excess spending. By plotting the amount of e-bike sales and matching it to the price of batteries at that year. Because the given data included many gaps, we supplemented it with data from Bloomberg via Statista, shown in Table 3.

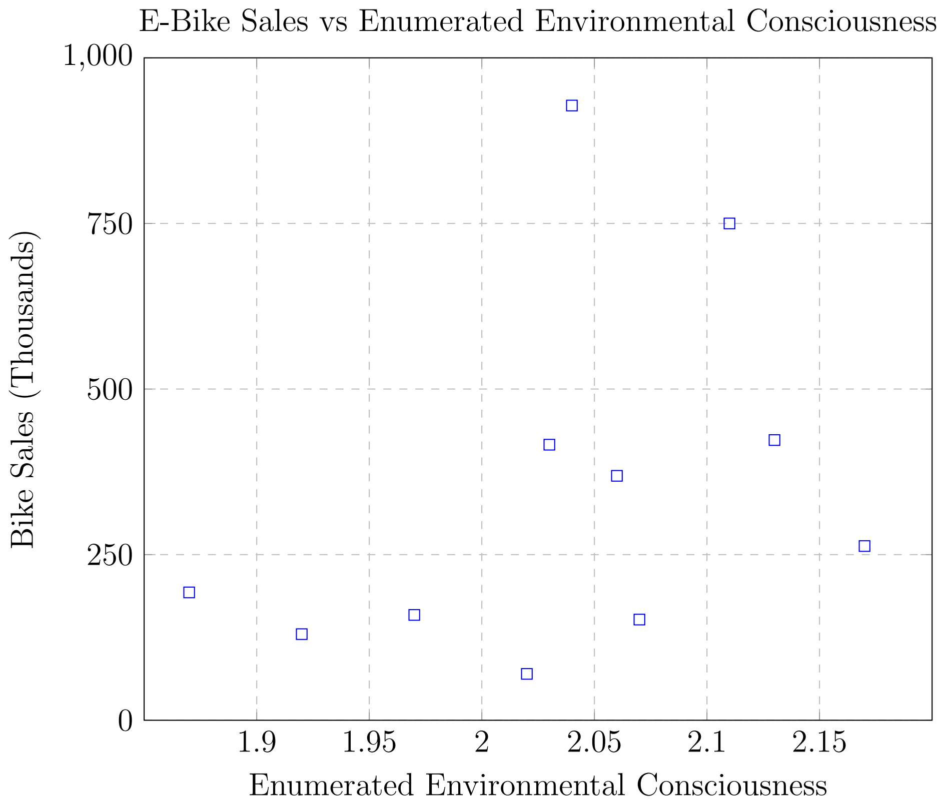

Figure 5: This graphs shows the weak relationship between enumerated environmental consciousness and bike sales

Year	Battery Price (USD/kWh)
2012	726
2013	668
2014	592
2015	384
2016	295
2017	221
2018	181
2019	157
2020	137

Table 3: Battery Prices

This produces a relation between e-bike sales and price shown in Figure 6. Running an ANOVA for the linearized set of points in Figure 6 yields the resutls shown in Table 3.3.4. The table shows that battery price, and thus the overall price of the bikes, has a significant relationship with the logarithm of the sales, so it is a key factor in the amount of e-Bikes being purchased in the US. It also gives an R^2 value of 0.675.

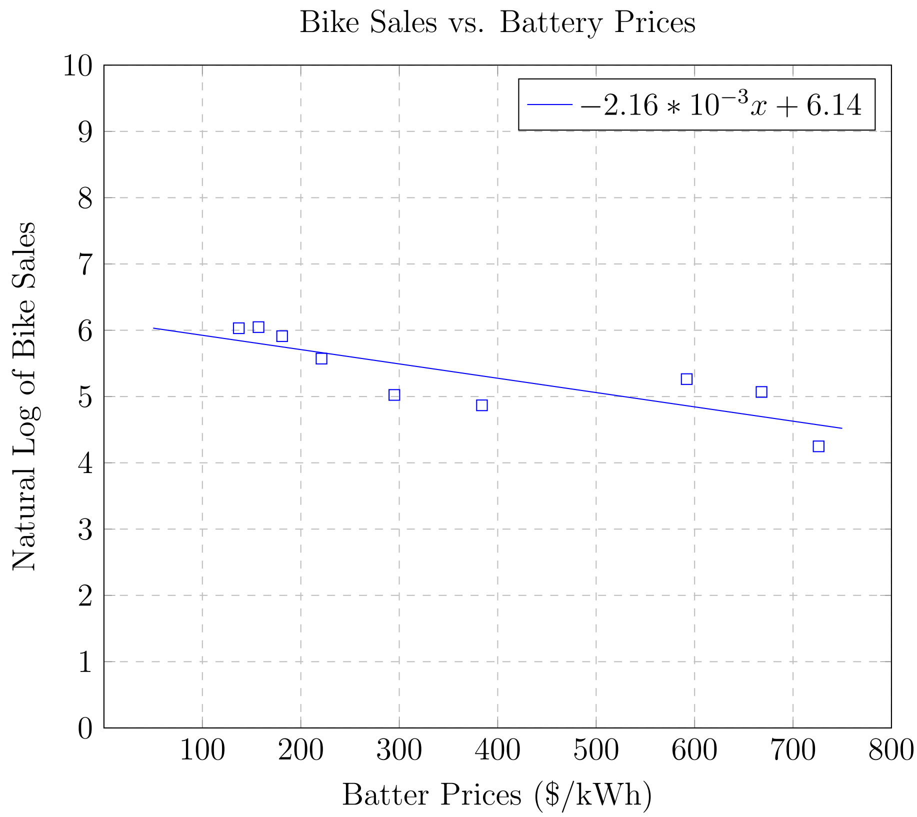

Figure 6: fill in

Source	DF	SS	MS	F-stat	P Value
Between Groups	1	609764.092	609764.092	22.7885	0.0002
Within Groups	16	428121.1261	26757.5704		
Total:	17	1037885.2181			

3.3.5 Petrol prices

The price of petrol may seem like a key contributor to the purchase of alternative forms of transportation especially in cities. As a result of rising gas prices, some may find it more worthwhile to purchase an electric vehicle or alternative forms of transport in order to circumvent gas prices. As a result there may be a strong link between the petrol price per gallon and the purchases of more e-bikes.

Source	DF	SS	MS	F-stat	P Value
Between Groups	1	663662.5429	663662.5429	17.9651	0.0004
Within Groups	20	738836.2126	36941.8106		
Total:	21	1402498.7556			

However, when looking at the plots and the ANOVA calculations, it can be seen that the correlation, while significant does not hold a very high R^2 and therefore is not as strong of a correlation that one would expect.

3.4 Conclusion

As seen by these ANOVA tests and looking at the R^2 values. the two most important factors are the average disposable income of Americans and battery cost (which by extension implies bike cost). This means that the main barrier to more people owning e-bikes are currently the amount of money available to be spent by the people and how much it would cost to purchase an e-bike.

3.5 Sensitivity Analysis

By testing the sensitivity of the model, we can see that minute changes in the petrol prices and environmental consciousness of a population have little to no effect on the predicted amounts of bikes purchased in the US. However, when changing the average disposable incomes and battery costs by similar ratios, the amount of bikes that are being sold increases more dramatically.

4 Q3: Off the Chain

4.1 Problem Restatement

This part of the problem requires us to examine how the increasing use of e-bikes will impact environmental, social, and economic factors. We examined the following: carbon emissions, risk to vehicle operator, and general health of operator.

4.2 Assumptions

1. *The coefficients for each mode of transportation considered do not vary within the group.* Since vehicles in each mode is more similar to other vehicles in the group than those in other groups, we can say this.

2. *With respect to carbon emissions and health aspects, vehicles are independent.* Carbon emissions are generally additive, so one vehicle's carbon emission does not affect another's. Health aspects are also personal to each vehicle operator, so another vehicle will not have an impact on a given operator's health.

3. *The number of passenger miles a certain vehicle type has is proportional to the number of people using that type.* As the proportion of people using a certain mode of transportation increases, the number of passenger miles also naturally increases. Since fluctuations from this variation would be minimal, it is safe to assume this.

4.3 Variables

Variable	**Definition**
X	The vector of the proportions of commuters by mode of transportation
Y	The vector containing the factors that are affected by transportation
f	The function that maps X to Y
$\hat{f}$	f before normalization
C	The vector representing the carbon emissions of each mode of transportation
D	The vector representing the passenger miles of each mode of transportation
I	The vector representing the injury risk of each mode of transportation
H	The vector representing the calories burned by each mode of transportation
T	The transition matrix for the Markov Chain representing how X evolves by year

4.4 Model

We first define a function that maps the proportion of people using each mode of transportation to the effects on individuals, society, the economy, and the environment. The modes of transportation examined are:

- car, truck, or van (alone, carpool of 2 people, carpool of 3 people, carpool of 4 or more people),
- public transportation,
- walking
- bicycle
- e-bike
- taxicab, motorcycle, or other means, and
- working from home.

This is a total of 10 input factors, which will be represented in the vector X. We are looking at 3 factors as the output of this function, which we represent by the vector Y. Thus, we aim to find a function $f : \mathbb{R}^{10} \to \mathbb{R}^3$ such that

$$f(X) = Y.$$

The values of Y are obtained from a base case Y_0, similar to how index values are obtained for the United States Consumer Price Index. To obtain such values, a base state X_0, is first defined where data from the 2021 American Community Survey 1-Year Estimates are taken:

$$X_0 = \begin{pmatrix} 0.678 \\ 0.059 \\ 0.012 \\ 0.008 \\ 0.025 \\ 0.022 \\ 0.004 \\ 0 \\ 0.015 \\ 0.179 \end{pmatrix}.$$

Letting $\hat{f}$ be the non-normalized version of the function f, it follows that

$$\hat{f}(X_0) \odot f = \hat{f},$$

where $\odot$ is the operator for element-wise multiplication.

Next, we want to find the individual functions that comprise f, which we call f_1, f_2, and f_3. These describe the relations between X and carbon emissions, traffic congestion, risk to person, and health of person, respectively.

4.4.1 Carbon Emissions

By our first assumption, the modes of transportation are independent of each other with respect to carbon emissions. The carbon emissions vector (that is, the vector containing information on CO_2 per passenger mile) is [6] [2]

$$C = \begin{pmatrix} 348 \\ 174 \\ 116 \\ 87 \\ 204 \\ 0 \\ 0 \\ 4.5 \\ 271 \\ 0 \end{pmatrix}.$$

Additionally, each vehicle of a certain mode have similar carbon emission rates per passenger mile. Finally, we have assumed that the number of passenger miles D for each mode transport is a function of X. With these ideas, we can say that

$$\hat{f}_1(X) = C \cdot D(X)$$

and

$$f_1(X) = \frac{C \cdot D(X)}{C \cdot D(X_0)},$$

since the dot product is a scalar quantity. We can additionally model the amount of passenger miles for a certain mode of transportation as being proportional to the fraction of people using that mode. This makes

$$f_1(X) = \frac{C \cdot X}{C \cdot X_0}.$$

4.4.2 Injury Risk to Operator

From Ioannides et. al., we can find the rate of injuries of certain modes of transportation per million people I. [5]

$$I = \begin{pmatrix} 8 \\ 8 \\ 8 \\ 8 \\ 8 \\ 2 \\ 15 \\ 115 \\ 104 \\ 0 \end{pmatrix}.$$

We can multiply each injury rate by the proportion of people using each mode of transportation to find the effective injury rate. The non-normalized function $\hat{f}_2$ is given by

$$\hat{f}_2(X) = I \cdot X,$$

so the normalized function is

$$f_2(X) = \frac{I \cdot X}{I \cdot X_0}.$$

4.4.3 General Health of Operator

We will measure the general health of an operator by amount of extra calories they burn by operating their vehicle. For example, since a car driver is simply sitting down, they are not burning extra calories through operation. The vector representing the calories burned per mile of each mode of transportation is [3] [7] [10]

$$H = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 100 \\ 50 \\ 40 \\ 0 \\ 0 \end{pmatrix}.$$

Similar to the other parts of the model, we can find the non-normalized $\hat{f}_3$ is

$$\hat{f}_3(X) = H \cdot X,$$

and the normalized function is

$$f_3(X) = \frac{H \cdot X}{H \cdot X_0}.$$

Thus, our final function is

$$f(X) = \begin{pmatrix} \frac{C \cdot X}{C \cdot X_0} & \frac{I \cdot X}{I \cdot X_0} & \frac{H \cdot X}{H \cdot X_0} \end{pmatrix}^T.$$

4.5 Results

We create a Markov Chain model to determine how people's commuting method will change over time. The system will evolve according to the following transition matrix:

$$T = \begin{pmatrix} 0.7 & 0.05 & 0.05 & 0.05 & 0 & 0 & 0 & 0.1 & 0 & 0.05 \\ 0 & 0.85 & 0.05 & 0.05 & 0 & 0 & 0 & 0 & 0 & 0.05 \\ 0 & 0 & 0.9 & 0.05 & 0 & 0 & 0 & 0 & 0 & 0.05 \\ 0 & 0 & 0 & 0.95 & 0 & 0 & 0 & 0 & 0 & 0.05 \\ 0.01 & 0.05 & 0.05 & 0.05 & 0.68 & 0 & 0 & 0.1 & 0.01 & 0.05 \\ 0.01 & 0.05 & 0.05 & 0.05 & 0.05 & 0.48 & 0.1 & 0.15 & 0.01 & 0.05 \\ 0.01 & 0.05 & 0.05 & 0.05 & 0.05 & 0 & 0.53 & 0.2 & 0.01 & 0.05 \\ 0.01 & 0.05 & 0.05 & 0.05 & 0.05 & 0 & 0 & 0.74 & 0 & 0.05 \\ 0.01 & 0.05 & 0.05 & 0.05 & 0.05 & 0 & 0 & 0 & 0.74 & 0.05 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

With a diagram containing 10 nodes and 100 connections, this large transition matrix works by associating each of the factors with each other. Specifically, each element T_{ij} contains the probability that a person using the ith mode of transportation switches to the jth.

We justify this transition matrix by noting that carpoolers have no incentive to switch to a mode of transportation that allows for fewer passengers, but there is a chance that a person who drives will carpool with an additional person or more. Additionally, with the growing popularity of electric bikes, people who do not use them will likely want to use them over traditional bikes. Finally, there is a small chance that any commuter will switch to remote work due to the increasing utility of working from home. Using these principles, we are able to construct a theoretical transition matrix.

The result of running this Markov Chain over eleven years (including 2021 and 2022) is Figures 7, 8, and 9, which display the evolution each of the factors over time, as well as the change in proportion of commuters using e-bikes.

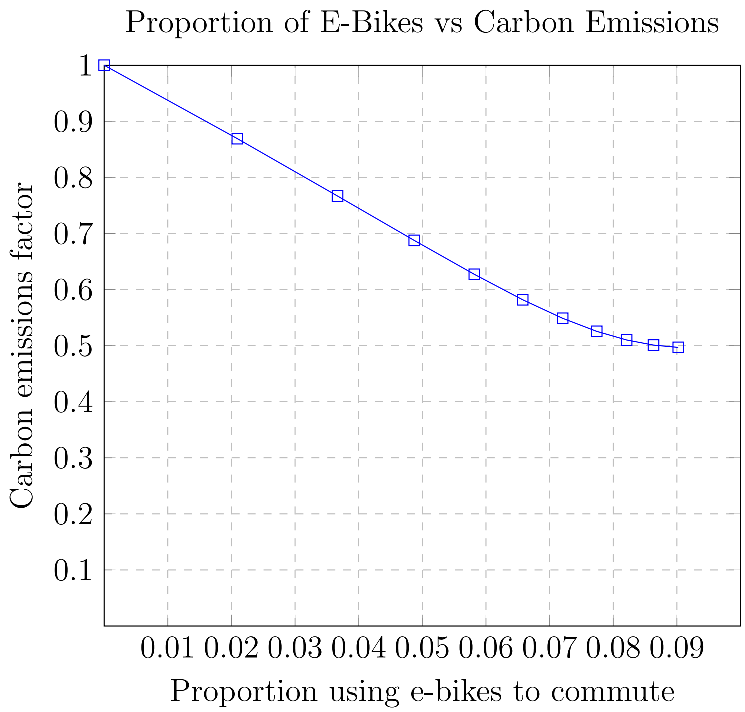

Figure 7: The carbon emissions factor as a function of the proportion of commuters using e-bikes.

4.6 Strengths and Weaknesses

The apparent increased injury risk of e-bike riders relative to bike riders may in part be a result of different rider characteristics. Part of the appeal of e-bikes is the reduced physical exertion required, which means that they are more appealing than traditional bikes to older and physically unfit populations. Furthermore, the exercise of cycling tends to attract those who are physically fit and the act itself increases strength and aerobic fitness. Consequently, e-bike riders are likely to have lower balance, weaker coordination, and potentially more fragile bodies, increasing the relative injury risk.

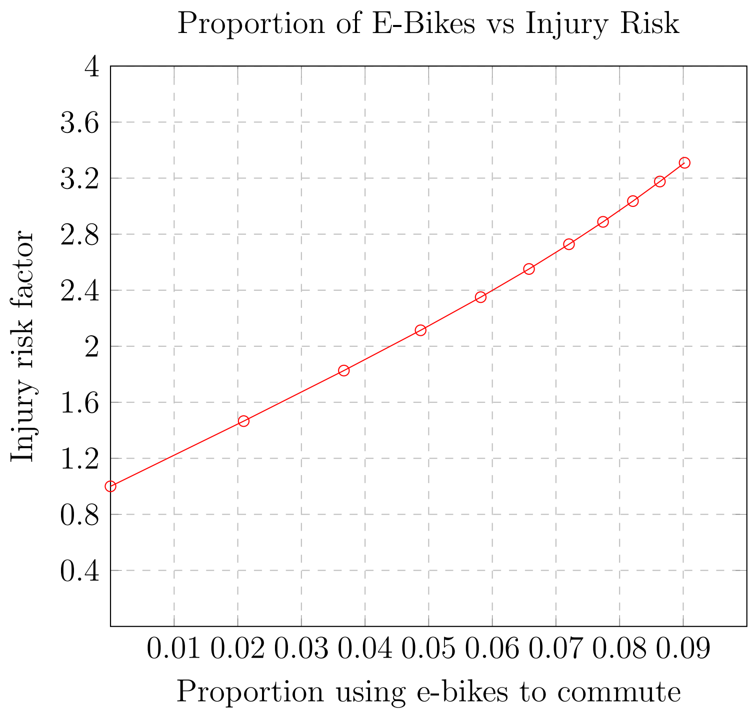

Figure 8: The injury risk factor as a function of the proportion of commuters using e-bikes.

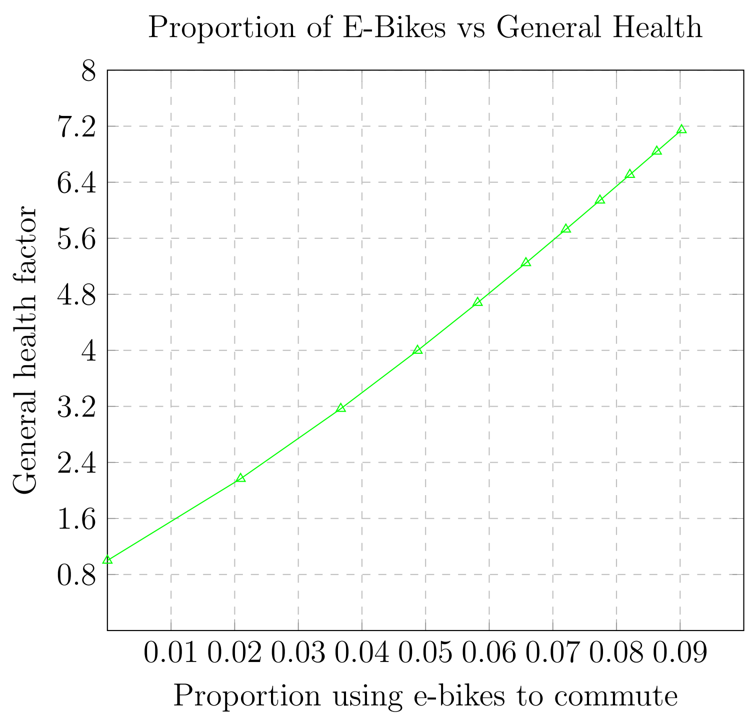

Figure 9: The general health factor as a function of the proportion of commuters using e-bikes.

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