Bike Sharing, Accidents, and the Role of Bicycle Infrastructure: Evidence from U.S. Cities

Garrett Shost

University of Wisconsin – Madison

Abstract: Bike sharing systems (BSS) have become prominent in many large U.S. cities as another transportation option. I quantify the effects of an increase in the usership of these systems on traffic accidents and discuss the mechanisms through which these effects occur. For my empirical analysis, I utilize daily data from 8 different U.S. cities between 2017 and 2023 of BSS ridership and traffic accidents. The primary identification strategy uses a Poisson Pseudo Maximum Likelihood model. Holding constant time-dependent city characteristics, month and day of week cycles, and weather events, I find that accidents per capita increase with BSS usage. Using similar models, I also find that bike infrastructure mitigates this increase in accidents and plays a significant role in improving overall traffic safety.

Keywords: Bike sharing systems, bicycle infrastructure, micromobility, traffic safety, urban development, panel data

1. Introduction

Bike sharing systems (BSS) have quickly emerged in the United States and become popular as an environmentally friendly and low-cost form of transportation that could help reduce the use of motor vehicles and subsequently lower emissions while reducing congestion in crowded cities. Increased cycling is often touted as a way to increase safety. A 2012 press release from New York City's Department of Transportation cited multiple statistics regarding how increased cycling does not increase serious bike crashes and that it leads to safer conditions for pedestrians (New York City Department of Transportation, 2013). However, New York implemented its BSS the following year and saw increases in accidents with cyclist fatalities hitting a 23 year high in 2023 with the majority coming from electric bike (e-bike) riders (Justine Re, 2024). Statistics like this call into question the overall benefit of these systems, especially if riders are uninformed over the true risk of using them.

BSSs work by allowing users to borrow a bicycle for a period of time and pay an hourly fee or use them through a subscription. The bikes can either be electric or manual, but most bikes are electric. In the United States, BSSs can be separated into docked and dockless systems. A docked BSS requires the user to borrow their bike from a set of docks and then return it to another one when they are finished. A dockless system does not require docks but instead allows users to find bikes using a mobile app. Once finished with their trip, the bike can be left almost anywhere so long as it complies with local ordinances.

The first large BSSs were implemented in the Unites States in the early 2010's (Bureau of Transportation Statistics (BTS), 2024), with the first systems being docked only. The number of systems grew quickly in the following years, and the only year that experienced a decline was 2020 due to the COVID-19 pandemic. In 2017, the first dockless BSS was opened, and this system has been the primary driver of new BSSs ever since. However, many older systems are still around in larger cities that maintain the docked systems. According to the BTS, in 2022 there were 61 docked BSSs and 345 dockless systems across the United States.

Although the e-bikes used in many BSSs utilize a battery, all of them are pedal-assisted, meaning the user must still pedal to operate the bike. Therefore, using e-bikes from a BSS can still benefit the user through many of the documented health benefits of increased physical activity, such as reduced risk of mortality (Lee et al., 1995) and reduced risk of chronic diseases including cardiovascular disease, diabetes, cancer, hypertension, obesity, and depression (Warburton et al., 2006). Encouraging individuals to substitute away from driving gasoline-powered vehicles additionally reduces local air pollution, which has positive health effects in the form of reduced risk of cardiovascular disease and reduced risk of premature births (Currie & Walker, 2011; Margaryan, 2021). However, given that biking is an overall riskier form of transportation per mile traveled than driving, walking, or public transportation (Beck et al., 2007), these health benefits may be offset by a mortality risk increase.

One of the biggest appeals of BSSs is their ease of use. While this is beneficial in terms of access and time savings, it means that users may operate the bikes unprepared. This is supported by surveys that find BSS users are far less likely to wear a helmet (Fishman et al., 2014). Since helmets are useful in preventing and lessening bike injuries (Høye, 2018), BSS users are already riskier than traditional cyclists. Furthermore, injuries sustained on e-bikes are more severe and utilize more hospital resources than on traditional bikes – faster speeds cause other drivers to miscalculate the e-bike's position and also lead to higher impact collisions in the case of an accident (Siman-Tov et al., 2018).

While the introduction of a BSS into a city provides an opportunity to reduce the negative effects of more traffic like pollution and congestion, the majority of people are using BSSs in place of walking, buses, or commuter rails (Fishman et al., 2013). Estimates for the fraction of people using a BSS in place of a car are typically between 2 and 10 percent, with the highest estimate at just over 20 percent. Though still nonzero, this means that the majority of BSS users were those who were not initially contributing to pollution and congestion in the first place. Trips that would have been made by public transit, a mode of transportation orders of magnitude safer than cycling, make up about 34 percent of BSS trips (United States Department of Economic and Social Affairs, 2011). In this project, I analyze the impact of BSS usage on traffic accidents, injuries, and fatalities by utilizing the variation in BSS usage across time in 8 major U.S. cities and examine how infrastructure can help mitigate any adverse effects.

2. Background

A. Bicycle Use and Safety

Cyclists have the highest injury and fatality rate per trip compared to pedestrians, drivers, and public transit users (Beck et al., 2007). However, these rates are based on a nationally representative sample which does not reflect the infrastructure and other characteristics of an urban environment where bike sharing is most common. Cycling is far more prevalent in urban settings, especially for commuting (Tribby & Tharp, 2019), and infrastructure and travel distance play a large role in choosing to bike (Parkin et al., 2008; Pucher & Buehler, 2006; Pucher, 2001). Infrastructure also improves cycling safety, as cycle tracks, dedicated bike lanes, and bike specific pathways all decrease cyclists' risk of being in an accident (Ling et al., 2020; Anne Harris et al., 2013; Teschke et al., 2012).

Cities with higher rates of cycling and walking also see lower rates of cyclists and pedestrians being involved in accidents. This is referred to as the "safety in numbers" effect in the literature. Studies focused solely on how mode share is related to accident rates have affirmed that this effect does occur (Ling et al., 2020; Elvik & Bjørnskau, 2017). This effect extends to motorists as well – higher rates of cycling and walking reduce the chance of a motorist colliding with cyclists or pedestrians (Jacobsen, 2003). This suggests that it may be the prevalence of cyclists and pedestrians that encourages more caution among motorists, as they are interacting more often. However, evidence suggests that most if not all of the correlation can be explained through city-level infrastructure (Marshall & Ferenchak, 2019) which keeps cyclists and pedestrians better separated from vehicles and encourages using these modes of transportation by making them safer.

Many of the determinants of bike use can be applied to bike sharing. Bike infrastructure is also an important predictor of BSS suage, as people are more likely to utilize bike sharing when dedicated lanes are prevalent (Fishman et al., 2013). However, evidence suggests that those using bike sharing are of a different profile than cyclists using private, manual bikes. Their ease of access allows people to use them unprepared and are sell-suited for tourists who are unfamiliar with the area and how to navigate it safely. People who use BSSs are also less likely to wear a helmet even when helmets are encouraged, compared to private, manual bikes (Haustein & Møller, 2016). Furthermore, the majority of BSSs utilize e-bikes which lead to users riding faster than normal cyclists. The speed of e-bikes increases accident rates and severity since motorists will incorrectly predict how fast they are going, assuming the speed is lower than it actually is (Siman-Tov et al., 2018).

B. Overall Traffic Safety

The determinants of traffic accidents and safety are complex but well-studied across a variety of fields. The many different treatment effects that have been looked at in the past provide models and methodologies for any research looking to determine causal effects (Anderson, 2008; Raynor et al., 2021; Wright & Dorilas, 2022). This paper will draw from these studies and build upon the broader literature of road safety.

Weather is a large factor that impacts overall traffic safety. Precipitation, especially when accompanied by severe snowstorms, plays the biggest role in causing accidents (Chang & Chen, 2005. This effect is also prevalent among pedestrians (Graham & Glaister, 2003) and cyclists (Kamel & Sayed, 2021) and is explained by rain and snowfall's effect on reducing visibility and increasing necessary reaction time and stopping distance for motorists. Precipitation also has a large impact on the demand for trips with rain and snowfall decreasing the overall demand for travel (Maze et al., 1948). Temperature is often associated with weather events like snow or rain, so disentangling their effects is difficult and has not been studied extensively. Several studies have found a negative impact of temperature on accidents (Hermans et al., 2006; Scott, 1986), though accident increases may be better explained through deviations from the monthly average temperature or extreme highs and lows (Brijs et al., 2008; Malyshkina et al., 2009). Wind is another weather event examined in the context of traffic safety, though whether it increases accidents is debated. Evidence suggests that extreme gusts may increase accidents (Hermans et al., 2006), but little research exists to support that lower wind speeds have a significant effect. Wind also has little effect on the demand for vehicle travel but does decrease the demand for trips taken with a bicycle (Thomas et al., 2013). This follows from intuition, as motorists are far more protected from the wind than cyclists, and wind makes cycling more difficult.

Congestion is another contributor to traffic safety that impacts accidents, especially as policies that impact transportation mode share will directly affect it. Congestion and its relationship with accidents, accident rates, injuries, and fatalities have been studied in a variety of environments. Within large cities, reducing congestion has been shown to reduce accidents and accident rates (Green et al., 2016; Sánchez González et al., 2021). The effect on freeways is less certain, though other studies suggest that the relationship between congestion and accidents is still positive or at least nonnegative (Gang-Len Chang & Hua Xiang, 2003; Wang et al., 2009).

Public transit is another factor, that while relieving congestion, also shifts people away from all other modes of transportation. City-wide public transit has been shown to relieve congestion while also reducing the number of people both driving and cycling (Adler & van Ommeren, 2016). Regarding safety, public transit decreases accidents and injuries (Bauernschuster et al., 2017; Lichtman-Sadot, 2019). It is important to note, however, that most of these studies rely on shocks to public transportation, like citywide implementation of public transportation or strikes that completely halt operation. It is uncertain whether these effects would persist at the same level in the long run.

C. Direct and Indirect Impacts of Bike Sharing Systems

A large portion of the literature on the impacts of BSSs has focused on their externalities in the form of air pollution. Switching from driving a car to riding a bike has the potential to reduce large amounts of gasoline consumption (Y. Zhang & Mi, 2018) and therefore reduce local air pollution. However, e-bikes often export their emissions through production, maintenance, and charging to the extent where their environmental benefit is at least partially offset (Ding et al., 2021; Z. Zhang et al., 2022), especially if they are being manufactured and charged using electricity produced through the burning of fossil fuels.

Biking and its effect on health has been well studied, both in its higher risk of mortality compared to other forms of transportation (Beck et al., 2007; Ulak et al., 2018), especially for e-bikes (Siman-Tov et al., 2018), as well as its use as a form of physical activity that reduces mortality risk (Deenihan & Caulfield, 2014). Additional studies have considered both the costs and benefits of cycling as a form of transportation, suggesting an ambiguous effect to slight decrease in mortality risk (Doorley et al., 2017). However, with e-bikes requiring less input from riders, this mortality risk reduction may not be as prominent or exist altogether for certain BSSs. Little research has been conducted regarding the health impacts of bike sharing, however by combining transportation mode shifts with BSS use, pollution, and accident data, it is estimated that bike sharing reduces mortality risk (Clockston & Rojas-Rueda, 2021).

D. Optimal Design of Bike Sharing Systems

Bike sharing systems are still a relatively new development in American cities and are in the process of being property integrated. Although surveys have suggested that BSSs are causing people to substitute away from buses and commuter rails (Fishman et al., 2014), designing and placing BSSs correctly can encourage them to be used alongside public transportation instead of in place of it, which helps improve social welfare (Shr et al., 2023).

Studies have also looked at the optimal service level and placement of BSSs, finding that docked BSSs have the potential to be placed more optimally to induce higher usership numbers (Mix et al., 2022), and that dockless systems are far better at encouraging demand for bike sharing (Soriguera & Jiménez-Meroño, 2020). BSSs are predicted to have high enough public benefits that systems should be subsidized by the government, so the optimal level of service is provided (Jara-Díaz et al., 2022). However, if additional costs like mortality risk are included, this may not be the case.

This paper adds to the literature by analyzing the effects of bike sharing on injury and mortality risk. It provides additional insight into the effects caused by the usage of bike sharing systems, as health impacts are understudied. I also improve upon the current health externality research by making fewer assumptions about the risks associated with BSS users. This analysis is conducted using a panel of multiple cities allowing for wider variety of infrastructure and demographics to better examine how infrastructure mitigates increases in accidents and improves the external validity of the results. The results of this paper contribute to a better understanding of the total costs associated with bike sharing systems. Currently, BSS design has been studied without the full idea of all the health costs associated with their use, which makes pricing difficult to accurately determine.

3. Methodology

A. *Theoretical Framework*

To understand and predict how BSS ridership affects accidents, it is important to consider all the channels through which it may do so. A higher level of BSS ridership indicates one of two things: (1) A trip that would not have happened is now occurring or (2) a trip that would have happened through another form of transportation is now occurring using a BSS. In the case of (1), this strictly means there are more cyclists on the road, without the other transportation modes being affected. This increases exposure to potential accidents but also affects accident rates through the safety in numbers effect. Furthermore, it can affect congestion if these cyclists are taking up space on roads. Many of these effects are competing in opposite directions, so the overall effect is uncertain. In the case of (2), when people change their mode of transportation to cycling using a BSS, there are fewer motorists or pedestrians, which decreases exposure of these modes, but increases exposure of cyclists.

Which of these effects dominates will also determine how a change in accidents translates to a change in injuries and fatalities. If the severity of accidents remains unchanged, the change in injuries and fatalities will be the same as the change in accidents. However, it is reasonable to believe that a change in BSS ridership will also affect the severity of accidents occurring. Accidents are likely to be less severe if there is a noticeable impact on driver awareness or safety in numbers. It is also possible that more congestion decreases accident severity, as accidents will happen at lower speeds. On the other hand, severity may increase if there are more car-to-cyclist accidents.

B. *Data*

I analyze daily bike sharing usage and traffic accidents from July 1, 2017 to December 31, 2023 across 8 U.S. cities: Austin, Texas; Boston, Massachusetts; Chicago, Illinois; Los Angeles, California; New York City, New York; San Francisco, California; San Antonio, Texas; and Washington, D.C. These cities and time frame were chosen due to their populations, length of time of uninterrupted service of bike sharing, and data availability. The data for traffic accidents was obtained individually from state departments of transportation. This data includes information on every person in an accident involving an injury, fatality, or $1,000 in property damage ($1,500 in Chicago and reporting an accident involving only property damage is not required in Washington, DC unless a vehicle must be towed). However, accidents are still often reported for those with less property damage, as they are often helpful for insurance claims. Within this data is information on each reported accident, the date and location it occurred, and the individuals involved including their type (driver, passenger, cyclist, pedestrian, etc.) and the level of injury they sustained. Accidents by city from 2017-2023 are shown in figure 1.

From this data, I calculate daily counts of accidents, people involved in accidents, injuries, and fatalities. I further break down these numbers by separating them into person types: motorist, cyclist, or pedestrian. These 3 categories make up over 99 percent of people in accidents. Average daily accident information by city is summarized in figure 2. I obtain individual trip-level bike sharing data from each of the eight systems involved in this study. The structure of these BSSs ranges from fully private to a publicly owned but privately operated partnership. Those with a public-private partnership provide data publicly while fully private systems require a special request. These trip-level data include the date of the trip, time and system of origin, and the time and system of termination. Each trip was capped at 3 hours to account for observations where bikes were not returned to a station after the ride was finished, which was fewer than 1 percent of trips. Trip duration was then aggregated on a daily level to determine daily ridership by city.

To account for additional contributors to accidents, I include a variety of weather factors. These factors are total precipitation, average wind speed, average cooling degrees (degrees above 65 Fahrenheit), and average heating degrees (degrees below 65 Fahrenheit). I acquired Temperature and precipitation data from the PRISM Climate Group and wind speeds from the National Oceanic and Atmospheric Administration (NOAA) local monitors. Accidents can be affected by factors that increase the number of trips taken or by increasing the accident rate of existing trips. These variables are commonly used in the traffic safety literature and have been shown to affect total accidents in at least one of the two aforementioned ways. I also control for demographic differences in observations by obtaining annual, city-level data from the American Community Survey (ACS). These differences include median household income, median age, fraction of population that is male, and fraction of population with a college degree. Using Open Street Map (OSM), I construct an annual ratio of kilometers of bike infrastructure (bike lanes or multiuse paths) to kilometers of roads. I calculate this measure at the daily level but take an annual maximum due to the seasonal pattern in bike infrastructure reporting[1]. A city-level summary of BSS usage and accidents can be found in tables A1 and A2 in the appendix. All other variables are summarized in table A3. These datasets are combined to create observations at the city-by-day level with 18,992 observations (8 cities across 6.5 years). 230 observations (1.2 percent) are dropped due to missing temperature readings and 28 are dropped for having 0 hours of BSS usage (0.15 percent).

[1] Plotting the ratio of bike infrastructure to roads, there is a cyclical pattern that repeats annually for every city in the sample. This is likely due to the nature of OSM as an open-source data platform. While infrastructure for roads and bicycles is often built together, OSM relies on open sourcing to update. Since cycling is far more common during warmer times of the year, reporting on bike infrastructure is often delayed until summer or fall months despite being constructed earlier in the year while roads are well reported year-round.

Figure 1: Log Monthly Traffic Accidents by City

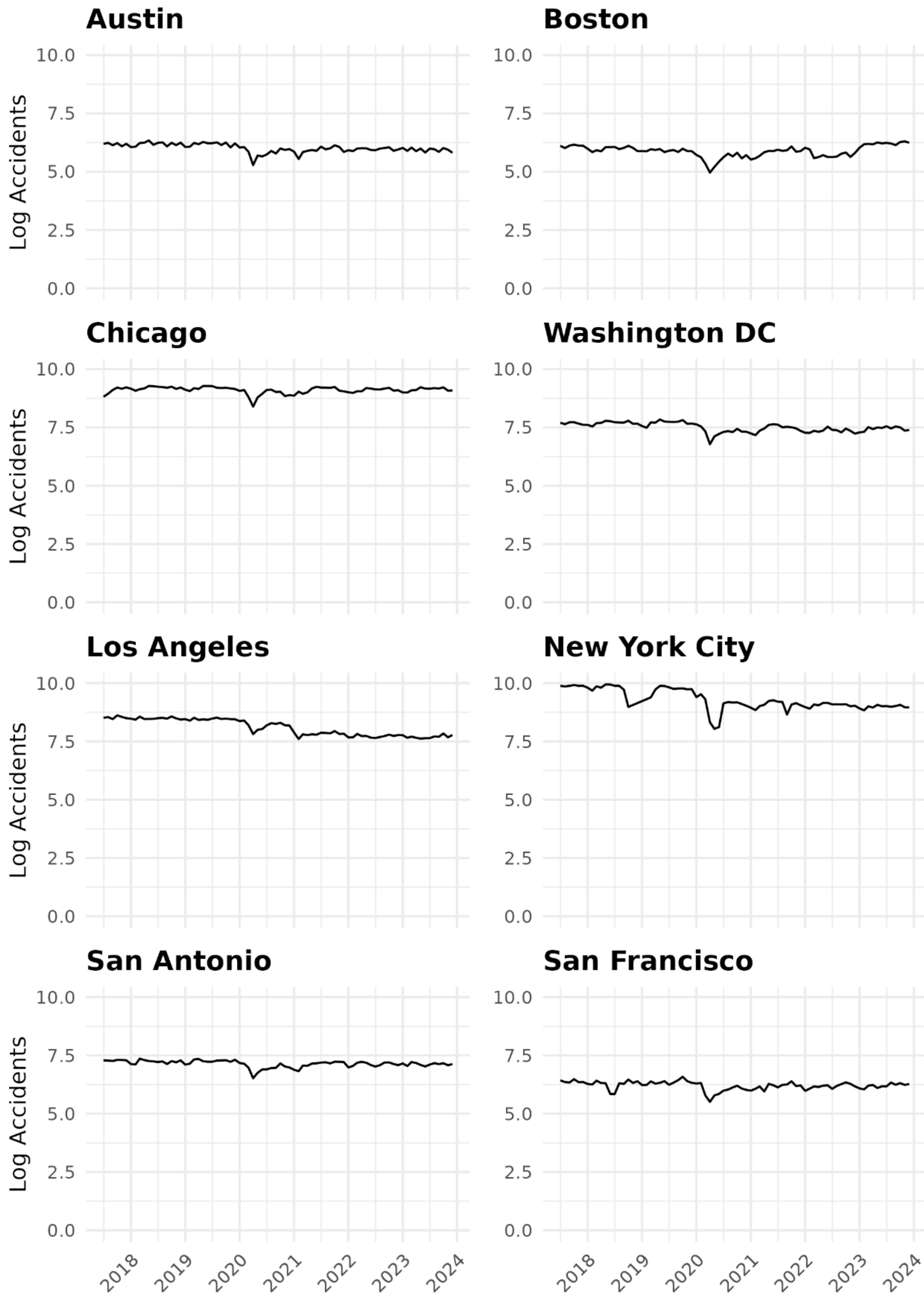
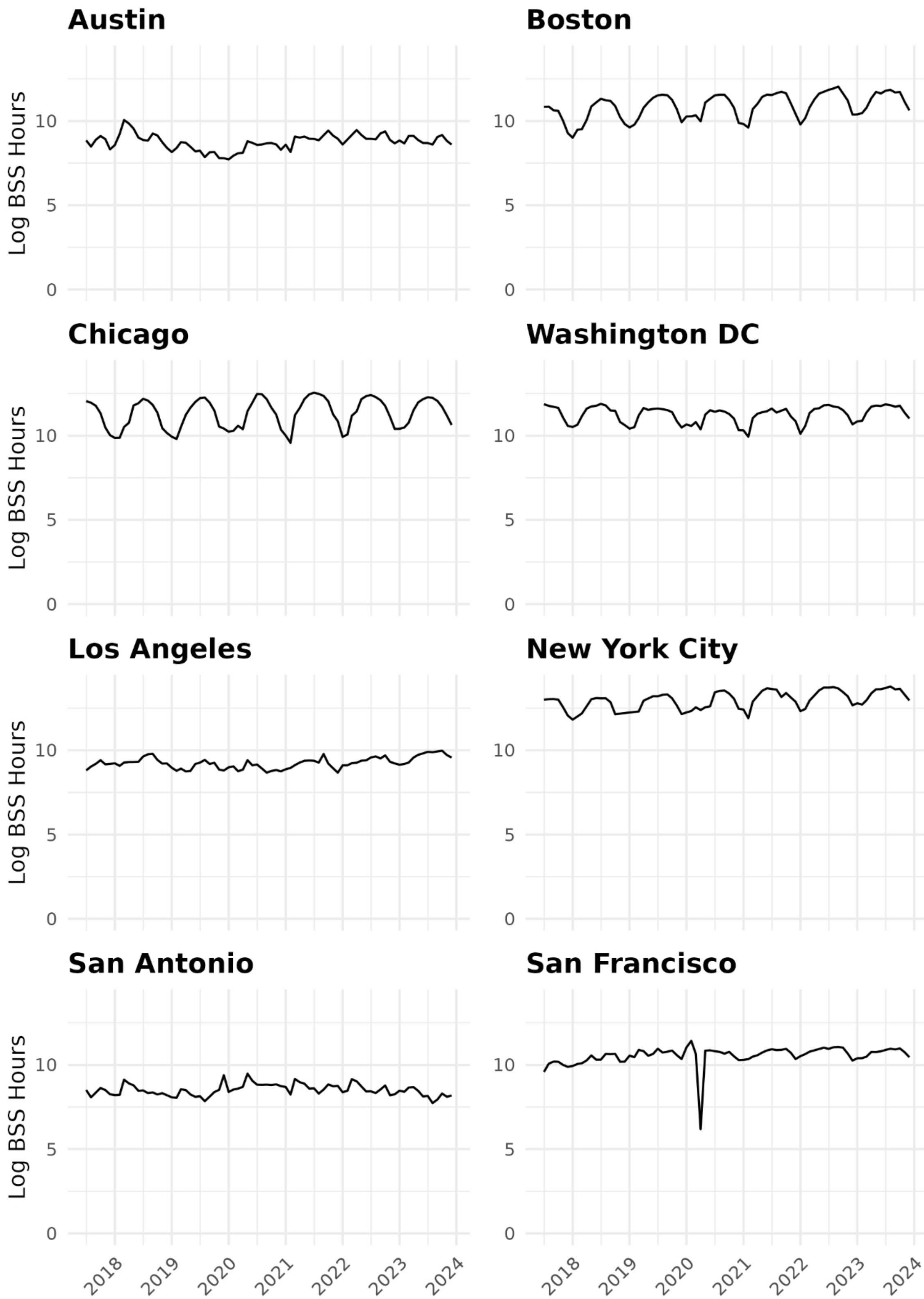


Figure 2: Log Monthly Hours of BSS Usage by City



C. *Model Specification*

I estimate the effect of BSS ridership on traffic accidents by regressing daily accidents on thousands of hours of BSS usage. The main specification for this model is a Poisson Pseudo Maximum Likelihood (PPML) model. This makes no assumptions about the distribution of the data, which allows for the mean and variance to differ – something not allowed in a classical Poisson model. This model estimates robust standard errors clustered at the city level. Additionally, I include the annual population as an offset in the model, so the estimated effects of BSS usage are per capita. The primary specification uses city×year, month of year, and day of week fixed effects. To better investigate the role of bike infrastructure and if it mitigates the impact of BSS usage on accidents, I relax this specification to city+year fixed effects and include models with city level time trends as well as annual demographic information. The main specification is shown in equation 1.

$$\mathrm{Y_{itmw}} = \beta_1 ln(X_{itmw}) + \beta_2\,\theta_{it} + ln(P_{it}) + \lambda_{it} + \delta_m + \mu_w + \varepsilon_{itmw} \qquad (1)$$

In this model, $\mathrm{Y_{itmw}}$ is the number of accidents in city *i* during year *t* in month *m* on the day of the week *w.* BSS usage, measured in the thousands of hours, is given by X_{itmw} and daily weather variable are given by θ_{it}. Fixed effects for city×year, month of year, and day of week are given by λ_{it}, δ_m, and μ_w. The error term is ε_{itmw}. Note that $ln(P_{it})$, where P_{it} is population, is included as a covariate with a fixed coefficient of 1, which offsets the dependent variable, making it accidents per capita instead of total accidents. Since a PPML model uses log-likelihood to estimate coefficients, by transforming BSS usage using a natural logarithm, the estimated β_1 can be interpreted as an elasticity – a 1 percent change in BSS usage increases accidents per capita by β_1 percent.

5. Results

A. *Accidents*

The results of estimating the baseline equation represented by Equation 1 are shown in column 1 of Table 1. The estimated coefficient on BSS usage suggests that a 1 percent increase in BSS usage increases accidents by 0.09 percent. This suggests a small but significant increase in total accidents when more people are using BSSs when accounting for time dependent differences across cities, exposure determined by month and day of week, and safety impacts and exposure effected by weather factors. Although the fit statistics suggest the results of the model predict outcomes within the sample very well (squared correlation of 0.966 and pseudo R squared of 0.942), it is possible that BSS usage is highly collinear with other factors that increase exposure or overall trip demand. If this is the case, the coefficient may be reporting the effect on accidents of more trips being taken of any kind instead of BSS usage alone. Unfortunately, comprehensive daily data on trips taken of all kinds is not available, so this estimate should be taken as an upper bound.

Column 2 replaces city×year fixed effects with city+year and adds city-level time trends to account for changes in infrastructure and other factors as well as annual demographic variables. The estimated coefficient on BSS usage is similar to the previous specification at about 0.07. The estimated coefficients for the city-level time trends are all negative and statistically significant – accidents per capita are decreasing in every city over the course of the study's period. These effects were previously absorbed through city×year fixed effects, but this result shows how safety is improving over time, possibly due to better infrastructure or other safety measures across cities.

Table 1: BSS Usage, Infrastructure, and Accidents

Dependent Variable:	Accidents			
Offset:	Population	Population	Population	BSS Usage
Model	(1)	(2)	(3)	(4)
Variables				
ln(BSS Usage)	0.0861***	0.0679**	0.1119**	
	(0.0243)	(0.0294)	(0.0558)	
Infrastructure Ratio			−0.0694	−0.1602*
			(0.0561)	(0.0972)
ln(BSS Usage) × Infrastructure Ratio			−0.0118**	
			(0.0054)	
Cooling Degrees	0.0042***	0.0043***	0.0050***	0.0084**
	(0.001)	(0.0012)	(0.0014)	(0.0033)
Heating Degrees	0.0024	0.0017	-6.69×10^{-5}	0.0423***
	(0.0014)	(0.0017)	(0.0024)	(0.0051)
Precipitation (in)	0.0077***	0.0070***	0.0032*	0.0398***
	(0.0009)	(0.001)	(0.0018)	(0.0043)
Wind Speed (mph)	0.0003	5.04×10^{-5}	−0.0004	0.0033***
	(0.0003)	(0.0004)	(0.0004)	(0.0011)
Median Income		-1.43×10^{-6}	-7.98×10^{-6}	-1.56×10^{-5}
		(6.73×10^{-6})	(1.06×10^{-5})	(1.20×10^{-5})
Fraction Female		−0.0717	−0.0548	−0.0537
		(0.0424)	(0.0479)	(0.0486)
Fraction with Bachelor's Degree		0.0022	−0.0522	−0.0869
		(0.0154)	(0.0418)	(0.0641)
Time Trend - Austin		−0.0007***		
		(0.0001)		
Time Trend – Boston		−0.0005***		
		(0.0001)		
Time Trend - Chicago		−0.0006***		
		(0.0001)		
Time Trend – Washington D.C.		−0.0007***		
		(0.0001)		
Time Trend – Los Angeles		−0.0010***		
		(0.0001)		
Time Trend – New York City		−0.0011***		
		(0.0001)		
Time Trend – San Antonio		−0.0006***		
		(0.0001)		
Time Trend – San Francisco		−0.0006***		
		(0.0001)		
Fixed effects				
City× Year	Yes	No	No	No
Day of Week	Yes	Yes	Yes	Yes
Month of Year	Yes	Yes	Yes	Yes
City	No	Yes	Yes	Yes
Year	No	Yes	Yes	Yes
Fit statistics				
Observations	18,726	18,726	18,726	18,726
Squared Cor.	0.96557	0.96263	0.94856	0.81024
Pseudo R^2	0.94174	0.93931	0.92836	0.82971

*Notes: Clustered (by city) standard-errors in parentheses. Codes for significance are given by: ***: 0.01, **: 0.05, *: 0.1.*

I then trade out city-level time trends for a specific infrastructure measure which is the ratio between bicycle infrastructure to roads. I drop the city-level time trends because this ratio is generally increasing over time in each city and therefore time trends would absorb much of its variation. This ratio and its interaction with BSS usage are included in column 3's estimation. The insignificant estimate on the infrastructure ratio indicates that bike infrastructure itself does not affect accident rates. However, the negative and statistically significant coefficient on the interaction term suggests that the increase in accident rate associated with more BSS usage is mitigated by better infrastructure – the effect of BSS usage on accident rate is lower in cities when there is a higher ratio of bike infrastructure to roads, which is consistent with infrastructure moderating traffic safety.

Lastly, I change the offset from population to BSS usage and estimate the effect of the infrastructure ratio on accidents per thousand hours of BSS usage. This model is another way to examine how better bike infrastructure affects safety by holding BSS usage constant. Like the previous model, better infrastructure is associated with better safety. The estimated coefficient on the infrastructure ratio is negative, albeit only at the 10 percent significance level (column 4) – conditional on BSS usage, better bike infrastructure reduces total accidents. Both models examining the role infrastructure plays in accidents indicate that cities with a higher ratio of bike infrastructure to roads are safer, as accidents are lower at the population level and BSS usage level. This consistency provides more confidence that the association between infrastructure and traffic safety is not a result of model specification.

B. *Accidents by Person Type*

In the next specifications, I examine the association between BSS usage and the types of accidents. These types include motorists involved in an accident, car-only accidents, cyclists in accidents, and pedestrians in accidents. By breaking down accidents into these various types, I look at how BSS usage affects each one of them and consider what mechanisms are involved. If accidents are affected purely through more cyclists getting into accidents, the mechanism is primarily increased exposure. However, the total increase in accidents may be offset by a reduction in other types of accidents if people are substituting away from these forms of transportation. On the other hand, BSS usage may have spillovers that result from increased usage of roads that could increase accidents of all forms if drivers and other commuters change their behavior in an attempt to accommodate the increased number of cyclists.

I estimate equation 1 again but for all four dependent variables that represent the type of accident. The results are shown in table 2. The estimated coefficient for the effect of BSS usage on cyclists in accidents is by far the highest, consistent with increased exposure of cyclists. However, the increase in accidents is not only explained by more cyclists getting in accidents, as the estimated effect of BSS usage on motorists in accidents, car-only accidents, and pedestrians in accidents are all positive and significant. This suggests that an increase in BSS usage is associated with higher accidents of all types. As discussed previously, a possible explanation for this is spillovers from the increased number of cyclists on the road. Drivers may become more distracted, thereby increasing the chance of being in an accident with another car, pedestrian, or cyclist. An important result to note as well is that the estimated coefficients are elasticities, and none are above 1. This means that even for cyclists in accidents, a 1 percent increase in BSS usage increases accidents by only 0.47 percent, and for pedestrians and motorists this is even lower. This supports the safety-in-numbers theory that each additional hour of BSS usage is safer than the usage, as when BSS usage increases, accidents per capita increase but at a slower rate.

As with the previous estimates, there is a possibility that BSS usage is a proxy for overall trip demand, caused by factors that would be correlated with BSS usage. However, the strong fixed effects account for slow moving variation over time and cyclical patterns over the week and year as well as time invariant city characteristics. Additionally, the different estimates across accident types are further evidence that BSS usage is not purely a proxy for general traffic patterns, as if that were the case I would expect the estimates to all be similar.

Table 2: BSS Usage and Accident Type

Dependent Variable:	Motorists	Car-only	Cyclists	Pedestrians
Offset:	Population	Population	Population	Population
Model	(1)	(2)	(3)	(4)
Variables				
ln(BSS Usage)	0.1170***	0.1126***	0.4652***	0.1436***
	(0.0274)	(0.0170)	(0.0579)	(0.0125)
Cooling Degrees	0.0046***	0.0041***	0.0029	0.0018
	(0.0008)	(0.0009)	(0.0021)	(0.0012)
Heating Degrees	0.0034***	0.0046***	−0.009	−0.0006
	(0.0008)	(0.0007)	(0.0047)	(0.0003)
Precipitation (in)	0.0078***	0.0085***	−0.0021	0.0194***
	(0.0006)	(0.0011)	(0.0031)	(0.0011)
Wind Speed (mph)	0.0003	0.0005*	0.0005	0.0019***
	(0.0002)	(0.0002)	(0.0004)	(0.0003)
Fixed effects				
City× Year	Yes	Yes	Yes	Yes
Day of Week	Yes	Yes	Yes	Yes
Month of Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	18,726	18,726	18,362	14,529
Squared Cor.	0.96963	0.96213	0.89023	0.83683
Pseudo R^2	0.97114	0.93572	0.72294	0.66909

*Notes: Clustered (by city) standard-errors in parentheses. Codes for significance are given by: ***: 0.01, **: 0.05, *: 0.1. Observation size differs due to the removal of observations that can be perfectly predicted using fixed effects.*

In tables 3 and 4, I replicate the previous estimates examining the role bike infrastructure plays in accidents both per capita (table 4) and per thousand hours of BSS usage (table 5) for motorists in accidents, car-only accidents, cyclists in accidents, and pedestrians in accidents. Overall, the results suggest that the previous results showing a mitigation effect of bike infrastructure on accidents are primarily driven by accidents involving vehicles. Per capita, the increase in car-only accidents when BSS usage is higher is lower when cities have better bike infrastructure. Similarly, the accidents per thousand hours of BSS usage involving motorists are lower when cities have better bike infrastructure. Estimates for accidents involving cyclists and pedestrians are imprecise and insignificant, likely due to the low number of accidents involving either form of transportation which results in insubstantial variation for estimations. There may also be competing effects in play where better infrastructure encourages trips to be taken with modes of transportation other than driving, as cyclists and pedestrians feel safer. Even if better infrastructure reduces accident probability by trip, the increase in trips can increase overall accidents thereby mitigating the reduction. With the same logic, accidents involving cars may decrease mechanically, as fewer people take trips using vehicles. However, this is unlikely the case for vehicle accidents – the increase in all accidents with more BSS usage is lower with better infrastructure and the similar magnitude in the estimated coefficients for car-only accidents suggests that it is this type that is driving the initial result.

Table 3: BSS Usage, Infrastructure, and Accident Type (per capita)

Dependent Variable:	Motorists	Car-only	Cyclists	Pedestrians
Offset:	Population	Population	Population	Population
Model	(1)	(2)	(3)	(4)
Variables				
ln(BSS Usage)	0.1898*	0.1546**	0.3116*	0.0680
	(0.0749)	(0.0532)	(0.1806)	(0.0571)
Infrastructure Ratio	-0.1226	-0.1009	0.0194	-0.0105
	(0.0854)	(0.0716)	(0.0192)	(0.0207)
ln(BSS Usage) × Infrastructure Ratio	-0.0164	-0.0127*	0.0164	0.0066
	(0.011)	(0.0074)	(0.0153)	(0.0048)
Cooling Degrees	0.0051***	0.0052***	0.0037**	0.0025*
	(0.0011)	(0.0009)	(0.0017)	(0.0015)
Heating Degrees	0.0019	0.0027*	-0.0106*	-0.0018*
	(0.0014)	(0.0014)	(0.0063)	(0.0010)
Precipitation (in)	0.0039	0.0045**	-0.0022	0.0185***
	(0.0024)	(0.0021)	(0.0042)	(0.0012)
Wind Speed (mph)	-0.0004	-6.15×10^{-5}	0.0007**	0.0019***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Median Income	-2.65×10^{-7}	-5.97×10^{-6}	-1.36×10^{-5}	-2.6×10^{-5}**
	(8.68×10^{-6})	(1.58×10^{-5})	(2.24×10^{-5})	(1.2×10^{-5})
Fraction Female	-0.0448	-0.0760	-0.0313	-0.1575
	(0.0452)	(0.0667)	(0.1285)	(0.1085)
Fraction with Bachelor's Degree	-0.0806*	-0.0790*	-0.0471	0.0341
	(0.0396)	(0.0469)	(0.057)	(0.0333)
Fixed effects				
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Day of Week	Yes	Yes	Yes	Yes
Month of Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	18,726	18,726	18,726	16,353
Squared Cor.	0.96207	0.94847	0.88199	0.84116
Pseudo R^2	0.96216	0.92201	0.71584	0.70063

*Notes: Clustered (by city) standard-errors in parentheses. Codes for significance are given by: ***: 0.01, **: 0.05, *: 0.1. Observation size differs due to the removal of observations that can be perfectly predicted using fixed effects.*

Table 4: BSS Usage, Infrastructure, and Accident Type (per thousand hours of BSS Usage)

Dependent Variable:	Motorists	Car-only	Cyclists	Pedestrians
Offset:	BSS Usage	BSS Usage	BSS Usage	BSS Usage
Model	(1)	(2)	(3)	(4)
Variables				
Infrastructure Ratio	-0.2555***	-0.2044**	0.034	-0.0099
	(0.0807)	(0.0959)	(0.0397)	(0.0444)
Cooling Degrees	0.0072***	0.0069**	0.0037	0.0019**
	(0.0023)	(0.0027)	(0.0025)	(0.0008)
Heating Degrees	0.0403***	0.0423***	0.0104***	0.0318***
	(0.0061)	(0.0052)	(0.0012)	(0.0048)
Precipitation (in)	0.0391***	0.0405***	0.0166***	0.0454***
	(0.0035)	(0.0043)	(0.0005)	(0.0036)
Wind Speed (mph)	0.0030***	0.0033***	0.0019***	0.0044***
	(0.0007)	(0.0010)	(0.0003)	(0.0004)
Median Income	-9.54×10^{-6}	-1.47×10^{-5}	-1.89×10^{-5}	-2.77×10^{-5}**
	(1.25×10^{-5})	(1.58×10^{-5})	(2.89×10^{-5})	(1.08×10^{-5})
Fraction Female	-0.0237	-0.0612	-0.0303	-0.1663
	(0.0416)	(0.0534)	(0.1508)	(0.1177)
Fraction with Bachelor's Degree	-0.1295***	-0.1215*	-0.0369	0.0195
	(0.0494)	(0.0652)	(1.89×10^{-5})	(0.0678)
Fixed effects				
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Day of Week	Yes	Yes	Yes	Yes
Month of Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	18,726	18,726	18,726	16,353
Squared Cor.	0.88016	0.83806	0.86377	0.73301
Pseudo R^2	0.90505	0.85219	0.70471	0.65610

*Notes: Clustered (by city) standard-errors in parentheses. Codes for significance are given by: ***: 0.01, **: 0.05, *: 0.1. Observation size differs due to the removal of observations that can be perfectly predicted using fixed effects.*

6. Discussion

In this study, I examine the relationship between the increased usage of bike sharing systems and traffic accidents as well as the role that more bike infrastructure plays in mitigating accidents. Utilizing a Poisson Pseudo Maximum Likelihood model, I find that a 1 percent increase in BSS usage is associated with a 0.07 to 0.09 percent increase in traffic accidents per capita depending on the model. Cities with a higher ratio of bike infrastructure to roads see a smaller increase in accidents when BSS usage increases suggesting a mitigation effect on accident increases. Additionally, holding BSS usage constant, more bike infrastructure is associated with fewer accidents. These two models suggest an important role that bike infrastructure plays in traffic safety.

I break down these accident numbers into person type, looking at motorists involved in accidents, car-only accidents, cyclists in accidents, and pedestrians in accidents. The results from these estimates show that all accidents of all forms increase with BSS usage, with cyclist accidents increasing the most. All the estimated elasticities were less than 0.5 meaning that a 1 percent increase in BSS usage is associated with less than a 0.5 increase in accidents – accidents per capita increase at a slower rate than BSS usage. This result supports the safety-in-numbers effect reported in the literature but also that there may be spillovers from BSS usage that increase accidents for other forms of transportation.

The introduction of bike sharing systems has provided an easy way for people to travel, commute, or even just sightsee in many cities across the United States. However, this fast introduction of a low-cost and easy to use form of micromobility has coincided with an increase in traffic accidents when holding other variables affecting travel demand constant. The fact that bike sharing systems have persisted and remain popular in many cities provides evidence of their value, but it is important to consider their direct costs and potential spillovers in traffic safety as well. The results of this paper show that while accidents increase with bike sharing usage, infrastructure plays a significant role in mitigating this effect. This particular insight suggests that better infrastructure for bicycles can lower accident rates, and cities that plan to implement or expand a BSS should improve bike infrastructure as well to lessen adverse effects from more cyclists while still benefitting from more cyclists.

7. References

Adler, M. W., & van Ommeren, J. N. (2016). Does public transit reduce car travel externalities? Quasi-natural experiments' evidence from transit strikes. *Journal of Urban Economics*, *92*, 106–119. https://doi.org/10.1016/j.jue.2016.01.001

Anderson, M. (2008). Safety for whom? The effects of light trucks on traffic fatalities. *Journal of Health Economics*, *27*(4), 973–989. https://doi.org/10.1016/j.jhealeco.2008.02.001

Anne Harris, M., Reynolds, C. C. O., Winters, M., Cripton, P. A., Shen, H., Chipman, M. L., Cusimano, M. D., Babul, S., Brubacher, J. R., Friedman, S. M., Hunte, G., Monro, M., Vernich, L., & Teschke, K. (2013). Comparing the effects of infrastructure on bicycling injury at intersections and non-intersections using a case-crossover design. *Injury Prevention*, *19*(5), 303–310. https://doi.org/10.1136/injuryprev-2012-040561

Bauernschuster, S., Hener, T., & Rainer, H. (2017). When labor disputes bring cities to a standstill: The impact of public transit strikes on traffic, accidents, air pollution, and health. *American Economic Journal: Economic Policy*, *9*(1), 1–37. https://doi.org/10.1257/pol.20150414

Beck, L. F., Dellinger, A. M., & O'Neil, M. E. (2007). Motor vehicle crash injury rates by mode of travel, United States: Using exposure-based methods to quantify differences. *American Journal of Epidemiology*, *166*(2), 212–218. https://doi.org/10.1093/aje/kwm064

Brijs, T., Karlis, D., & Wets, G. (2008). Studying the effect of weather conditions on daily crash counts using a discrete time-series model. *Accident Analysis and Prevention*, *40*(3), 1180–1190. https://doi.org/10.1016/j.aap.2008.01.001

Bureau of Transportation Statistics. (2024, November 22). *Bikeshare and e-scooters*. https://www.bts.gov/topics/passenger-travel/micromobility

Chang, L. Y., & Chen, W. C. (2005). Data mining of tree-based models to analyze freeway accident frequency. *Journal of Safety Research*, *36*(4), 365–375. https://doi.org/10.1016/j.jsr.2005.06.013

Clockston, R. L. M., & Rojas-Rueda, D. (2021). Health impacts of bike-sharing systems in the U.S. *Environmental Research*, *202*. https://doi.org/10.1016/j.envres.2021.111709

Currie, J., & Walker, R. (2011). Traffic congestion and infant health: Evidence from E-Zpass. *American Economic Journal: Applied Economics*, *3*(1), 65–90. https://doi.org/10.1257/app.3.1.65

Deenihan, G., & Caulfield, B. (2014). Estimating the health economic benefits of cycling. *Journal of Transport and Health*, *1*(2), 141–149. https://doi.org/10.1016/j.jth.2014.02.001

Ding, Q., Li, J., Wang, Q., Li, C., & Yue, W. (2021). Carbon Emission Effect of the Dock-Less Bike-Sharing System in Beijing from the Perspective of Life Cycle Assessment. *Journal of Environmental Accounting and Management*, *9*(1), 31–41. https://doi.org/10.5890/JEAM.2021.03.004

Doorley, R., Pakrashi, V., & Ghosh, B. (2017). Health impacts of cycling in Dublin on individual cyclists and on the local population. *Journal of Transport and Health*, *6*, 420–432. https://doi.org/10.1016/j.jth.2017.03.014

Elvik, R., & Bjørnskau, T. (2017). Safety-in-numbers: A systematic review and meta-analysis of evidence. *Safety Science*, *92*, 274–282. https://doi.org/10.1016/j.ssci.2015.07.017

Fishman, E., Washington, S., & Haworth, N. (2013). Bike Share: A Synthesis of the Literature. In *Transport Reviews* (Vol. 33, Number 2, pp. 148–165). https://doi.org/10.1080/01441647.2013.775612

Fishman, E., Washington, S., & Haworth, N. (2014). Bike share's impact on car use: Evidence from the United States, Great Britain, and Australia. *Transportation Research Part D: Transport and Environment*, *31*, 13–20. https://doi.org/10.1016/j.trd.2014.05.013

Gang-Len Chang, & Hua Xiang. (2003). *THE RELATIONSHIP BETWEEN CONGESTION LEVELS AND ACCIDENTS*.

Graham, D. J., & Glaister, S. (2003). Spatial variation in road pedestrian casualties: The role of urban scale, density and land-use mix. *Urban Studies*, *40*(8), 1591–1607. https://doi.org/10.1080/0042098032000094441

Green, C. P., Heywood, J. S., & Navarro, M. (2016). Traffic accidents and the London congestion charge. *Journal of Public Economics*, *133*, 11–22. https://doi.org/10.1016/j.jpubeco.2015.10.005

Haustein, S., & Møller, M. (2016). E-bike safety: Individual-level factors and incident characteristics. *Journal of Transport & Health*, *3*(3), 386–394. https://doi.org/10.1016/J.JTH.2016.07.001

Hermans, O., Hermans, E., Brijs, T., Stiers, T., & Offermans, C. (2006). *The Impact of Weather Conditions on Road Safety Investigated on an Hourly Basis*.

Høye, A. (2018). Bicycle helmets – To wear or not to wear? A meta-analyses of the effects of bicycle helmets on injuries. *Accident Analysis and Prevention*, *117*, 85–97. https://doi.org/10.1016/j.aap.2018.03.026

Jacobsen, P. L. (2003). *Safety in numbers: more walkers and bicyclists, safer walking and bicycling*. www.injuryprevention.com

Jara-Díaz, S., Latournerie, A., Tirachini, A., & Quitral, F. (2022). Optimal pricing and design of station-based bike-sharing systems: A microeconomic model. *Economics of Transportation*, *31*. https://doi.org/10.1016/j.ecotra.2022.100273

Justine Re. (2024). *Bike deaths in the city are at a 23-year high, report says TRANSIT*. https://ny1.com/nyc/manhattan/traffic_and_transit/2024/03/06/bike-deaths-in-the-city-are-at-a-23-year-high--report-says

Kamel, M. B., & Sayed, T. (2021). Accounting for seasonal effects on cyclist-vehicle crashes. *Accident Analysis and Prevention*, *159*. https://doi.org/10.1016/j.aap.2021.106263

Lee, I.-M., Hsieh, C.-C., & Paffenbarger, R. S. (1995). Exercise Intensity and Longevity in Men. *JAMA*, *273*(15), 1179–1184. https://doi.org/10.1001/jama.1995.03520390039030

Lichtman-Sadot, S. (2019). Can public transportation reduce accidents? Evidence from the introduction of late-night buses in Israeli cities. *Regional Science and Urban Economics*, *74*, 99–117. https://doi.org/10.1016/j.regsciurbeco.2018.11.009

Ling, R., Rothman, L., Cloutier, M. S., Macarthur, C., & Howard, A. (2020). Cyclist-motor vehicle collisions before and after implementation of cycle tracks in Toronto, Canada. *Accident Analysis and Prevention*, *135*. https://doi.org/10.1016/j.aap.2019.105360

Malyshkina, N. V., Mannering, F. L., & Tarko, A. P. (2009). Markov switching negative binomial models: An application to vehicle accident frequencies. *Accident Analysis and Prevention*, *41*(2), 217–226. https://doi.org/10.1016/j.aap.2008.11.001

Margaryan, S. (2021). Low emission zones and population health. *Journal of Health Economics*, *76*. https://doi.org/10.1016/j.jhealeco.2020.102402

Marshall, W. E., & Ferenchak, N. N. (2019). Why cities with high bicycling rates are safer for all road users. *Journal of Transport and Health*, *13*. https://doi.org/10.1016/j.jth.2019.03.004

Maze, T. H., Agarwal, M., & Burchett, G. (1948). Whether Weather Matters to Traffic Demand, Traffic Safety, and Traffic Operations and Flow. In *Transportation Research Record: Journal of the Transportation Research Board*.

Mix, R., Hurtubia, R., & Raveau, S. (2022). Optimal location of bike-sharing stations: A built environment and accessibility approach. *Transportation Research Part A: Policy and Practice*, *160*, 126–142. https://doi.org/10.1016/j.tra.2022.03.022

New York City Department of Transportation. (2013). *Facts on Citi Bike*. https://www.nyc.gov/html/dot/html/pr2013/facts-on-citi-bike.shtml

Parkin, J., Wardman, M., & Page, M. (2008). Estimation of the determinants of bicycle mode share for the journey to work using census data. *Transportation*, *35*(1), 93–109. https://doi.org/10.1007/s11116-007-9137-5

Pucher, J. (2001). *Cycling safety on bikeways vs. roads*. https://www.researchgate.net/publication/235356659

Pucher, J., & Buehler, R. (2006). Why Canadians cycle more than Americans: A comparative analysis of bicycling trends and policies. *Transport Policy*, *13*(3), 265–279. https://doi.org/10.1016/j.tranpol.2005.11.001

Raynor, J. L., Corbett, G., Grainger, A., & Parker, D. P. (2021). Wolves make roadways safer, generating large economic returns to predator conservation. *Proceedings of the National Academy of Sciences*. https://doi.org/10.1073/pnas.2023251118/-/DCSupplemental

Sánchez González, S., Bedoya-Maya, F., & Calatayud, A. (2021). Understanding the effect of traffic congestion on accidents using big data. *Sustainability (Switzerland)*, *13*(13). https://doi.org/10.3390/su13137500

Scott, P. P. (1986). MODELLING TIME-SERIES OF BRITISH ROAD ACCIDENT DATA. In *Accid. Anal. & Prev* (Vol. 18, Number 2).

Shr, Y. H. (Jimmy), Yang, F. A., & Chen, Y. S. (2023). The housing market impacts of bicycle-sharing systems. *Regional Science and Urban Economics*, *98*. https://doi.org/10.1016/j.regsciurbeco.2022.103849

Siman-Tov, M., Radomislensky, I., Peleg, K., Bahouth, H., Becker, A., Jeroukhimov, I., Karawani, I., Kessel, B., Klein, Y., Lin, G., Merin, O., Bala, M., Mnouskin, Y., Rivkind, A., Shaked, G., Sivak, G., Soffer, D., Stein, M., & Weiss, M. (2018). A look at electric bike casualties: Do they differ from the mechanical bicycle? *Journal of Transport and Health*, *11*, 176–182. https://doi.org/10.1016/j.jth.2018.10.013

Soriguera, F., & Jiménez-Meroño, E. (2020). A continuous approximation model for the optimal design of public bike-sharing systems. *Sustainable Cities and Society*, *52*. https://doi.org/10.1016/j.scs.2019.101826

Teschke, K., Harris, M. A., Reynolds, C. C. O., Winters, M., Babul, S., Chipman, M., Cusimano, M. D., Brubacher, J. R., Hunte, G., Friedman, S. M., Monro, M., Shen, H., Vernich, L., & Cripton, P. A. (2012). Route infrastructure and the risk of injuries to bicyclists: A case-crossover study. *American Journal of Public Health*, *102*(12), 2336–2343. https://doi.org/10.2105/AJPH.2012.300762

Thomas, T., Jaarsma, R., & Tutert, B. (2013). Exploring temporal fluctuations of daily cycling demand on Dutch cycle paths: The influence of weather on cycling. *Transportation*, *40*(1), 1–22. https://doi.org/10.1007/s11116-012-9398-5

Tribby, C. P., & Tharp, D. S. (2019). Examining urban and rural bicycling in the United States: Early findings from the 2017 National Household Travel Survey. *Journal of Transport and Health*, *13*, 143–149. https://doi.org/10.1016/j.jth.2019.03.015

Ulak, M. B., Ozguven, E. E., Vanli, O. A., Dulebenets, M. A., & Spainhour, L. (2018). Multivariate random parameter Tobit modeling of crashes involving aging drivers, passengers, bicyclists, and pedestrians: Spatiotemporal variations. *Accident Analysis and Prevention*, *121*, 1–13. https://doi.org/10.1016/j.aap.2018.08.031

UNITED NATIONS DEPARTMENT OF ECONOMIC AND SOCIAL AFFAIRS Commission on Sustainable Development Nine teenth Session New York, 2-13 BICYCLE-SHARING SCHEMES: ENHANCING SUSTAINABLE MOBILITY IN URBAN AREAS. (2011).

Wang, C., Quddus, M. A., & Ison, S. G. (2009). Impact of traffic congestion on road accidents: A spatial analysis of the M25 motorway in England. *Accident Analysis and Prevention*, *41*(4), 798–808. https://doi.org/10.1016/j.aap.2009.04.002

Warburton, D. E. R., Nicol, C. W., & Bredin, S. S. D. (2006). Health benefits of physical activity: The evidence. In *CMAJ* (Vol. 174, Number 6, pp. 801–809). https://doi.org/10.1503/cmaj.051351

Wright, N. A., & Dorilas, E. (2022). Do Cellphone Bans Save Lives? Evidence From Handheld Laws on Traffic Fatalities. *Journal of Health Economics*, *85*, 102659. https://doi.org/10.1016/J.JHEALECO.2022.102659

Zhang, Y., & Mi, Z. (2018). Environmental benefits of bike sharing: A big data-based analysis. *Applied Energy*, *220*, 296–301. https://doi.org/10.1016/j.apenergy.2018.03.101

Zhang, Z., Guo, Y., & Feng, L. (2022). Externalities of dockless bicycle-sharing systems: Implications for green recovery of the transportation sector. *Economic Analysis and Policy*, *76*, 410–419. https://doi.org/10.1016/j.eap.2022.08.009

8. Appendix

Table A1 – BSS Usage Summary

Variable	N	Mean	Std. Dev.	Min	Max	Description
BSS Usage – Austin	2,373	-1.67	0.71	-7.07	0.15	Daily BSS usage in Austin, TX. This value is the natural logarithm transformation of BSS usage measured in thousands of hours. Data accessed from: https://data.austintexas.gov/Transportation-and-Mobility/Austin-MetroBike-Trips/tyfh-5r8s/about_data
BSS Usage – Boston	2,371	0.46	0.91	-5.22	2.22	Daily BSS usage in Boston, MA. This value is the natural logarithm transformation of BSS usage measured in thousands of hours. Data accessed from: https://s3.amazonaws.com/hubway-data/index.html
BSS Usage – Chicago	2,372	0.89	1.01	-3.01	2.78	Daily BSS usage in Chicago, IL. This value is the natural logarithm transformation of BSS usage measured in thousands of hours. Data accessed from: https://divvy-tripdata.s3.amazonaws.com/index.html
BSS Usage – Washington D.C.	2,373	0.84	0.67	-1.89	2.35	Daily BSS usage in Washington D.C. This value is the natural logarithm transformation of BSS usage measured in thousands of hours. Data accessed from: https://s3.amazonaws.com/capitalbikeshare-data/index.html
BSS Usage – Los Angeles	2,374	-1.13	0.47	-3.41	1.21	Daily BSS usage in Los Angeles, CA. This value is the natural logarithm transformation of BSS usage measured in thousands of hours. Data accessed from: https://bikeshare.metro.net/about/data/
BSS Usage – New York City	2,165	2.66	0.67	-2.89	3.83	Daily BSS usage in New York, NY. This value is the natural logarithm transformation of BSS usage measured in thousands of hours. Data accessed from: https://s3.amazonaws.com/tripdata/index.html
BSS Usage – San Antonio	2,373	-1.96	0.73	-7.87	-0.17	Daily BSS usage in San Antonio, TX. This value is the natural logarithm transformation of BSS usage measured in thousands of hours. Data accessed through a private request to San Antonio BCycle.
BSS Usage – San Francisco	2,325	0.25	0.46	-2.31	1.44	Daily BSS usage in San Francisco, CA. This value is the natural logarithm transformation of BSS usage measured in thousands of hours. Data accessed from: https://s3.amazonaws.com/baywheels-data/index.html

Table A2 – Accident Summary

Variable	N	Mean	Std. Dev.	Min	Max	Description
Accidents – Austin	2,373	2.54	0.40	0.00	3.47	Daily traffic accidents in Austin, TX. This value is the natural logarithm transformation of traffic accidents. Data accessed from: https://cris.dot.state.tx.us/secure/Share/app/extract-request/my-extract-requests
Accidents – Boston	2,371	2.40	0.48	0.00	3.85	Daily traffic accidents in Boston, MA. This value is the natural logarithm transformation of traffic accidents. Data accessed from: https://geodot-massdot.hub.arcgis.com/pages/open-data-portal
Accidents – Chicago	2,372	5.68	0.21	4.43	6.37	Daily traffic accidents in Chicago, IL. This value is the natural logarithm transformation of traffic accidents. Data accessed from: https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if/about_data
Accidents – Washington D.C.	2,373	4.07	0.29	2.71	4.79	Daily traffic accidents in Washington D.C. This value is the natural logarithm transformation of traffic accidents. Data accessed from: https://opendata.dc.gov/datasets/crashes-in-dc/about
Accidents – Los Angeles	2,374	4.67	0.38	3.69	5.58	Daily traffic accidents in Los Angeles, CA. This value is the natural logarithm transformation of traffic accidents. Data accessed from: https://data.ca.gov/dataset/ccrs
Accidents – New York City	2,165	5.91	0.42	4.53	6.90	Daily traffic accidents in New York, NY. This value is the natural logarithm transformation of traffic accidents. Data accessed from: https://data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Crashes/h9gi-nx95/about_data
Accidents – San Antonio	2,373	3.70	0.27	2.40	4.49	Daily traffic accidents in San Antonio, TX. This value is the natural logarithm transformation of traffic accidents. Data accessed from: https://cris.dot.state.tx.us/secure/Share/app/extract-request/my-extract-requests
Accidents – San Francisco	2,325	2.77	0.35	0.69	3.74	Daily traffic accidents in San Francisco, CA. This value is the natural logarithm transformation of traffic accidents. Data accessed from: https://data.ca.gov/dataset/ccrs

Note: Observation size varies by city due to missing weather or BSS usage values.

Table A3 – Additional Variable Summary

Variable	N	Mean	Std. Dev.	Min	Max	Description
Precipitation	18,726	0.93	3.18	0.00	74.69	Daily precipitation measured in inches. Data access from: https://www.ncei.noaa.gov/access/search/index
Wind Speed	18,726	38.07	16.85	0.00	170.00	Daily average wind speed measured in miles per hour. Data accessed from: https://www.ncei.noaa.gov/access/search/index
Cooling Degrees	18,726	4.65	7.05	0.00	29.55	Degrees the daily average temperature is above 65 degrees Fahrenheit. Data accessed using the *prism* R Package.
Heating Degrees	18,726	8.32	11.35	0.00	81.33	Degrees the daily average temperature is below 65 degrees Fahrenheit. Data accessed using the *prism* R Package.
Infrastructure Ratio	56	9.74	5.10	3.94	28.42	The annual maximum ratio of bicycle infrastructure to roads, measured as a percent from 0 to 100. Data accessed from: https://dashboard.ohsome.org/
ln(Population)	56	14.30	0.87	13.39	15.98	The natural logarithm of the annual population. Data accessed from U.S. Census data using the *ipumsr* R package.
Median Income	56	90,501	21,454	61,172	145,193	The annual median income. Data accessed from U.S. Census data using the ipumsr R package.
Fraction Female	56	48.04	2.39	44.50	53.20	The annual ratio of female population to total population, measured as a percent from 0 to 100. Data accessed from U.S. Census data using the *ipumsr* R package.
Fraction with Bachelor's Degree	56	49.00	12.81	29.80	72.30	The annual ratio of population with a bachelor's degree or higher to the total population, measured as a percent from 0 to 100. Data accessed from U.S. Census data using the *ipumsr* R package.