The Effect of Bike Sharing Systems on Traffic Accidents, Injuries, and Fatalities

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1 Abstract

Bike sharing systems (BSS) have become prominent in the majority of large U.S. cities as another transportation option. I quantify the effects of an increase in the usership of these systems on traffic accidents, injuries, and fatalities and discuss the mechanisms through which these effects occur. For my empirical analysis, I utilize daily data from 8 different U.S. cities between 2014 and 2022 of BSS ridership and traffic accidents. The primary identification strategy uses a negative binomial model with average wind speed as an instrument for BSS ridership. I find that a 1 standard deviation increase in BSS ridership increases accidents by 11 percent, injuries by 24.3 percent, and fatalities by 96 percent. Additional model specifications suggest factors like bike infrastructure play the biggest role in overall safety.

2 Introduction

Bike sharing systems (BSS) have quickly emerged in the United States and become popular as a environmentally-friendly, low-cost form of transportation that could help reduce the use of motor vehicles and subsequently lower emissions and reduce congestion in crowded cities. Increased cycling is also 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 has recently seen a 23 year high in cyclist fatalities, with the majority coming from electric bike (e-bike) riders (Re, 2024). Statistics like these 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 e-bikes. 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 in to another one when they are finished. A dockless BSS does not use docks but instead allows users to find bikes using an 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 United States in the early 2010's (Bureau of Transportation Statistics, 2022), 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. As of 2022, there are 61 docked BSSs and 345 dockless BSSs serving over 155 cities in the United States (Bureau of Transportation Statistics, 2022).

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 reduced local air pollution, which has positive health effects in the form of reduced risk of cardiovascular disease and reduced risk of premature births (Margaryan, 2021; Currie and Walker, 2011). However, given that biking is an overall riskier form of transportation than driving, walking, and taking 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-bikes position and also leads to higher impact collisions in the cases 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 (Fishman et al., 2013). 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 (Fishman et al., 2013; Department of Economic and Social Affairs, 2011). In this project, I analyze the impact of BSS usage on traffic accidents, injuries, and fatalities. I do this by utilizing the variation in BSS usage across time and cities to determine a causal effect on traffic accidents.

3 Literature Review

3.1 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 and Tharp, 2019), and infrastructure and travel distance play a large role in choosing to bike (Parkin et al., 2008;

Pucher and 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; 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 the how mode share is related to accident rates have affirmed that this effect does occur (Lee et al., 2019; Elvik and 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 most if not all of the correlation can be explained through city-level infrastructure (Marshall and Ferenchak, 2019), as individuals are more likely to walk or ride a bicycle if they feel more safe to do so.

Many of the determinants of bike use can be applied to bike sharing. Bike infrastructure is also an important predictor of BSS usage, 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 well-suited for tourists who may not have their own bike or car. People who use BSSs are less likely to wear a helmet even when helmets are encouraged, compared to private, manual bikes (Haustein and Møller, 2016). Furthermore, the majority of BSSs utilize e-bikes which leads 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).

3.2 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 a causal effect (Wright and Dorilas, 2022; Raynor et al., 2021; Li, 2019; Anderson, 2008). This paper will draw from these studies and build up upon the broader literature of road safety.

Weather is a large factor that impacts overall traffic safety. Precipitation, especially that in the form of severe snowstorms, plays the biggest role in causing accidents (Maze et al., 2006; Chang and Chen, 2005). This effect is also prevalent among pedestrians (Graham and Glaister, 2003) and cyclists (Kamel and Sayed, 2021) and can likely be explained by rain and snowfall reducing visibility and increasing 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., 2006). 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 (Malyshkina et al., 2009; Brijs et al., 2008). 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 has been studied in a variety of environments. Within large cities, reducing congestion has been shown to reduce accidents and accident rates (González et al., 2021; Green et al., 2016). 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 (Wang et al., 2009; Chang and Xiang, 2003).

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 and van Ommeren, 2016). In regards to safety, public transit decreases accidents and injuries (Lichtman-Sadot, 2019; Bauernschuster et al., 2017). It is important to note however, that most of these studies rely on shocks to public transportation, like citywide implementation or strikes. It is uncertain if these effects would persist at the same level in the long run.

3.3 Direct and Indirect Impacts of Bike Sharing Systems

The majority 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 (Zhang and Mi, 2018) and therefore reduce local air pollution. However, e-bikes often export their emissions through production and maintenance costs to the extent where their environmental benefit is at least partially offset (Zhang et al., 2022; Ding et al., 2021), especially if they are being manufactured and charged using electricity produced through burning 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 (Ulak et al., 2018; Beck et al., 2007), 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 and 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. 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 predicted that bike sharing reduces mortality risk (Clockston and Rojas-Rueda, 2021).

This paper adds to this 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 will be improving upon the current health externality research by making fewer assumptions about the risks associated with BSS users. Instead of assuming BSS cyclists have the same mortality rate as manual cyclists, my analysis allows for them to differ. It will also be conducted using a panel of multiple cities allowing for a wider variety infrastructure and demographics to improve external validity of the results.

3.4 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 properly integrated. Although surveys have suggested the 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 and 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 still be the case.

The results from this paper will contribute a better understanding of the total costs involved 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.

4 Theoretical Model

To understand and predict how BSS ridership affects accidents, it is important to consider all of the channels through which it may do so. A higher level of BSS ridership indicates one of two things: (1) A trip that wouldn't 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 would increase accidents through increased exposure but could decrease accidents through the safety in numbers effect or by increasing driver awareness. Furthermore, it would affect congestion, though the literature is divided on if this would increase or decrease accidents. In the case of (2), when people change their mode of transportation to cycling using a BSS, there are fewer motorists and pedestrians, which decreases accidents, but more cyclists increases accidents. These effects and their impact on overall accidents, an increase (+), decrease (-), or ambiguous (?), are shown in figure (1).

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.

5 Data

I analyze daily bike sharing usage and traffic accidents from 2014-2022 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, DC. These cities were chosen due to their populations, length of time of uninterrupted service of bike sharing, and availability of data.

5.1 Traffic Accidents

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 2014-2022 are shown in figure (2).

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 table (1).

5.2 Bike Sharing Usage

I obtain individual trip level bike sharing data from each of the 8 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 the data publicly while the fully private systems required a special request. This trip level data includes the date of the trip, the time and station the trip originated at, and the time and station the trip finished at. Each trip was capped at 3 hours to account for observations where bikes were likely not returned to a station after the ride was finished. Trip duration was then aggregated on a daily level to determine the daily ridership by city.

The date range included is 2014-2022, though 2 systems did not begin operation until later — Los Angeles in 2016 and San Francisco in 2017. Additionally, Boston did not begin operating year-round until 2018. Because of this, I omit all observations for which ridership is zero to only compare observations for which there is the option of biking using a BSS. Across all 8 cities, the average ridership was 2,915 hours per day with a standard deviation of 5,275 hours per day. A breakdown of average daily ridership by city is shown in Table (2).

5.3 Additional Contributors to Accidents

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). 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). I include median household income, median age, percentage of the population male, and percentage of the population with a college degree.

6 Methodology

I estimate the effect of BSS ridership on traffic accidents by regressing daily accidents on hours of ridership. The primary specification is a standard OLS model that controls for time and city differences in addition to other contributors to accident numbers. The results from this specification help to assess the validity of utilizing an instrumental variable specification to address potential endogeneity concerns. These results are also compared with that of a Poisson model, which is included due to the nature of the data being counts as well as helping address the large number of zeros in the dependent variable.

6.1 Regression Specification

I regress daily accident numbers on hours of BSS ridership, using a transformation of *accidents* to account for nonlinearity. Typically, nonlinear data is transformed with a logarithmic transformation, however, the large number of zeros makes this difficult. While a commonly used technique of dealing with zeros would be to instead transform the dependent variable Y, as $ln(Y + 1)$, this can bias the results. Therefore, I transform both variables using the inverse hyperbolic sine function ($sinh^{-1}$). This transformation is chosen due to it its results being interpreted the same as those of a log transform while also being able to deal with zeros. The inverse hyperbolic sine function, which transforms a random variable, x, into a new, transformed variable, $\tilde{x}$ is given by

$$\tilde{x} = sinh^{-1}(x) = ln(x + \sqrt{x^2 + 1}). \qquad (1)$$

Except for very small values of x, $sinh^{-1}$ is approximately equal to $ln(2x)$ or $ln(2) + ln(x)$ allowing for the same interpretation as that of a log transformed variable.

The primary regression specification for this analysis is a standard ordinary least squares (OLS) model which is given by

$$sinh^{-1}(Y_{it}) = \beta_1 X_{it} + \beta_2 \theta_{it} + \lambda_i + \delta_t + \varepsilon_{it} \qquad (2)$$

where Y_{it} represents the number of accidents in city i in year t, and X_{it} is the number of hours of bike ridership. The coefficient of interest in this model is β_1, which is the percent change in accidents given a 1,000 hour increase in BSS ridership. Throughout, the regressions include weather and demographic controls θ_{it}, city fixed effects λ_i, and date fixed effects δ_t. Of particular concern is wind speed, which is initially included as a weather control, but also included to assess its validity as an instrument for BSS ridership.

6.2 Instrumental Variable: Average Wind Speed

Wind speed is often considered as a factor that may impact traffic safety, though the literature is mixed over the significance of its effect. Certain results suggest there may be an impact specifically from high speed gusts (Hermans et al., 2006) , though little evidence exists to suggest there is an effect on traffic safety, particularly in cities where this analysis takes place. Therefore, it has potential as an instrument due to its well documented effect on discouraging cycling (Thomas et al., 2013).

I consider an instrumental variable specification due to concerns over endogeneity that may arise from selection on non-random factors that affect overall transportation patterns. Accidents are likely to be higher on days when more people are travelling which will correspond with higher BSS ridership. While the OLS specification attempts to control for all of these variables that impact overall travel, any omitted variables will lead to a bias in the estimates. Therefore, by utilizing an instrument that is a good predictor of BSS ridership while not having a direct impact on accidents, I will be able to eliminate any bias introduced by omitted variables.

In this analysis, I utilize the variation in average wind speed as an instrument for BSS ridership. Wind speed has a direct effect on BSS ridership by making it more difficult and less enjoyable leading to fewer total hours in days with higher wind speeds. I show that this line of reasoning plays out in practice by estimating the first stage, which is shown by

$$X_{it} = \pi_1 W_{it} + \pi_2 \phi_{it} + \lambda_i + \delta_t + \nu_{it} \qquad (3)$$

where W_{it} represents the average wind speed, ϕ_{it} includes all the controls in θ_{it} except wind speed, and λ_i and δ_t are the same fixed effects as those from (2).

In order for average wind speed to be a valid instrument, it must also be independent of accidents except through its effect on BSS ridership after controlling for covariates that also impact accidents as well as city and date fixed effects. This is argued empirically through the results from the OLS estimations from (2). Additionally, I estimate

$$sinh^{-1}(Y_{it}) = \beta_1 W_{it} + \beta_2 \phi_{it} + \lambda_i + \delta_t + \xi_{it}, \qquad (4)$$

which is (2) without BSS ridership, to show how wind speed affects accidents by affecting BSS ridership. From the first stage (3), I calculate the fitted values

$$\widehat{X_{it}} = \pi_1 W_{it} + \pi_2 \phi_{it} + \lambda_i + \delta_t$$

which are then used to estimate the second stage

$$sinh^{-1}(Y_{it}) = \beta_{IV} \widehat{X_{it}} + \mu \phi_{it} + \lambda_i + \delta_t + \epsilon_{it} \qquad (5)$$

where the variables are the same as the previous equations.

6.3 Generalized Linear Model: Negative Binomial

Although *accidents* can theoretically take on infinite values, a sample of this data forces it to take on one of a finite number of values. This is the nature of discrete variables like count data, and modelling it with a standard OLS is more difficult, as the skew of count data, typically towards 0, means the values are unlikely to be normally distributed. Although OLS can give similar results if the mean of the data is large enough, data with a positive skew is better modeled using a discrete probability distribution.

The most popular choice when modelling count data is to use the Poisson distribution, which expresses the probability of a given number of discrete events. It's probability distribution function is categorized by parameter λ and is is given by

$$f_P(k|\lambda) = Pr(y = k) = \frac{\lambda^k e^{-\lambda}}{k!}, \ \lambda > 0, \ k = 0, 1, 2, ... \qquad (6)$$

where λ is both the mean and variance of random variable y. However, this characteristic also means the model is highly restrictive, as with count data the variance often exceeds the mean in a phenomenon called *overdispersion*. In this case, it is common to use a negative binomial (NB) model, which is derived from the Poisson model but models the parameter λ as a random variable itself. This freedom allows for the negative binomial model to address the lack of fit of a Poisson model when there is overdispersion.

In this analysis, I consider the use of a Poisson model and test for overdispersion. In the case the data is overdispersed, I instead use a negative binomial model and test for its goodness of fit to best model the data. With large enough means, these models will provide similar results to OLS, as both Poisson and negative binomial distributions converge to a normal distribution as the mean grows unbounded. Therefore, OLS is likely to provide similar results to these count models for variables like *accidents* and *injuries*, which have sample means of about 90 and 69 respectively. On the other hand, it likely to be a poor fit for more skewed variables like *fatalities*, which has a mean of 0.25.

7 Results

7.1 Baseline Specification

The results of the baseline specification are given in column 1 of table (3). They suggest that a 1,000 hour per day increase in BSS ridership will increase all traffic accidents by 1.4 percent. Given the standard deviation of ridership is 5,275 hours, an increase in ridership by one standard deviation increases traffic accidents by about 7.4 percent. While the majority of the controls show significant effects on accident numbers, average wind speed is not a significant factor in determining accidents. However, column 3 indicates that it *is* significant when removing BSS ridership, suggesting average wind speed could have an effect through its impact on cycling — an important note for the IV specification. Column 2 uses a very similar specification to the baseline, however, it uses date level fixed effects instead of year, month, day, and day of week. The estimated coefficient is very similar to the baseline model's. While date level fixed effects are more precise, the estimation from column 2 shows that there is little loss in precision by using the time fixed effects from the baseline model. Therefore, I use these for future specifications due to the stark decrease in computing power necessary for estimating the models.

7.2 IV

To assess the validity of average wind speed as an instrument, it must be both (1) relevant and (2) satisfy the exclusion restriction. Evidence for relevance is shown by the results of the first stage, given in table (4). Average wind speed is a significant factor that impacts BSS ridership — a 1 mile per hour increase in average wind speed decreases BSS ridership by 93 hours. I argue that the exclusion restriction also holds using evidence from table (3) and past traffic safety literature. From the baseline specification's results, average wind speed does not have a significant effect on accidents. However, when not controlling for BSS ridership (column 3), the results show that average wind speed does have an effect, suggesting that its effect is through its impact on BSS ridership. Furthermore, past studies have not identified wind as a significant factor affecting traffic accidents, as detailed in previous sections.

The results from the full IV specification are shown in column 1 of table (5). The estimated coefficient on BSS ridership is higher than the baseline OLS model — increasing BSS ridership by 1,000 hours increases accidents by 2.1 percent. This suggests a negative bias of the OLS estimate, which is different than initially expected. I utilized an IV model to tease out factors that impact overall transportation patterns which would likely increase both BSS ridership and accidents. However, if this were true, the IV estimate would be lower than the OLS estimate. Since the opposite is true, any omitted variable(s) either has a positive covariance with accidents and a negative covariance with BSS ridership or vice versa. There are a couple of possible explanations for this. One is that there is something positively correlated with accidents but negatively correlated with BSS ridership. The most obvious explanation would be a weather factor that makes travelling more dangerous but highly discourages cycling. However, all relevant weather variables have been controlled for, so this is unlikely to be the case. On the other hand, a factor that is negatively correlated with accidents but positively correlated with BSS ridership would have the same bias. This criteria suggests something related to safety, such as infrastructure change, specifically that which makes cycling safer like dedicated lanes or paths. Omitting measures of traffic infrastructure that affects bike safety would lead to the effect of BSS ridership on accidents being underestimated in the OLS model.

7.3 NB and NBIV

Due to the nature of the data as counts, I next estimate a Poisson regression using the same controls as OLS and IV. However, the results from a dispersion test suggest that the data is overdispersed: the variance is higher than the mean of the data, which violates the assumptions of a Poisson model. To account for this, I instead estimate a negative binomial regression to allow for a differing mean and variance. The results are shown in column 2 of table (5). Because a negative binomial model is estimated using maximum likelihood, the results can be interpreted similar to those from the OLS and IV models as a percent increase in the dependent variable from a 1 unit increase in the independent variable. As expected due to the large mean of *accidents*, the estimated coefficient is similar to the OLS estimate; a 1,000 hour increase in BSS ridership increases accidents by about 1.4 percent. Results using an IV regression with a negative binomial second stage are also shown in column 3 of table (5) and give similar results to the standard IV model.

7.4 People, Injuries, and Fatalities

To further analyze the results, I next look at people in accidents, injuries, and fatalities in addition to total accidents. I estimate the effect of increased BSS ridership on these outcomes using a negative binomial IV model due to continued concerns over overdispersion and endogeneity. The results are shown in table (6). The estimated coefficients on BSS ridership indicate that a 1,000 hour increase in usage increases the number of people in accidents by 3 percent, injuries by 4.6 percent, and fatalities by 18.6 percent.

All three of these estimates are positive, which follows from the previous results on the effect of BSS ridership on accidents. More accidents likely lead to more people in accidents, more injuries, and more fatalities, unless the dominating effect from BSS ridership increasing is a decrease in accident severity, which is possible if BSS ridership affects congestion in a significant way. However, since injuries and fatalities increase with accidents, it is increased exposure and/or a greater use of more a dangerous form of transportation that result from higher BSS ridership.

7.5 Breaking Down Results by Type

In an attempt to investigate the channels through which accident, injury, and fatality numbers change, I estimate the effect of BSS ridership on each of these outcomes for motorists, pedestrians, and cyclists using a negative binomial model. I do not use an IV specification, since average wind speed is a poor instrument for specific modes of transpiration like walking or cycling: it no longer affects accidents, injuries, and fatalities of these transportation modes solely through its impact on BSS ridership, and thus the exclusion restriction is no longer satisfied.

The results for cyclists are shown in table (7). The estimated effects of BSS ridership on cyclists in accidents, injured, or killed are maybe the most obvious. A 1,000 hour increase in BSS ridership increases cyclist accidents by 3 percent, cyclist injuries by 4.5 percent, and cyclist fatalities by 2.3 percent. However, it is important to note that the effect on fatalities is not statistically significant, likely due to very low counts of cyclist fatalities. An increase in BSS ridership should strictly increase the number of cyclists, which would lead to higher numbers of all three of these metrics, provided accident rates don't decrease considerably. Whether or not there is a change in the accident, injury, and fatality rate, however, is unclear from these estimates, so it is not possible to make any conclusions about if there is a safety in numbers effect or change in cyclist profile.

What is perhaps more interesting are the effects of BSS ridership on motorist accidents, which are displayed in column 1 of table (8). An increase in BSS ridership leads to more motorist accidents, with a 1,000 hour increase in ridership leading to a 1.7 percent increase in motorist accidents. Although the effect on injuries is not significant, there is a significant effect on fatalities. However, the the estimated effect on fatalities is a 3 percent increase for a 1,000 hour increase in BSS ridership, which is almost twice that of the effect on accidents. This would suggest motorist accidents become more severe when there is a higher level of BSS ridership, which seems unlikely. Instead, there is likely an omitted covariate that is positively correlated with BSS ridership and motorist fatalities which is biasing the result.

For pedestrians involved in accidents, the results are shown in table (9). A 1,000 hour increase in BSS ridership decreases pedestrians in accidents by 0.4 percent. The impact on injuries and fatalities is not statistically significant. This, however, may be due to there being not enough data to draw conclusions, as a decrease in pedestrians in accidents should also mean fewer getting injured or killed. There are a few possible mechanisms for the decrease in pedestrian accidents. One is through BSS ridership's impact on motorists — more cyclists can increase drivers' awareness and decrease the possibility of them getting in an accident. However, the higher number of motorists involved in accidents discredits this slightly, unless the majority of additional accidents caused by increased BSS ridership were with cyclists. The more probable explanation is that fewer people are walking, and instead using a BSS as their chosen form of transportation. This follows from some aforementioned surveys in that the majority of BSS trips are those that replace walking as opposed to driving.

8 Conclusion

In this study, I estimate the effect of increased usage of bike sharing systems on traffic accidents. Utilizing a negative binomial instrumental variable model, I find that a 1,000 hour increase in BSS ridership increases traffic accidents by 2.1 percent, people in accidents by 3 percent, injuries by 4.6 percent, and fatalities by 18.2 percent. With the standard deviation of BSS ridership being 5,275 hours, a one standard deviation increase in BSS ridership increases accidents by 11 percent, people in accidents by 15.8 percent, injuries by 24.3 percent, and fatalities by 96 percent. These significant, positive estimates are supported by a standard OLS and IV model as well as a regular NB model.

When examining how different transportation modes are affected, BSS ridership increases the number of motorists and cyclists in accidents but decreases the number of pedestrians in accidents. This suggests that BSS trips are mainly replacing walking. While it is difficult to draw conclusions regarding additional effects like safety in numbers or increased driver awareness, the fact that cyclist and motorist accidents did not decreases suggests that the effect of increased exposure was far higher than either of these two effects.

Overall, I find the estimates for the NB IV models to be higher than their non-instrumented counterparts. This negative bias suggests the omission of important covariates that could include city level infrastructure change or additional deterrents of cycling that also impact safety. These variables would have opposite correlations with accidents and BSS ridership, which would lead to the negative bias. Addressing these concerns, however, is difficult. Infrastructure data on the city by year level is not readily available and determining every cycling deterrent that affects safety is a complicated task.

With a perfect instrument, this would not be grounds for concern. However, average wind speed has its limits when it comes to its validity in this study. I show that it satisfies the two conditions necessary for instruments when regarding *accidents* as an outcome, although it is far less perfect for some of the remaining dependent variables. To address this in future research, I would need to adjust the standard NB model by adding the necessary covariates or find a better instrument.

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9 Tables and Figures

Figure 1: BSS Ridership Mechanisms

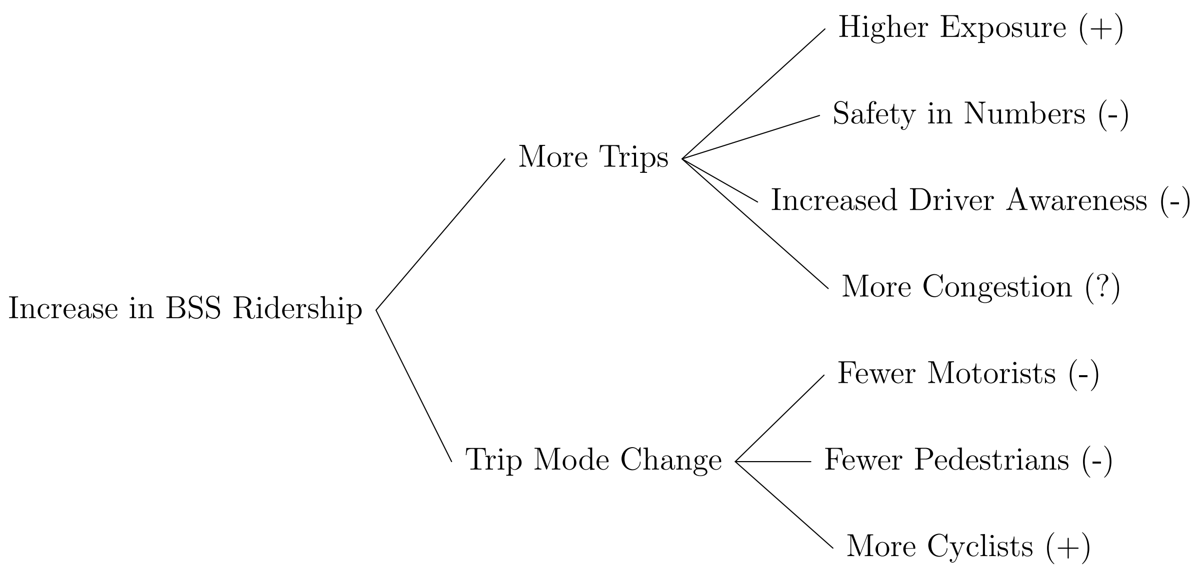
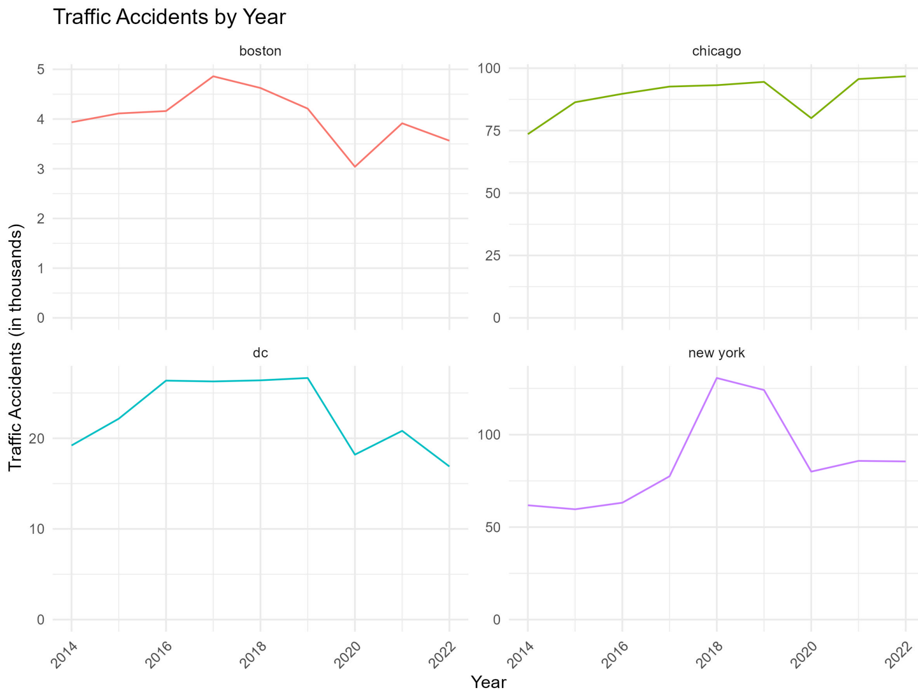


Figure 2: Traffic Accidents by City and Year



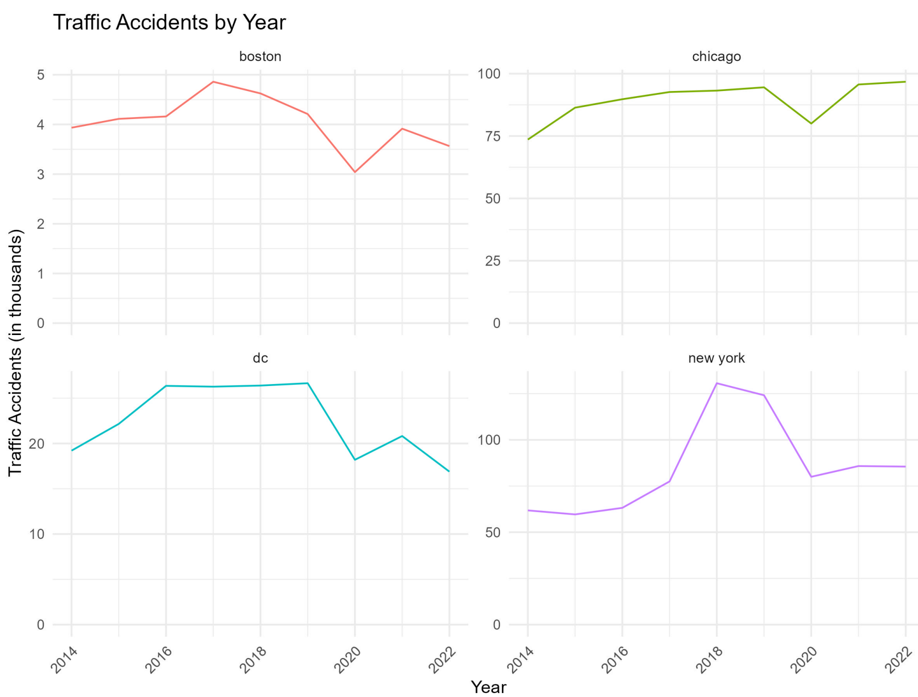


Table 1: People Involved in Traffic Accidents (Daily Average from 2014 to 2022)

	Austin	Boston	Chicago	DC	Los Angeles	New York	San Antonio	San Francisco
People	27.80	25.83	744.96	145.50	121.09	509.09	84.08	16.19
-*Motorists*	27.72	24.57	731.02	139.52	109.67	472.37	83.78	12.68
-*Cyclists*	0.01	0.40	4.50	1.43	3.72	11.97	0.04	1.27
-*Pedestrians*	0.00	0.79	9.11	2.84	7.37	24.75	0.00	1.94
Injuries	6.57	4.45	230.53	20.01	93.55	163.83	14.95	12.39
-*Motorists*	6.54	4.42	220.75	16.78	82.57	127.96	14.85	8.93
-*Cyclists*	0.01	0.01	2.34	1.00	3.68	11.55	0.03	1.27
-*Pedestrians*	0.00	0.01	7.34	2.15	6.99	24.31	0.00	1.89
Fatalities	0.03	0.05	0.23	0.10	0.85	0.65	0.07	0.10
-*Motorists*	0.03	0.05	0.13	0.07	0.42	0.29	0.06	0.04
-*Cyclists*	0.00	0.00	0.01	0.00	0.05	0.05	0.00	0.01
-*Pedestrians*	0.00	0.00	0.08	0.03	0.38	0.31	0.00	0.05

Table 2: Average Daily BSS Ridership

City	2014	2015	2016	2017	2018	2019	2020	2021	2022
Austin	180	192	232	248	341	128	154	262	282
Boston	777	771	843	913	1386	1940	1946	2430	2985
Chicago	1834	2362	2597	2710	2899	3199	3584	4784	4110
DC	2226	2514	2731	3162	2937	2619	2159	2457	3001
Los Angeles	0	0	84	227	398	277	255	334	393
New York	1624	6501	11083	11711	11103	13161	15930	19585	20301
San Antonio	173	154	160	172	165	149	226	202	179
San Francisco	0	0	0	367	1109	1452	1515	1451	1681

Table 3: OLS Estimations

	Dependent variable:		
	$sinh^{-1}(Accidents)$		
	(1)	(2)	(3)
BSS Ridership in Thousands of Hours	0.014***	0.012***	
	(0.001)	(0.001)	
Average Wind Speed	−0.001	−0.00003	−0.002***
	(0.001)	(0.001)	(0.001)
Year, Month, Day, and Day of Week FE	X		X
Date FE		X	
City FE	X	X	X
Weather Controls	X	X	X
Demographic Controls	X	X	X
Observations	23,586	23,586	23,586
R^2	0.932	0.947	0.931
Adjusted R^2	0.932	0.938	0.931
Residual Std. Error	0.324 (df = 23514)	0.309 (df = 20283)	0.326 (df = 23515)
F Statistic	4,561.000*** (df = 71; 23514)		4,559.000*** (df = 70; 23515)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: First Stage

	Dependent variable:
	BSS Ridership in Thousands of Hours
	(1)
Average Wind Speed	-0.093^{***}
	(0.005)
Year, Month, Day, and Day of Week FE FE	X
City FE	X
Weather Controls	X
Demographic Controls	X
Observations	23,586
R^2	0.736
Adjusted R^2	0.735
Residual Std. Error	2.660 (df = 23515)
F Statistic	937.100^{***} (df = 70; 23515)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5: IV, NB, and NBIV Estimates

	Dependent variable:		
	Accidents		
	IV	NB	NB IV
BSS Ridership in Thousands of Hours	0.021*** (0.007)	0.013*** (0.001)	0.021*** (0.006)
Year, Month, Day, and Day of Week FE	X	X	X
City FE	X	X	X
Weather Controls	X	X	X
Demographic Controls	X	X	X
Observations	23,586	23,586	23,586
R^2	0.932		
Adjusted R^2	0.932		
Log Likelihood		−94,209.000	−94,461.000
θ		19.810*** (0.264)	19.040*** (0.251)
Akaike Inf. Crit.		188,562.000	189,064.000
Residual Std. Error	0.324 (df = 23515)		

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Impact of BSS Ridership on All People

	Dependent variable:			
	Accidents	People	Injuries	Fatalities
	(1)	(2)	(3)	(4)
BSS Ridership in Thousands of Hours	0.021*** (0.006)	0.030*** (0.008)	0.046*** (0.013)	0.182*** (0.060)
Year, Month, Day, and Day of Week FE	X	X	X	X
City FE	X	X	X	X
Weather Controls	X	X	X	X
Demographic Controls	X	X	X	X
Observations	23,586	23,586	23,586	23,586
Log Likelihood	−94,461.000	−118,320.000	−96,302.000	−11,583.000
θ	19.040*** (0.251)	7.531*** (0.077)	3.211*** (0.033)	2.658*** (0.256)
Akaike Inf. Crit.	189,064.000	236,782.000	192,747.000	23,308.000

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Impact of BSS Ridership on Cyclists

	Dependent variable:		
	Cyclists	Injuries	Fatalities
	(1)	(2)	(3)
BSS Ridership in Thousands of Hours	0.030^{***}	0.045^{***}	0.023
	(0.002)	(0.002)	(0.014)
Year, Month, Day, and Day of Week FE	X	X	X
City FE	X	X	X
Weather Controls	X	X	X
Demographic Controls	X	X	X
Observations	23,586	23,586	23,586
Log Likelihood	−33,018.000	−27,205.000	−1,287.000
θ	5.152^{***} (0.160)	6.556^{***} (0.248)	2.576 (2.700)
Akaike Inf. Crit.	66,181.000	54,554.000	2,718.000

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8: Impact of BSS Ridership on Motorists

	Dependent variable:		
	Motorists	Injuries	Fatalities
	(1)	(2)	(3)
BSS Ridership in Thousands of Hours	0.017***	−0.002	0.030***
	(0.001)	(0.001)	(0.006)
Year, Month, Day, and Day of Week FE	X	X	X
City FE	X	X	X
Weather Controls	X	X	X
Demographic Controls	X	X	X
Observations	23,586	23,586	23,586
Log Likelihood	−117,217.000	−94,610.000	−8,305.000
θ	7.455*** (0.077)	2.903*** (0.030)	0.947*** (0.082)
Akaike Inf. Crit.	234,578.000	189,364.000	16,753.000
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Impact of BSS Ridership on Pedestrians

	Dependent variable:		
	Pedestrians	Injuries	Fatalities
	(1)	(2)	(3)
BSS Ridership in Thousands of Hours	-0.004^{***}	0.001	0.008
	(0.001)	(0.001)	(0.006)
Year, Month, Day, and Day of Week FE	X	X	X
City FE	X	X	X
Weather Controls	X	X	X
Demographic Controls	X	X	X
Observations	23,586	23,586	23,586
Log Likelihood	−41,068.000	−35,213.000	−5,560.000
θ	5.383^{***} (0.120)	7.060^{***} (0.182)	6.805^{**} (2.722)
Akaike Inf. Crit.	82,279.000	70,571.000	11,263.000

Note: *p<0.1; **p<0.05; ***p<0.01