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Motor-vehicle drivers' behavioral response to increased bicycle traffic ☆

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ABSTRACT

Introduction: This paper investigates whether motor-vehicle driver behavior changes when there are more bicycles on the road. *Method*: Data on trips on a rapidly expanding public bike share scheme in Chicago are combined with speed violations captured by a network of 79 cameras. Using weekly data from July 2014 to December 2016, violations at 26 sites where there was a considerable increase in bicycle traffic are compared with a control group of 53 locations where rental bicycles are not available. *Results*: An increase in rental bicycle usage is statistically related to a reduction in the number of speeding violations, with an estimated elasticity of −0.04. *Conclusion*: The increased presence of bicyclists makes at least some motorists drive more cautiously. *Practical Application*: This research provides some insight into the mechanism behind the observed reduction in crash rates as bicyclists become more numerous. Some motorists moderate their speeds allowing more time to avoid collisions and a reduction in the severity of the vehicle-bicyclist collisions that still occur.

1. Introduction

Cycling is a particularly risky mode of transportation. Elvik (2009) using Norwegian data from 1998 to 2005 found that cyclists were 7.5 times more likely to sustain an injury per kilometer of travel than were automobile occupants. Moreover, nonfatal bicycle-involved collisions are likely to be under-reported because, unlike automobiles, bicycles do not have the same insurance requirements (Elvik & Mysen, 1999). Physics tells us that cyclists suffer worse outcomes in a motor vehicle-bicycle collision relative to automobile occupants.

Nonetheless, one ray of hope for proponents of cycling has been the safety-in-numbers hypothesis. This hypothesis argues that as bicycle usage increases, there is a less than proportional increase in the occurrence of collisions with motor vehicles. One possible explanation is that the greater presence of cyclists results in drivers having a greater awareness of these other road users and consequently taking more care to avoid collisions.

This work investigates the issue by combining two data sets from Chicago. The first is an extraordinarily detailed database on the details of every trip made using the public bike share program (see Fishman, Washington, & Haworth, 2013, for a review of the literature on bike share schemes). The Chicago scheme, known by the tradename "Divvy," has expanded rapidly in recent years both in its geographical coverage and in its popularity. The second data set measures motor-vehicle driver behavior using speed violations detected by enforcement cameras that were installed citywide near parks and schools. This paper investigates whether speed violations decrease at locations with increased shared bicycle usage relative to locations that were not served by the bike share program.

2. Literature review

2.1. Safety-in-numbers literature

There are several recent meta-analyses that report on almost 50 individual studies that examine whether increased pedestrian and/

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or bicycle traffic result in a less than proportionate increase in collisions with motor vehicles (Elvik, 2017; Elvik & Bjørnskau, 2017; Elvik & Goel, 2019). The majority of the studies look for the effect on a micro-level, examining a cross-section of individual pedestrian crossings or intersections. Others, however, look at a more macro level, such as at the number of crashes in a traffic zone or municipality.[1] In general, all of the papers demonstrate some degree of a safety-in-numbers effect and that the effect weakens with a larger number of pedestrians or cyclists.

Much of the literature is cross-sectional in nature with comparisons of collision rates at different locations. Such analyses have difficulty untangling two competing explanations. One is a pure safety-in-numbers explanation. As the number of cyclists on the road increase "the larger is the number of 'living warning signs' and the greater the consideration shown them by motorists" (Brüde & Larsson, 1993). The alternative explanation is that cyclists utilize streets where the infrastructure is more conducive to safe cycling. Consequently, the highest bicycle traffic is observed in locations where the collision rate is the lowest. This is referred to as the numbers-in-safety hypothesis.

Cross-sectional studies can account for the numbers-in-safety effect by including variables on highway design such as the speed limit and the presence of protected bicycle lanes. However, a time-series analysis of locations where bicycle traffic varies, but the infrastructure remains the same, is better for isolating the safety-in-numbers effect.

2.2. Theoretical behavioral literature

Authors have postulated theoretical models that provide intuition for the safety-in-numbers hypothesis. Jacobsen, Ragland, and Komanoff (2015) argue that changes in motorist behavior must be the dominant explanation. This explanation becomes more convincing when paired with theories of driver psychology, and the empirical testing of these theories in driving simulators (Ranney, 1994). A widely cited theoretical model by Wilde (1982) utilizes the economics concept of risk homeostasis. In broad terms, this model hypothesizes that drivers have some target level of risk that they wish to bear in return for the benefits of driving from A to B. When the increased presence of cyclists leads to a higher risk of a collision, drivers compensate with actions that might include reducing speed and more reconnoitering.

Risk homeostasis combined with the zero risk theory (Näätänen & Summala, 1974) led to the Task-Capability Interface (TCI) model (Fuller, 2005). The TCI model measures the output of an individual driver's performance in terms of "task demand" and "capability." While driving, any individual driver balances the difficulty of their tasks, such as making a tight turn or overtaking, with their individual capability. If capability exceeds task difficulty, driving is easy and drivers perform well. If task difficulty exceeds capability, the driver's performance falters and they fail the task. For example, this may result in a motorist veering off the road or running a stop sign.

As drivers do not wish to crash, they compensate with actions that lower the difficulty when it approaches their personal capability. In laboratory studies to test the TCI model, Fuller, McHugh, and Pender (2008) found that on every type of roadway there was a close relationship between ratings of task difficulty and driver speed. In other words, drivers compensate for the potential difficulty caused by the presence of cyclists by either slowing down or by taking other actions such as curtailing conversations with passengers.

Another possible mechanism is discussed by Michon (1985) and van der Molen and Bötticher (1987). Their models argue that as cyclists become more numerous then motorists become more skilled in tasks such as recognizing how the cyclist may act, and in maneuvering around them. As a result, collision risks decrease. The problem with such an explanation is that skills learned in higher cycling locations should also manifest themselves when the motorist encounters a cyclist at a location with low bicycle volumes.

3. Theoretical model

This paper is in the spirit of the risk homeostasis and Task-Capability Interface framework. We argue that each individual driver, denoted by subscript i, has a target level of risk. They then traverse the highway network at time t and encounter various locations, subscripted by a. We assume that this target risk, which we denote by a bar above the risk variable, applies equally at all parts of the network

Given the personal target level of risk, drivers balance their inherent capabilities, the nature of the highway infrastructure at a particular location, the presence of other road users, and environmental factors such as the weather (that is presumed to be the same at all locations within the city at a given time), with the intensity with which they drive. This is described in Eq. (1).

$$\overline{Risk_i} = f(capability_i, intensity_{iat}, infrastructure_{at}, other\,users_{at}, weather_t) \quad (1)$$

While driving intensity encompasses both speed selection and other actions such as greater reconnoitering, this paper utilizes data on speed. We also focus on the presence of bicycles as a particular type of other road users. Consequently, the equation can be rearranged as

$$speed_{iat} = g\left(capability_i, \overline{Risk_i}, infrastructure_{at}, bikes_{at}, weather_t\right). \quad (2)$$

Presuming that the presence of more bicycles makes the driving task more difficult, and reducing speed makes the driving task easier, we should find a negative relationship between bicycle presence and motor-vehicle speed.

4. Empirical application

We do not have data on the speed of each individual vehicle at each location. Rather we only know the number of speeding violations captured by the speed camera. Consequently, the number of violations found at location a at time t is based on Eq. (2) but with additional variables representing the average annual daily (motor vehicle) traffic (AADT), and the posted speed limit that triggers the camera.

$$count\ of\ violations_{at} = h\left(capability_i, \overline{Risk_i}, infrastructure_{at}, bikes_{at}, weather_t, AADT_{at}, speed\ limit_{at}\right) \quad (3)$$

Chicago has four distinct seasons. Winter months are not favorable to bicycling. Motor-vehicle traffic volumes also vary by season. Moreover, cameras located in school zones are not permitted to issue violations during school vacations. Consequently, the empirical analysis compares violations in a given week with those a year earlier. While one could compare equivalent days (the second Tuesday in August, for example) from one year to the next, we decided to use a week rather than an individual day as the unit of analysis. We did so primarily to reduce the random noise in

[1] Of direct relevance to this paper, Tasic, Elvik, and Brewer (2017) used macroscopic data on 801 Census tracts in Chicago. Data on the rates of collisions between bicycles or pedestrians and motor vehicles are compared with estimates of walking and bicycle trips provided by the metropolitan planning agency. A strong safety-in-numbers effect was observed for both pedestrians and bicyclists.

the number of violations and rental bicycle usage from day to day. At some locations, the number of daily speeding violations can be in the single digits.

In our application, Eq. (3) is simplified because variables such as the nature of the infrastructure and the speed limit do not change between the initial period and the same week a year later. Further simplification is possible by utilizing a difference-in-differences approach (Angrist & Pischke, 2009, chapter 5). In these types of models, changes in a particular outcome for a set of observations that receive a particular treatment are compared with the changes observed in a control group that did not receive treatment. For example, the well-known paper by Card and Krueger (1994) investigated whether an increase in the minimum wage in New Jersey in 1992 led to a decline in employment in fast food restaurants. Their paper compared employment before and after the change in New Jersey with the experience over the same period in neighboring Pennsylvania where the minimum wage did not change.

In our analysis, we compare a treatment group of 26 speed cameras where there was a change in the rental bicycle usage in the vicinity with 53 control group locations where rental bikes are not available. The comparison with a control group allows the analysts to take into account seasonal fluctuations in traffic motor-vehicle volumes and weather conditions.

Consequently, Eq. (3) can be simplified and the count of violations at location a in week $t = 52$ can be written as

$$count\ of\ violations_{a52} = k\left[count\ of\ violations_{a0}, \left(\frac{bikes_{a52}}{bikes_{a0}}\right), \left(\frac{count\ of\ violations\ at\ control\ group_{\ 52}}{count\ of\ violations\ at\ control\ group_{\ 0}}\right)\right]. \quad (4)$$

The first term on the right-hand side, the count of violations a year earlier (in period $t = 0$), implicitly measures factors in Eq. (3) that have not changed during the year such as the capability of drivers, their target risk preferences, the speed limit, and road geometry. The second term measures the treatment as measured by the proportional change in rental bicycle usage at the location. The final term captures weather, exogenous effects on traffic volumes such as gasoline prices, and any other general exogenous time trends.

The specific functional form is taken to be multiplicative

$$count\ of\ violations_{a52} = count\ of\ violations_{a0}\left(\frac{bikes_{a52}}{bikes_{a0}}\right)^{\beta_1} \left(\frac{count\ of\ violations\ at\ control\ group_{\ 52}}{count\ of\ violations\ at\ control\ group_{\ 0}}\right)^{\beta_2}. \quad (5)$$

Dividing by violations in period 0 and taking logarithms, produces the equation to be estimated

$$ln\left(\frac{count\ of\ violations_{a52}}{count\ of\ violations_{a0}}\right) = \beta_1 ln\left(\frac{bikes_{a52}}{bikes_{a0}}\right) + \beta_2 ln\left(\frac{count\ of\ violations\ at\ control\ group_{\ 52}}{count\ of\ violations\ at\ control\ group_{\ 0}}\right). \quad (6)$$

5. Data

5.1. Study period

Data were collected for 130 weeks. The first week starts Sunday July 6, 2014, and the final week starts Sunday December 25, 2016. Because the analysis looks at changes from one week to the equivalent week a year earlier, the maximum number of observations used in the regression for any location is 78.

5.2. Location selection

Speed enforcement cameras were installed by the City of Chicago starting in August 2013 with the express purpose of protecting children. By law, they can only be located within an eighth of a mile of a school or park. Enforcement hours are 7 a.m. to 7 p.m. on Mondays through Fridays for cameras in school zones and from 6 a.m. to 11 p.m. daily for cameras near parks. All of the locations are on streets with a 30 mph posted limit that is reduced to 20 mph in school zones. This is a separate program from the installation of cameras to enforce violations of red lights at signalized intersections.

The program envisioned as many as 300 cameras, but only 150 were operational by the end of 2016. While the City of Chicago did target locations with a history of crashes, high vehicle counts, and known high speeds, political considerations dictated that they were installed in all areas of the city. Each of the six traffic regions within the city had to receive at least 10% of the cameras (City of Chicago, 2018). The exact latitude and longitude is known for each camera. At 42 locations, a pair of cameras is in operation facing in opposite directions. In these locations, data from each pair were combined. In other locations, a single camera can capture both directions. Nine locations were found to have relatively few violations, defined as an average over the 130 weeks of 25 or fewer a week, resulting in considerable noise in the violation counts. These locations were excluded from the analysis. The net result was 99 possible locations.

5.3. Violation data

Data are available on the number of daily speed violations. They are aggregated into a weekly violation count. Abnormalities in the data were observed. These may have been due to mechanical malfunctions or because cameras in school zones cannot issue citations during school vacations. In addition, highway maintenance may result in traffic reduction due to lane closures, and possibly the obstruction of the camera's view. A rule was adopted whereby observations for a particular week at a particular location were dropped from the data set if zero violations were recorded, or if the number of violations was less than a quarter of the median non-zero weekly violations at that location. Because the violations data are heavily left (negatively) skewed, the second rule excluded relatively few non-zero observations.

5.4. Bicycle usage data

Data are not generally available on volumes of private bicycle traffic. However, the public bike share program in Chicago makes available a detailed log of every trip taken. The system began operation in August 2013. It expanded rapidly, increasing its geographic coverage within the city, the density of docking stations, and the number of bicycles. By the end of 2016, about 6000 bicycles were available from 580 docking stations.

Riders buy either a daily pass or an annual membership. In either case, users are allowed unlimited rides. At the time of the study, bicycles had to be returned to a docking station within 30 min to avoid assessment of steep penalty charges. Users taking longer rides have incentives to check-in at intermediate docking stations.

For each of the 9 million trips logged between July 2014 and December 2016, the origin and destination stations, and the date and time are recorded. The exact latitude and longitude are known for each docking station. Trip data were aggregated up to the same weekly format as the violations data. The start and end coordinates of every trip were imported into ArcMap.

One option is to use a routing algorithm to assign the likely route that the cyclist takes. However, this may not predict the route taken by all cyclists. Chicago is flat and the streets are arranged in a grid pattern with few diagonal roads. Therefore, excepting cases where the origin and destination are on the same street, cyclists have multiple possible routings with similar travel times to get from A to B.[2]

Consequently, an alternative methodology was used by drawing a straight line from origin to destination. The weekly volume of bicycle trips each week at a camera location is not just determined by whether or not the straight line passes through the exact location of the camera. A 500-foot radius circle was constructed in ArcMap around the camera. This is equivalent to about three-quarters of a city block. Fig. 1 illustrates how bicycle volumes were calculated, using just three trips for purposes of clarity. The length of each trip that lies within the 500-foot radius circle was measured and a summation made of the trip segments that intersect the circle in that week. This produces a measure of total weekly trip segment length within the circle that is measured in feet. This measure is then divided by the circle area (*pi* times 500^2) to produce a rental bike trip density measure. Inherently trips that likely pass the camera directly are given a higher weight.

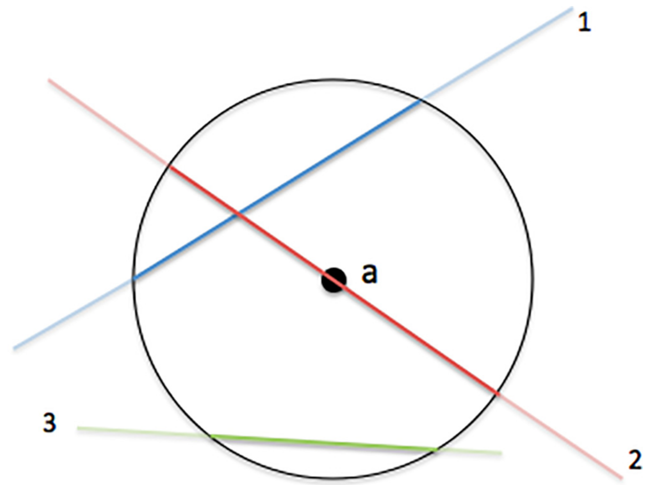

Fig. 1. Calculation of bicycle trip density.

5.5. Treatment group versus control group

Of the 99 possible locations, the control group consists of 53 locations that did not record any rental bike trips in any of the 130 weeks.

The treatment group consists of two subgroups. The first subgroup comprises 14 locations that had rental bike presence in all, or nearly all, possible weeks (there were some weeks at three locations with zero bike usage associated with the aftermath of heavy snowstorms).[3]

The second treatment subgroup comprises 12 locations where bicycle presence started part way through the study period. This was the result of the geographical expansion of the Divvy system. Locations were treated as being part of the treatment group when they consistently recorded trips in both of weeks *t* and week *t*-52. These locations averaged 36 weeks in the treatment group.

The remaining 20 locations had a random mix of weeks when bike trips were recorded and weeks when they were not. These locations are neither in the treatment nor in the control groups. The full listing of camera locations and the groups in which they are classified is in an Appendix.

5.6. Sample size

In theory, there could be 2252 observations in the treatment group. This consists of 78 observations for the 14 locations where bike trips were recorded in nearly all weeks, and an average of 36.17 weeks for the 12 locations where the Divvy scheme started part way through the study period. However, observations were dropped either because there were zero trips in either week *t* or *t*-52 or if there were zero or an abnormally low number of violations in either week *t* or *t*-52. Consequently, the final treatment data set contained 1198 observations.

6. Results

6.1. Descriptive Statistics

The Divvy system has proved to be very popular, and usage has grown as the system developed. The average year-over-year increase in weekly trip density in the treatment group is 78.6%. Perhaps surprisingly, the year-over-year increase is practically identical for both treatment locations that are in the data set for all weeks (78.5%) and those that subsequently joined the treatment group (78.9%). However, there is considerable variability by location and over time. While the ratio of bicycle trip density in period *t* to *t-52* is 1.786 on average, the standard error is 2.669.

Speeding violations detected at the control group locations are generally declining over time. Speed cameras were introduced relatively recently, and Chicagoans might be getting used to their presence and adjusting their speeds to avoid violation notices. The year-over-year decline averages 3.9%. However, as with bicycle trip usage, there is considerable variation. Even when averaged over the 53 locations in the control group, the year-over-year changes in the weekly violations ranged from an 80% increase to a 33% decrease. This variation reflects extreme weather events and the fact that holidays fall in different weeks in different years.

6.2. Regression results

Three regressions were conducted. The first was an unconstrained OLS estimation. The second was a correction to robust standard errors based on clustering by week. The third was a constrained version of the second regression with the coefficient on the control group variable set equal to one. This presumes that the factors that affected the control group, such as changes in automobile traffic volume and weather, had a similar effect on speed violations in the treatment group as they did within the control group.

The results are shown in Table 1. A notable feature is that the explanatory power of the unconstrained regression, where a traditional R^2 can be calculated, is very low. Inherently, there is considerable noise in both the bicycle usage and violations data by camera and by week. However, the statistical significance of the variables is strong.

The coefficient on the change in violations in the control group is 0.76 in the unconstrained regressions. This implies that the change in violations over time is less pronounced at the treatment group locations than at the control group locations (the reader

[2] The problem is somewhat mitigated because the 30-minute rental limit forces users to check in frequently, breaking up longer or complex trips.

[3] Data were excluded from the regression analysis for weeks at locations where there was zero rental bike trip density in either or both of week *t* and week *t*-52. One location recorded zero trips in one week, one had two zero-trip weeks and one recorded three zero-trip weeks.

Table 1
Regression results on the logarithm of the year-over-year change in weekly speed violations at the 26 treatment group sites with t statistics in parentheses.

	Unconstrained OLS	Unconstrained OLS with robust standard errors based on clustering by week	OLS with coefficient on control group change constrained to 1, and robust standard errors based on clustering by week
Ln of year-over-year change in weekly rental bicycle trip density	−0.038 (1.64)	−0.038 (2.16)	−0.041 (2.51)
Ln of year-over-year change in weekly speed violations at control group sites	0.763 (2.43)[a]	0.763 (1.85)[a]	1
Number of observations	1198	1198	1198
F	31.58	18.12	6.28
Adjusted R^2	0.049		

[a] t-test conducted on null hypothesis that coefficient equals 1.

should remember that generally speed violations have been declining over time). A t-test is conducted relative to the null-hypothesis that the coefficient is one, implying that that exogenous weather and traffic effects are the same at the treatment and control groups. The null hypothesis is rejected, albeit that the level of significance is greater than 5% when robust standard errors are based on clustering by week. In the third regression, we enforce the constraint that exogenous weather and traffic effects are the same at the treatment and control groups.

All three regressions produce a similar estimated elasticity of rental bicycle usage on violations. The estimated coefficient is approximately −0.04 in all regressions. Given the logarithmic functional form, the estimated coefficients can be interpreted as point elasticities. However, calculating robust standard errors by clustering by week improves statistical significance. Clustering in the unconstrained regression improves the statistical significance of the bicycle usage variable from the 10% level to the 5% level, and when the regression is constrained, the significance further improves to almost the 1% level.

7. Concluding comments

7.1. Insights into driver behavior

Unlike many studies of the safety-in-numbers hypothesis, this study has a time-series component and is not purely cross-sectional. Consequently, we are observing how drivers' behavior changes over time as the number of bicycles increases. Moreover, we are comparing that change in behavior to a control group of locations in other parts of the city where rental bikes are not available.

Our analysis finds that a small change in rental bicycle usage reduces speeding violations with an elasticity of 0.04. The reader is reminded that this is a *point* elasticity appropriate for measuring the effect of small changes in bicycle usage. The rapid expansion of the bike share program has led to annual increases in bicycle use density approaching 80%. Large changes such as these call for an *arc* elasticity. Using the constrained regression, and holding the exogenous effects constant, the effect of an increase of 80% in rental bicycle use density is a 2.4% reduction in speeding violations. Expressed in a different way, for the typical treatment location that records about 300 speeding violations a week, a reduction of this magnitude reduces the number of violations by about eight.

In summary, we find that the increased presence of bicyclists makes at least some motorists drive more cautiously. The proportion of drivers exceeding the posted limit declines, albeit modestly. A theoretical explanation is that the presence of bicyclists makes the driving task more difficult, and drivers compensate by reducing speed.

7.2. Implications for safety

Of course, society is ultimately interested in the implications for safety. There is a growing literature to support the safety-in-numbers hypothesis. Our results show evidence for a possible mechanism behind the safety-in-numbers effect. Decreased speeds allow motorists to more easily avoid collisions, and reduce the severity of the vehicle-bicyclist collisions that still occur. The treatment locations in this analysis are on roads with posted limits of 20 mph in school zones, and 30 mph otherwise. The literature (see Tefft, 2013, for pedestrians and Nie & Yang, 2014, for bicyclists) clearly shows that the risk to vulnerable road users increases greatly at speeds around and above 30 mph. Even if the number of collisions does not decrease, the severity does. Of course, moderation of vehicle speeds has safety benefits not just to bicyclists but also to pedestrians and other motorists.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsr.2020.04.002.

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