USING TIME-BASED METRICS TO COMPARE CRASH RISK ACROSS MODES AND LOCATIONS

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ABSTRACT

The objective of this work is to identify better metrics of exposure when comparing traffic crash risk across modes or across locations. We propose that total time travelled should be used for road user exposure to crash risk. The idea behind this is that travel time reflects the differences in speeds across different modes and hence should be used as the basic exposure metric from which crash risk based on other metrics, such as travel distance, can easily be derived. We also propose that when comparing crash risk of different modes across different locations the time-based mode share should be used as an explanatory variable. By using mode share we are generalizing the safety in numbers concept which focuses on absolute numbers. This work presents a discussion on why these two metrics were chosen and how they are different from the commonly used metrics. Quantitative evidence for the choice of time-based metrics is also presented using travel survey data to compare crash risk across modes and locations.

INTRODUCTION

Crash risk, defined as the number of injuries (or deaths) per unit of exposure, is often used to report on the safety of travelling on roadways. Several different metrics for quantifying and comparing exposure to crash risk exist, including total distance travelled; total number of trips made; and total population. When considering crash risk of a single mode at a single location, the choice of exposure metric is often irrelevant due to the similar travel speeds, travel distances and mode share. However, when considering multiple modes or multiple locations, there is a lack of understanding of the implications of using these different metrics. The speed difference between modes can significantly alter the relative magnitudes of different exposure metrics which may change the comparisons of risk for different travel modes. Also, the mix of modes at different locations can change how different modes interact with each other, changing the crash risk of given modes at different locations.

While there is some literature investigating different exposure metrics, these studies focus solely on a single location or a single mode. Hence, there is no comprehensive study on identifying metrics to better quantify differences in crash risk across different modes or locations. In light of this, this paper focuses on qualitatively and quantitatively identifying appropriate metrics of exposure for comparing such crash risk across modes or across locations. We will propose and provide evidence that a time-based exposure metric is a better metric to use when comparing risk associated with travel by different modes, and also argue that a time-based mode share is a powerful explanatory variable for understanding the differences in crash risk across locations.

The remainder of the paper is organized as follows. The next section will present a discussion of the different metrics used in the literature to compare crash risk across modes or across locations. Following this literature review, a discussion of the merits of time-based exposure and time-based mode share for comparison of crash risk across modes and locations, respectively, is presented. The data used to quantitatively support these arguments is presented next, followed by the analysis on associations between exposure and risk. Finally, some concluding remarks along with future research directions will be presented.

LITERATURE REVIEW

Though papers investigating different exposure metrics exist in the literature (*1*, *2*, *3*, *4*), these studies focus on a single location, or single mode to highlight the difference between exposure metrics. One study identified three exposure metrics; population-based, time-based and distance-based, and across these three metrics compared the risk of travel by walking and motor vehicles in the United States (*1*). As a result of this comparison, the authors concluded that a time-based metric better captured the difference in speeds between the modes. In another study, authors explored the differences in time versus distance as exposure metrics (*2*) and then looked at the use of number of drivers, total distance travelled and total time travelled as the exposure metric for identifying crash rates (*3*) using data collected in Ontario, Canada. These studies concluded that the results of these metrics are not comparable and should be chosen carefully. However these works only considered drivers and did not look at multiple modes. Another study analyzed the traffic death rates for San Francisco and Stockholm using population, total distance travelled and total time travelled as the exposure metrics (*4*). The author reviewed three different modes: motor vehicle occupants, pedestrians, and bicyclists. The results showed that the three different exposure metrics can lead to significantly different results when comparing risk across modes. A multi-modal analysis which used person-trips as the exposure metric was employed for another study which compared the nonfatal injury rates for different modes in the United States (*5*). The authors found that motorcyclists had the highest fatality rate, followed by vehicle occupants, bicyclists and pedestrians. However, this study is limited in that it only used the number of trips as its exposure metric. Another study looked at understanding the difference in crash risk across different vehicle types using vehicle miles driven for each mode as the exposure metric (*6*). This research provided crash risk of different vehicle types and crash categories.

The main body of literature on multi-modal crash risk analysis is conducted under the topic of safety in numbers. Safety in numbers is based on the conjecture that people travelling by certain modes, specifically bicyclists and pedestrians, would have lower crash risks as the exposure increased. To this end, performance functions to describe the variation in crash risk using different explanatory variables are often presented in the literature. The explanatory variables used vary largely: average distance travelled by a given mode (7,*8, 9, 10*); total number of users a given mode (*7,11*); mode share (*7*); total time travelled by a given mode (*12*); and total number of users of a motorized mode (*13*). Also while some of these studies looked at comparing crash risk across different locations (*7, 8, 11, 13*) others looked at time-series analysis for a given location (*7, 12*). In these studies, the reason for the choice of the explanatory variable is often missing and could be restricted by availability of data. The variation in methods and variables used makes it difficult to compare the results of these studies to determine comprehensive analyses on how to reduce crash risk, especially for non-motorized modes.

CHOICE OF METRICS

There is a lack of understanding about the appropriate metric of exposure to use when comparing crash risk across modes and locations. As mentioned earlier, the choice of exposure metric is not crucial when considering crash risk of a single mode. This is true since, for a single given mode, the travel characteristics of individuals would be similar. For example, if looking solely at the car mode, the distances travelled by car and the average speeds of car travel are often similar among different users. Therefore a time-based, distance-based or trip-based metric can be derived from each another and will reveal similar qualitative results when comparing across locations. However when considering multiple modes, the varied travel characteristics of these modes should be taken into consideration. For example, a pedestrian will often travel more slowly and a shorter distance than a car user. These differences in travel characteristics can significantly alter the magnitudes of a time-based, distance-based, or trip-based exposure metric. Therefore it is important to identify the metric which can be most accurately used as the basis for comparison across different modes.

Comparing Crash Risk across Modes

Here we propose that the appropriate metric of exposure to use when comparing crash risk across modes at the aggregate level is total time travelled. This metric is chosen because it reflects the differences in speeds across modes. Private motorized vehicles travel at higher speeds compared with public transportation, bicycling or walking modes. Hence if the same distance is travelled by car versus bicycle, for example, the car user will be on the roadway for a shorter duration of time. Assuming that these trips are completed on roadways with similar urban use, this means that the car user will be exposed to crash risk on the roadway for a shorter duration of time. Looking at a trip-based exposure metric would fail to recognize these differences and inherently assume that the risk associated with these two trips is the same. However, since the bicyclist will be on the roadway for a longer duration, the crash risk of this mode would be greater. To summarize, particularly when comparing the crash risk associated with different modes, a time-based metric can highlight the speed differences across modes and hence provide a more accurate estimate of exposure than using a trip-based exposure metric. However, it is more difficult to understand how a time-based exposure metric would compare with a distance-based one. While private motorized modes travel at higher speeds, these modes also usually travel greater distances. Therefore, given the same duration of travel, a private motorized trip can cover a greater distance than a walking or bicycling trip. In this case it is not clear whether the distance travelled, or the time spent traveling would be a better metric for determining the exposure to crash risk. However, some of the results found in this paper support the use of a time-based metric over a distance-based metric. This will be discussed further in the remainder of the paper.

Comparing Crash Risk across Locations

The second comparison of crash risk is conducted across different locations for a given mode. To do so, we suggest that the time-based mode share should be used as an explanatory variable for changes in crash risk. A time-based mode share is a good indicator of the presence of a given mode on the roadway. The time-based mode share could be thought of as the mix of modes that a person travelling in a given mode for a given duration would encounter. This is an important metric since it not only provides insights on the allocation of road space across modes, but also on the awareness of other modes on the road space for trip makers. This metric takes into account the differences in speeds of the modes by being time-based, and also accounts for the relative exposure of each mode by including the mode share. Omitting this consideration can alter the results of the analysis significantly since analyzing only absolute numbers of exposure can be misleading if the other modes' share are significantly different across the locations compared. Therefore, to better reflect the interactions of travelers with different modes on a given trip, a time-based mode share is chosen in this paper over of a trip-based mode share. We also compare the classic definition of trip-based mode share with a time-based definition where the mode share is the percentage of time travelled via a particular mode to the total time travelled. Time-based and trip-based mode shares can be significantly different due to the differences in typical speeds and travel distances across modes. A trip-based metric would predict higher shares of a mode with higher speeds or shorter travel distances. Since different modes have different combinations of typical speed and travel distances, the comparison between a time-based and trip-based mode share is unclear. For example, walking trips are often slower and shorter, while car trips are faster and longer.

DATA

This section describes the data collected for both the crash risk and the exposure metrics. Crash data for the risk metric was obtained from the Statewide Integrated Traffic Reporting System (SWITRS) database, a census of police collision reports in California. From this database, the total number of injuries suffered by different modes for each county of interest over five years (2005-2009) was identified. A summary of this data can be found in Table 1.

TABLE 1 Total number of Injuries Suffered by Mode and County

County \ Mode	Car	SUV	Transit	Bicycle	Pedestrian
Alameda	16,580	2,196	235	2,570	2,733
Contra Costa	9,498	1,521	86	1,091	1,072
Imperial	1,429	490	9	130	144
Los Angeles	125,376	18,109	1,810	14,896	22,219
Orange	1,429	6,538	386	4,958	3,602
Riverside	24,501	6,533	205	1,674	1,791
San Bernardino	25,665	6,137	218	1,354	2,049
San Francisco	5,319	561	278	1,784	3,412
Santa Clara	13,447	1,715	93	2,967	2,167
Ventura	7,790	1,820	25	1,255	886

To determine the exposure data, two household travel surveys from California were used: the Bay Area Travel Survey (BATS) and Southern California Association of Governments Regional Travel Survey (SCAGRTS). The counties of Alameda, Contra Costa, San Francisco, and Santa Clara from the BATS and Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura from the SCAGRTS were chosen for analysis. These counties were chosen since they are relatively large, and there exists a spread of mode share across them. The household travel surveys collected a diary of all the trips made for two days for sample households. Using this data, travel mode used and duration for the different trip legs were determined. The data also included origins and destinations of trips, however since intermediate stop locations were not provided distances calculated using the origins and destinations were found to be unreliable. This data (weekday travel for travelers older than age 5) was then aggregated at the county level through the use of the provided weights. Finally, the data was compiled to represent the total time travelled by each mode per day for the specified counties. Also, using the total time travelled by each mode, the time-based mode share can be determined for each county. This compilation of total time travelled and time-based mode share can be found in Table 2. The table shows the total time travelled (columns labeled: Time, hrs) by each mode in hours and the share of different modes (columns labeled: %) for the ten counties listed. The travel times for the different modes were consistent and reasonable across regions (the average for car and SUV was ~33 mins, for transit was ~50 min, for bicycles was ~23 mins, and for pedestrians was ~17 min), The mode shares in different counties followed our expectations. Orange, Ventura, and Los Angeles counties have the highest share of cars while San Francisco has the smallest. It is interesting to note that while Alameda has the second smallest mode share of cars, there is still a large gap in mode share of cars between San Francisco and Alameda (~15% difference). Using the travel survey data, total number of trips by mode per day (columns labeled: # of Trips) and a trip-based mode share (columns labeled: %) were also obtained, as shown in Table 3.

TABLE 2 Total Time Travelled per Day (Time, in hours) and the Time-Based Mode Share (%)

Mode / County	Car		SUV		Transit		Bicycle		Pedestrian	
	Time (hrs)	%	Time (hrs)	%	Time (hrs)	%	Time (hrs)	%	Time (hrs)	%
Alameda	1,635,520	46.6	961,013	27.4	578,399	16.5	69,946	2.0	266,391	7.6
Contra Costa	1,068,877	49.2	730,211	33.6	222,626	10.3	23,194	1.1	126,328	5.8
Imperial	60,443	50.7	43,047	36.1	5,236	4.4	419	0.4	10,072	8.4
Los Angeles	5,100,080	55.7	2,682,087	29.3	516,238	5.6	57,127	0.6	793,623	8.7
Orange	1,430,048	58.9	780,055	32.1	60,378	2.5	19,378	0.8	138,257	5.7
Riverside	713,948	51.2	518,458	37.2	77,906	5.6	6,363	0.5	76,457	5.5
San Bernardino	748,627	52.3	512,983	35.8	75,021	5.2	6,236	0.4	87,550	6.1
San Francisco	784,475	31.4	417,809	16.7	945,073	37.8	40,330	1.6	310,050	12.4
Santa Clara	2,113,606	53.5	1,280,459	32.4	294,569	7.5	47,471	1.2	212,145	5.4
Ventura	292,642	57.1	174,997	34.1	11,900	2.3	5,072	1.0	28,087	5.5

TABLE 3 Total Number of Trips per Day (# Trips) and the Trip-Based Mode Share (%)

Mode / County	Car		SUV		Transit		Bicycle		Pedestrian	
	# of Trips	%	# of Trips	%	# of Trips	%	# of Trips	%	# of Trips	%
Alameda	2,421,835	43.6	1,486,723	26.7	602,903	10.8	163,500	2.9	880,562	15.8
Contra Costa	1,710,939	50.8	1,097,245	32.6	210,244	6.2	31,626	0.9	317,542	9.4
Imperial	126,245	46.2	100,655	36.8	8,489	3.1	2,610	1.0	35,186	12.9
Los Angeles	9,931,399	51.3	5,335,845	27.5	758,952	3.9	182,374	0.9	3,154,118	16.3
Orange	3,060,125	54.8	1,756,219	31.4	113,708	2.0	78,120	1.4	573,449	10.3
Riverside	1,464,024	49.2	1,036,693	34.8	130,145	4.4	21,275	0.7	324,963	10.9
San Bernardino	1,526,217	50.7	1,043,608	34.7	130,783	4.3	22,538	0.7	284,145	9.4
San Francisco	1,013,529	27.4	533,420	14.4	1,059,592	28.6	82,184	2.2	1,012,235	27.3
Santa Clara	3,360,457	53.0	1,924,773	30.4	326,778	5.2	112,929	1.8	610,775	9.6
Ventura	692,344	51.7	455,071	34.0	25,184	1.9	20,252	1.5	147,249	11.0

RESULTS

This section quantifies the crash risk and compares it across modes and locations. Evidence for the power of a time-based metric as the exposure metric for comparing crash risk across modes, and the time-based mode share as an explanatory variable for comparing crash risk across locations are presented in the two following subsections.

Comparing Crash Risk across Modes

To compare the crash risk across modes by a given mode is calculated using Table 1 together with Table 2 or 3. Crash risk for the two exposure metrics (total time travelled in million hours; and total number of trips in millions) is shown in Table 4 for different modes in the ten counties of interest.

TABLE 4 Crash Risk (Number of Injuries per Million Hours of Travel or per Million Trips) by Mode and County

County	Exposure Metric	Number of Injuries per Exposure Metric				
		Car	SUV	Transit	Bicycle	Pedestrian
Alameda	Time (million hours)	5.55	1.25	0.22	20.13	5.62
Contra Costa		4.87	1.14	0.21	25.77	4.65
Imperial		12.95	6.24	0.94	169.83	7.83
Los Angeles		13.47	3.70	1.92	142.88	15.34
Orange		13.84	4.59	3.50	140.19	14.28
Riverside		18.80	6.90	1.44	144.16	12.84
San Bernardino		18.79	6.56	1.59	118.97	12.82
San Francisco		3.72	0.74	0.16	24.24	6.03
Santa Clara		3.49	0.73	0.17	34.25	5.60
Ventura		14.59	5.70	1.15	135.59	17.28
Alameda	Trip (millions)	3.75	0.81	0.21	8.61	1.70
Contra Costa		3.04	0.76	0.22	18.90	1.85
Imperial		6.20	2.67	0.58	27.29	2.24
Los Angeles		6.92	1.86	1.31	44.76	3.86
Orange		6.47	2.04	1.86	34.78	3.44
Riverside		9.17	3.45	0.86	43.11	3.02
San Bernardino		9.21	3.22	0.91	32.92	3.95
San Francisco		2.88	0.58	0.14	11.89	1.85
Santa Clara		2.19	0.49	0.16	14.40	1.94
Ventura		6.17	2.19	0.54	33.95	3.30

The results show that while the bicycle mode always has the highest crash risk, the number of injuries per travel time varies widely across the different locations. On the other hand, the transit mode appears to be the safest, while still exhibiting a wide range of crash risk values. However, it is important to note that the total travel time by transit also includes the access time to this mode. Therefore while the travel times by this mode are slightly over-predicted, the risk of travel by this mode is under-predicted. It is interesting to note that with a time-based exposure metric, walking is safer than the car mode in several counties including Imperial, Riverside, and San Bernardino which have relatively high car mode shares. This is not the case when a trip-based exposure metric is used. With the trip-based exposure metric, while the bicycle mode remains the most risky, it is followed by the car mode, and walking is relatively safer than the car mode. To summarize, the comparison of the relative safety of modes across different locations is significantly different when a time-based metric is used compared with a trip-based metric.

To highlight how the time-based metric and trip-based metric compare, an average crash risk for the ten counties is calculated. The average crash risk for the individual modes is then normalized with respect to the car mode so that the relative risk, which is defined as how much more likely an individual is to get injured by travelling in a certain mode compared with travelling by a car per unit of exposure, is determined. The relative risk of different modes calculated using total time travelled versus total number of trips as the exposure metric can be seen in Figure 1. The crosses represent the relative risk when using total time travelled as the exposure and the values of relative risk can be found to the left of these points in bold. The squares represent the relative risk when using total number of trips as the exposure and the values for relative risk can be found to the right of these points in italics. This figure shows that bicycling is the riskiest mode of travel and that the risk is significantly higher than that associated with travel by any other mode. However, when compared with the car mode, the bicycle mode is predicted to be 6.23 times more likely to result in injury if a time-based metric is used, compared with 4.34 when a trip-based metric is used. There is an obvious discrepancy in the predictions of these two metrics. Another difference can be observed between the two exposure metrics when comparing walking with the car mode. While walking has relatively the same risk as the car mode when a time-based metric is used, the risk of walking is predicted to be about half that of travelling by car when a trip-based metric is used. While these comparisons are true at the aggregate level, similar conclusions can be drawn at the individual county levels as well. At the county level, the ratio of the relative safety of the transit mode predicted by the time based exposure to the trip based exposure is between 59 and 89%, between 93% and 112% for SUV’s; 157% and 252% for pedestrians, and between 150% and 297% for bicyclists.

The literature on the perceived risk of travel by different modes corroborate the assertion that bicycling is significantly riskier than driving or walking, while the latter two modes are perceived to have similar crash risk. This finding gives support to the use of a time based metric to assess crash risk. Recent research (*14*) shows that while similar percentages of people feel safe walking and driving on commercial streets (72% and 81%, respectively), the percentage of people who feel safe bicycling is significantly lower (28%). The results of this study (*14*) qualitatively match with the results shown in Figure 1. A study on perceptions of crash risk of different modes demonstrates that perceptions closely follow reality, confirming the validity of qualitatively comparing the crash risk data to perceptions of safety (*15*).

This study (*15*) also compares a relative realized fatality rate (using a distance-based metric) with a relative perceived fatality rate. The results show that while these two values match closely for most modes, the realized risk is greater than the perceived risk for walking and bicycling. While a distance-based metric was not available for our analysis, an informed guess about how this metric would have performed compared with the findings shown in Figure 1 can be made. If a distance-based metric were used to determine the average crash risk, we would expect to find a greater risk for walking or bicycling than those predicted by a time-based metric. This assumption is justified by quantitative results (which will be presented in the following section) which show that compared with the car mode people travel on average shorter distances walking or bicycling. Combining this with the slower speeds of these two modes implies that the relative magnitude of exposure for these two modes would be even smaller if a distance based metric was used compared against a time based metric. Hence, if the authors had used a time-based metric for the study (*15*), the relative realized risk for bicycling and walking modes would be lower and would have better matched the perceived risk for these modes.

If a figure similar to that of Figure 1 was plotted using a distance-based metric, the even greater relative risks of walking and bicycling would have conflicted with the literature on the perceived risk of travel by these modes (*14*). Therefore, the results presented in Figure 1 support the use of a time-based metric compared with a distance-based (and also a trip-based) one and give the authors confidence that a time-based metric more accurately represents the risk of travelling by different modes.

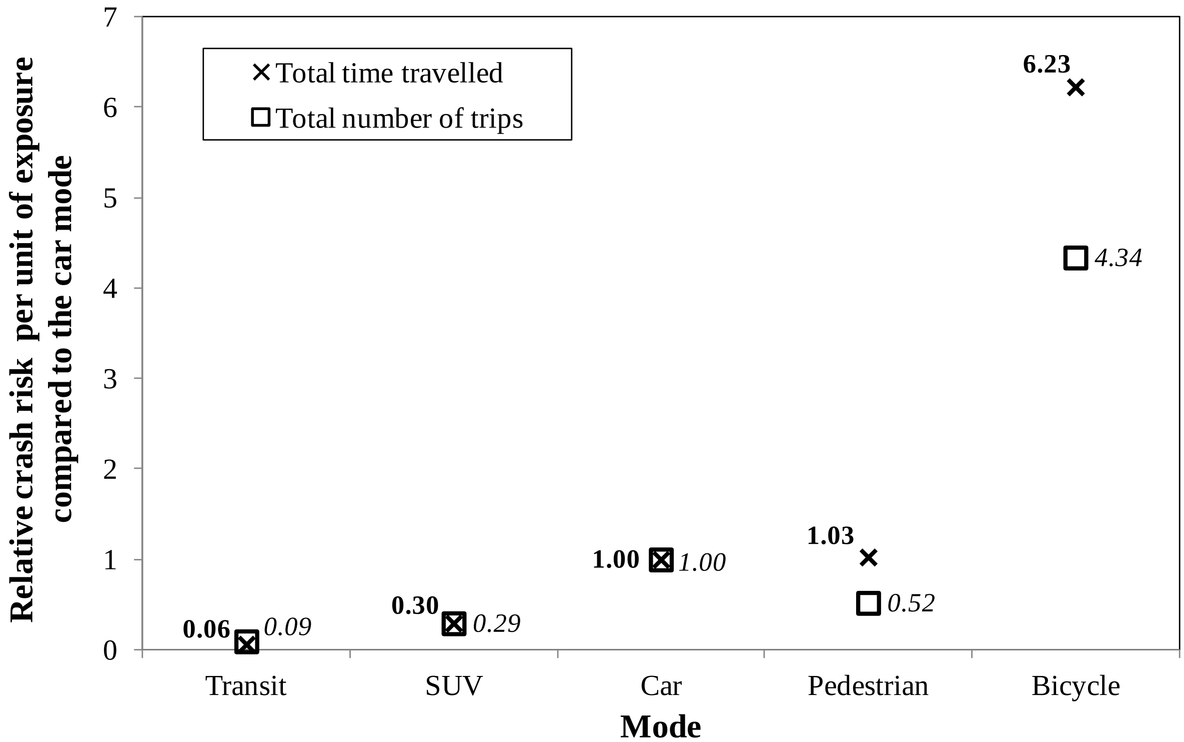

FIGURE 1 Relative Crash Risk of Modes Compared Against the Car Mode for Two Exposure Metrics: a) Total Time Travelled; and b) Total Number of Trips

Comparing Crash Risk across Locations

For any given travel mode, there exists a wide range of values for the crash risk across the different locations of interest. Consequently, next we compare the crash risk of a given mode across different locations, using a similar approach as applied in the safety in numbers literature described above. According to the literature, the classic approach would be to use total time travelled (since risk is defined as injuries per total time travelled) as the explanatory factor to identify the differences in crash risk for a given mode across different locations.

However, here we will explore the use of four different explanatory variables: total number of trips via given mode; total time travelled via given mode; trip-based mode share; and time-based mode share. First it is important to understand how a trip-based mode share compares to a time-based mode share. This comparison is shown in Figure 2. For the points lying above the diagonal line, a trip-based metric predicts a higher mode share than a time-based one, and the opposite holds for points below the diagonal line.

This figure shows that the mode share of walking varies significantly for the two metrics. All points for this mode lie above the diagonal line, meaning that a trip-based metric over-predicts this mode's share. This implies that pedestrian trips are significantly shorter in duration than other trips made on other modes. Since the pedestrian mode is much slower than all the other modes, the reason for the duration of trips being shorter is that pedestrian trips are generally of shorter distances. Hence, the over-prediction would be expected to be even more pronounced if a trip-based metric were compared with a distance-based one.

Bicyclists are similar to the pedestrians, since their mode share is also over-predicted using the trip-based metric compared with the time-based metric. However, the difference between the two metrics is less pronounced since bicycles' mode shares are very small.

A significant difference between the two exposure metrics can also be observed for the transit mode. As shown in the figure, all the points for this metric lie below the diagonal line, indicating that a trip-based metric under predicts the share of this mode compared with a time-based metric. This implies that transit trips are on average longer in duration. People often travel similar (or shorter) distances on transit and hence the difference in the mode share for the two metrics can be attributed to the transit mode being slower than other modes. However, the travel time data for the transit mode also includes the access time. This implies that the transit travel times are over-estimated in this dataset. Hence in reality, the mode share predictions of a time-based and trip-based metric could be closer than found in this study.

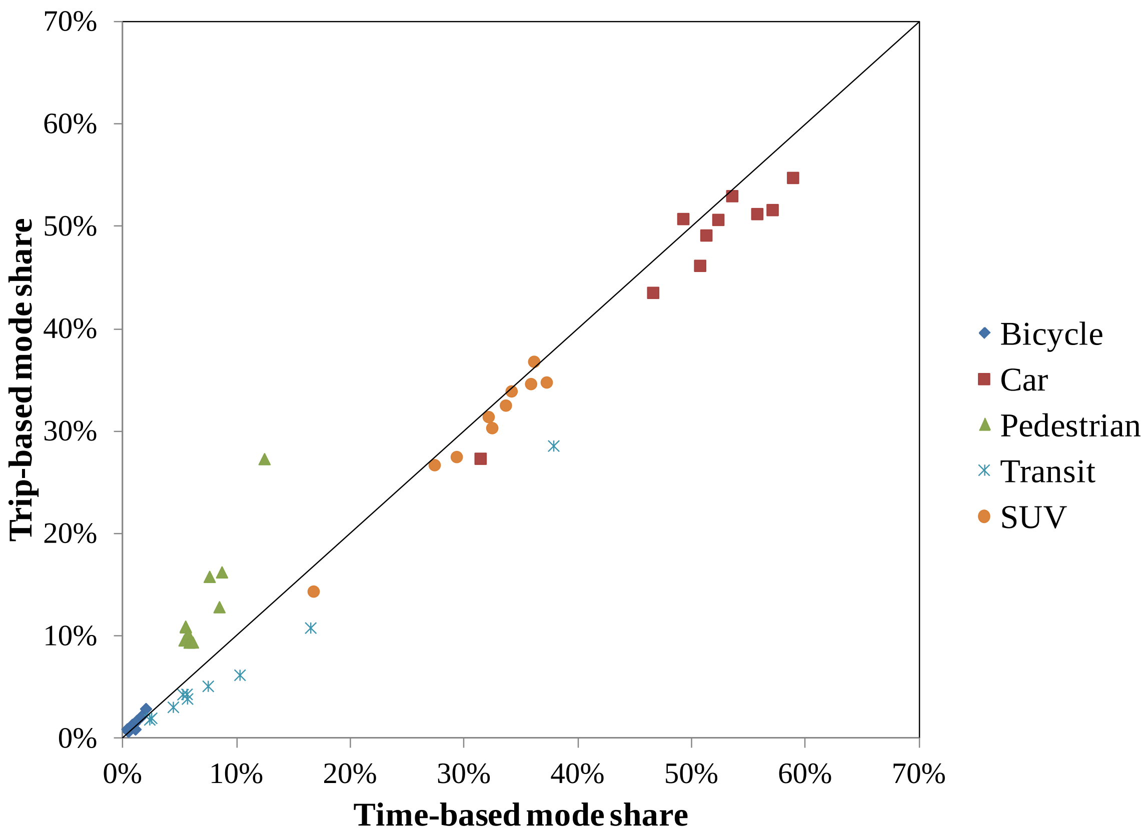

FIGURE 2 Trip-Based versus Time-Based Mode Share

For the SUV and car modes, the points lie close to the diagonal implying that these two modes' travel times are representative of the average travel time in their respective counties. Hence the trip-based and time-based metrics produce similar mode shares.

We can now continue to explore the use of different explanatory variables to describe differences in crash risk across different modes. As mentioned above, the four different explanatory variables are: total number of trips via a given mode; total time travelled via a given mode; trip-based mode share; and time-based mode share. Based on the data and the literature, a power function is chosen to describe the shape of the data as:

$$Y = a * X^b,$$

where Y is the number injuries per total time travelled (in units of millions of hours) on a given mode, X is the time-based mode share of that given mode, and a and b are estimated constants.

Table 5 presents the parameter estimates and the corresponding r-squared values for the power functions, which describe the injuries per total time travelled using the four explanatory variables for all modes.

TABLE 5 Parameter Estimates of a Power Function for Different Explanatory Variables and Modes

Explanatory Variable	**Mode**	**Parameter Estimates**				**R-squared**
		a	***p-value***	***b***	***p-value***	
Time-based mode share	Bicycle	0.13	0.19	-1.31	0.00	0.72
Trip-based mode share		0.30	0.60	-1.25	0.04	0.45
Total time travelled (hr) on bicycle		2296	0.00	-0.36	0.05	0.41
Total number of trips on bicycle		2696	0.00	-0.34	0.15	0.24
Time-based mode share	Pedestrian	2.72	0.56	-0.45	0.47	0.06
Trip-based mode share		5.04	0.17	-0.29	0.58	0.05
Total time		18.77	0.11	-0.06	0.67	0.02
Total trip		6.72	0.23	0.02	0.83	0.006
Time-based mode share	Transit	0.04	0.00	-1.09	0.01	0.64
Trip-based mode share		0.03	0.00	-1.09	0.01	0.57
Total time		42.66	0.16	-0.36	0.12	0.27
Total trip		34.02	0.27	-0.33	0.22	0.18
Time-based mode share	Car	42.05	0.00	2.19	0.08	0.34
Trip-based mode share		30.44	0.00	1.59	0.16	0.23
Total time		75.83	0.14	-0.15	0.44	0.08
Total trip		28.86	0.29	-0.08	0.71	0.02

Initially we will focus on the bicycle mode. Table 5 suggests that using mode share is better in explaining the variation in the data across the different locations compared with using absolute quantities of total time travelled or total number of trips. The absolute quantities explain some of the differences in crash risk across the different locations, as observed by the r-squared values of 0.41 and 0.24 for total time travelled and total number of trips respectively. However, time-based mode share proves to be better in explaining these variations as evidenced by the significantly greater r-squared value of 0.72. Both parameters a and b remain significant when the time-based mode share is used as the explanatory variable. The mode share was found to provide greater explanatory power than the absolute quantities for all other modes as well. For the transit and car modes this is evidenced by the high r-squared values along with the low p-values on the two parameter estimates indicating that the explanatory power of the time-based explanatory variables are high.

In addition, comparing a time-based mode share with a trip-based one shows that the former is significantly more powerful as an explanatory variable as evidenced by the higher r-squared. This was also found to be the case for most other modes. As a side note, the estimate of *b* has a negative sign implying that as the time-based mode share increases, the injuries per time exposed decrease, supporting the safety in numbers conjecture. The results show that the choice of time-based mode share to explain the differences in crash risk across different locations is effective, and should be used instead of the classical variables of absolute quantities. Similar conclusions can be drawn for the remaining three travel modes. Focusing on the time-based mode share for these three modes, the estimate of *b* has a negative sign for pedestrian and transit as well, implying that the safety in numbers conjecture might hold for these two modes as well. However, the car mode has a positive estimate for the value of *b*, (with a low p-value), implying that as the car mode share increases the crash risk increases as well. This is reasonable since if there are relatively more cars on the roadways the chances of two colliding with each other would increase.

CONCLUSIONS

This paper suggests that total time travelled is the appropriate exposure metric to use when evaluating risk across different modes. This metric reflects the differences in speeds across modes, which can significantly alter the magnitudes of the exposure metric. While arguments that this metric is a better indicator of exposure for multimodal analysis than a trip-based one are presented, the effectiveness of this metric over a distance-based metric was also shown.

This paper looks at data at an aggregated level. This method is chosen to highlight the differences of using time, trip or distance based exposure metrics when evaluating the safety of different modes. The models developed are meant to describe the advantages in using time based exposure metrics when comparing the safety of different modes rather than using these models for predicting crash risk. At the individual link level the safety of different modes could be different than those predicted in this paper simply due to the specific mode mixture of the links and the existing facilities for these different modes.

This paper also suggests that a time-based mode share is a better explanatory variable to use when evaluating risk of a given mode across different locations. Comparison of crash risk data across ten counties using different explanatory variables shows that time-based mode share often has the highest explanatory power for differences in crash risk across locations. This does not imply that mode share is the sole explanatory variable for comparing crash risk across different locations; however it does imply that the explanatory power is greater than the absolute variables covered in the literature. The time-based mode share metric quantifies the presence of other modes on the roadway and allows for the number of users relative to the overall traffic mix to determine risk. However this paper determines the models to predict crash risk across locations with the use of one dataset. To verify the predictive power of this model the authors would also like to test the predictions against an independent data set in the future. Historically it has been difficult to obtain an accurate estimate of total time travelled by a given mode. Household surveys, which are often based on a small number of samples, are the only way to collect the necessary data for the time-based metrics described above. Recent technological advances are increasing the reliability due to the use of mobile probes for transportation data collection. As the penetration rate of these mobile probes increases, more accurate data on travel behavior of individuals, including travel times and mode choices, will become available. In the coming years, this data could be available to the use of agencies while no additional data collection resources are required by the agencies themselves. With the possible availability of this richer dataset in the future, the authors strongly believe that transportation agencies should start using total time travelled as the exposure metric for comparing crash risk across modes and locations.

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