HHS Public Access
Author manuscript
Accid Anal Prev. Author manuscript; available in PMC 2021 July 01.

Published in final edited form as:
Accid Anal Prev. 2020 July ; 142: 105576. doi:10.1016/j.aap.2020.105576.

Comparing Distance and Time as Driving Exposure Measures to Evaluate Fatal Crash Risk Ratios

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Abstract

Background: The use of an appropriate driving exposure measure is essential to calculate traffic crash rates and risks. Commonly used exposure measures include driving distance and the number of licensed drivers. These measures have some limitations, including the unavailability of

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Conflict of interests
The funding sources had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

disaggregated estimates for consecutive years, low data quality, and the failure to represent the driving population when the crash occurred. However, the length of driving time, available annually from the American Time Use Survey (ATUS), can be disaggregated by age, gender, time-of-day, and day-of week, and addresses the temporal discontinuity limitation of driving distance on the United States (U.S.) national scale.

Objectives: The objective of this study is to determine if the length of driving time as a driving exposure measure is comparable to driving distance by comparing distance-based and time-based fatal crash risk ratios by driver age category, gender, time-of-day, and day-of-week.

Methods: The 2016–2017 National Household Travel Survey (NHTS) provided driving distance, and 2016–2017 Fatality Analysis Reporting System provided the number of drivers in fatal crashes. The distributions of driving distance and length of driving time by driver age category (16–24, 25–44, 45–64, and 65 years or older), gender, time-of-day, day-of-week were compared. Two negative binomial regression models were used to compute the distance-based and time-based fatal crash risk ratios.

Results: The distributions of driving-distance were not different from the length-of-driving-time distributions by driver age category, gender, time-of-day, and day-of-week. Driving distance and the length of driving time provide similar fatal crash risk ratio estimates.

Conclusions: The length of driving time can be an alternative to driving distance as a measure of driving exposure. The primary advantage of driving time over driving distance is that, starting from 2003, the disaggregated estimates of the length of driving time are available from ATUS over consecutive years, curtailing the discontinuity limitation of driving distance. Furthermore, the length of driving time is related to drivers' perceived risks about their driving conditions and as a result, may be a better exposure measure than driving distance in comparing crash risks between drivers whose likelihood of traveling in hazardous driving conditions (e.g., nighttime) varies substantially.

Keywords

Driving exposure; Age category; Gender; Time-of-crash; American Time Use Survey

1. Introduction

Traffic deaths are among the leading causes of death globally (World Health Orgnanization, 2018). In 2016, motor vehicle crashes accounted for more than 1.3 million deaths worldwide (World Health Orgnanization, 2018). To help identify and prioritize efforts to reduce traffic injuries and deaths, a significant amount of research effort has gone into evaluating traffic safety and measuring the crash risks for various driver groups or driving conditions. To compare the crash risks between driver groups or driving environments, researchers usually convert the absolute crash frequencies into crash rates by controlling the intensity of travel exposure (Chapman, 1973). The commonly used measures of travel exposure include the number of licensed drivers and the driving distance (vehicle miles driven).

Many limitations have been identified in using the number of licensed drivers and driving distance as driving exposures. First, the distribution of licensed drivers represents the general driving population and is not equivalent to the specific driving population at the time of the crash (Curry, Pfeiffer, & Elliott, 2016). Driving exposure often varies substantially among driver subgroups. Using the number of licensed drivers as the exposure measure would over-estimate the crash risks for those who drive more frequently than others. For example, males drive more distance than females and should therefore have greater exposure. By failing to account for the difference in exposure, the number-of-licensed-drivers-based fatal crash rate ratio between male and female drivers is 2.17, whereas the distance-based fatal crash rate ratio at 1.62 in 2017, United States (U.S.) (Federal Highway Administration, 2017b; Insurance Institute for Highway Safety, 2018). Additionally, the quality of the U.S. license data available from the Federal Highway Administration has been challenged, and the number of licensed teenage drivers were underreported in the database (Foss & Martell, 2013; Curry, Kim, & Pfeiffer, 2014). Several studies simply used the population as an alternative exposure measure (Tefft, 2014; Chaudhuri et al., 2019). However, population is not equivalent to the general driver population, nor does it directly reflect travel intensity.

Driving distance (vehicle miles driven) is usually regarded as the "gold standard" to estimate the intensity of driving exposure. However, it is not always feasible to disaggregate estimates of driving distance by driver age, gender, time-of-day (daytime versus nighttime), and day-of-week (weekday versus weekend) for consecutive years on the U.S. national scale. Researchers usually obtain estimates of driving distance from the National Household Travel Survey (NHTS) which records an individual's daily traveling behaviors (Ouimet et al., 2010; Zhu et al., 2015; Zhu et al., 2016). However, this survey is not conducted every year, and the three most recent surveys were conducted in 2001–2002, 2008–2009, and 2016–2017 (Federal Highway Administration, 2017c). The estimated numbers of vehicle miles travelled (regardless of the vehicle type) were similar between the 2001–2002 and 2008–2009 NHTS surveys, (2,274,769 versus 2,245,111 million miles), but the number increased to 2,431,558 million miles in the 2016–2017 survey. Thus, there was no obvious linear trend in the number of vehicle miles over the survey years. Such nonlinearity makes it difficult to interpolate driving distance for consecutive years and restricts researchers from evaluating the crash risk trajectories for a specific driver group or a driving condition. Additionally, Chipman et al. (1992) and (1993) have argued that driving distance does not consider the roadway hazards and the risk of driving conditions. The distancebased crash risk for drivers who drive more frequently on hazardous roadways or risky driving conditions may be overestimated (Chipman et al., 1992, 1993). The estimated distance-based crash risk for those drivers may be mixed with the risk of the driving conditions. Therefore, using these common travel exposures (including the number of licensed drivers and driving distance) in evaluating crash risks could misstate the true crash risks when the driving exposure varies substantially among driver groups or driving conditions.

Using length of driving time as a travel exposure has the potential to address the limitations posed by driving distance The American Time Use Survey (ATUS), conducted starting from 2003, is a large-scale U.S. national activity-based time-use survey, where driving activities along with their durations for each survey respondent can be identified. Thus, disaggregated estimates are available for the length of driving time (vehicle hours driven) over consecutive years (2003–2018) by driver age, gender, time-of-day, and day-of-week (U.S. Census

Bureau, 2017). The availability of annual estimates of length of driving time curtails the discontinuity limitation of driving distance.

Some recent studies conducted in England and Australia have used the length of traveling time as the travel exposure measure to evaluate crash risks for cyclists and pedestrians due to the unavailability of the conventional risk exposures for those roadway users (e.g., riding distance or walking distance) (Mindell, Leslie, & Wardlaw, 2012; Santamarina-Rubio et al., 2014). Previous studies, which compared the distance-based and time-based crash risk ratios by driver age category and gender, have suggested that the length of driving time was a feasible measure for driving exposure (Chipman et al., 1992, 1993). However, the driving distance and the length of driving time used by Chipman et al. (1992) and (1993) were collected by a survey conducted in the fall of 1988, in Ontario, Canada. Their findings may not be generalizable to the U.S. roadway system for recent years. Furthermore, Chipman et al. (1992) and (1993) did not compare the distance-based and time-based fatal crash risk ratios by driving condition, which limits their conclusion that the length of driving time is a better risk exposure measure than driving distance when people have substantially different exposures to hazardous driving situations. To our knowledge, no previous studies have utilized the length of driving time as the driving exposure measure to evaluate crash risks among U.S. drivers. The discontinuity of the driving distance obtained from NHTS necessitates an alternative driving exposure measure for consecutive years.

Bose and Sharp (2005) compared the 2003 U.S. American Time Use Survey (ATUS) with the 2000–2001 NHTS and found that these two surveys provided similar estimates (or relationships between estimates) for the distributions of trips between gender and age and the distribution of trips by day-of-week. However, they did not test the difference in utilizing the driving distance and length of driving time as risk exposure measure to evaluate crash risks. Additionally, the time windows for the surveys used in Bose and Sharp (2005) were not matched.

Due to the discontinuity limitations of driving distance as a driving exposure, as well as the large volume of research on fatal crash risk that uses data from the U.S., further work is needed to determine if length of driving time is as appropriate of an exposure as driving distance to study crash risk in the U.S. More specifically, there is a need to (1) compare the two exposure methods using more recent and relevant (i.e. U.S.) data; and (2) perform an explicit comparison of fatal crash risk between the two exposures for both driver characteristics and driving conditions. This study aims to address these needs by comparing the distance-based and timebased fatal crash risks and risk ratios by driver age category, gender, time-of-day, and day-of-week among U.S. drivers from 2016 to 2017.

2. Methods

Datasets

Estimates of driving distance in vehicle miles driven by privately owned vehicles (POV) were obtained from the 2016–2017 National Household Travel Survey (NHTS). A detailed description of the 2016–2017 NHTS can be found in Federal Highway Administration (2017c), but we briefly describe the database here. Using a stratified random sample of U.S.

households, the NHTS provides data on individual and household travel behavior (Federal Highway Administration, 2017a). The definition of POV includes cars, sports utility vehicles, vans, pickup trucks, motorcycles/mopeds, recreational vehicles, and rental cars (Federal Highway Administration, 2017a). Every survey participant was aged 5 years or older and kept a diary (or their proxy kept a diary for them) about all their trips during a 24-hour day, including the mode of transport, trip duration, and trip distance. Each participant was assigned a final weight to normalize their data to the U.S. national scale. The variance of the distance estimates can be computed through Jackknife approximation using a set of 98 replicate weights assigned to each observation (Federal Highway Administration, 2017c). The travel dates of the survey started on April 19, 2016 and ended on April 25, 2017 (Federal Highway Administration, 2017c). The survey data were weighted to 12-month period to provide annual travel estimates (Federal Highway Administration, 2017c). We selected the travel records of the survey participants aged 16 years or older.

Estimates of the length of driving time in vehicle hours driven were provided by the American Time Use Survey (ATUS), which aims to understand how U.S. residents 15 years or older spend their time (U.S. Census Bureau, 2017). Each respondent reported their daily activities starting at 4:00 am on the previous day and ending at 4:00 am on the interview day. If an activity was travel-related and took place in a POV where the respondent was a driver, the activity was counted as a driving-related activity. Each respondent's observations were weighted to the national scale using their assigned final weight, and a set of 160 replicate weights were used to calculate the variance of the estimates using successive difference replication (U.S. Census Bureau, 2017). The annual estimates of vehicle hours driven used in this study were based on the diary dates between May 1, 2016 and April 30, 2017 to best match the survey time window for NHTS, and the records of survey respondents aged 16 years or older were included in this study.

The number of drivers in fatal crashes was obtained from the 2016–2017 Fatality Analysis and Reporting System (FARS). FARS is a census of all crashes on U.S. public roadways that result in at least one fatality within 30 days following the crash (National Highway Traffic Safety Administration, 2018). Drivers aged 16 years or older in POVs (i.e., passenger vehicles and motorcycles) between May 1, 2016 and April 30, 2017 were selected.

The number of drivers in fatal crashes was calculated by age category (i.e., 16–24, 25–44, 45–64, and 65 years or older), gender, time-of-day (daytime or night-time), and day-of-week (weekday or weekend). Based on FARS definitions, crashes that occurred between 6:00 am – 5:59 pm were classified into daytime crashes, and crashes that occurred at 6:00 pm Friday through 5:59 am Monday were coded as weekend crashes (National Highway Traffic Safety Administration, 2018). The number of vehicle miles driven, estimated from NHTS, and the number of hours driven, estimated from ATUS, were also disaggregated by driver age category, gender, time-of-day, day-of-week, and quarter. We used the departure time for each trip in NHTS and ATUS to classify the trip into daytime/nighttime (6:00 am – 5:59 pm/6:00 pm – 5:59 am) and weekday/weekend (6:00 am Monday through 5:59 pm Friday/6:00 pm Friday through 5:59 am Monday). The number of drivers in fatal crashes, vehicle miles driven, and vehicle hours driven were further disaggregated by quarters to control for the seasonality effects on fatal crash risk estimates (January to March was quarter 1, April to

June was quarter 2, July to September was quarter 3, and October to December was quarter 4). We did not stratify the data by state because not all state-level estimates of vehicle miles driven or vehicle hours driven by driver groups or driving conditions could be obtained from NHTS or ATUS. Overall, every individual observation corresponded to the number of drivers in fatal crashes, vehicle miles driven, and vehicle hours driven for a specific combination of driver age category, gender, time-of-day, and day-of-week, and quarter.

Statistical analysis

We compared the distributions of the driving distance (vehicle miles driven) and the length of driving time (vehicle hours driven) by driver age category, gender, time-of-day, and day-of-week. Driver fatal crash rates per 100 million vehicle miles driven and per 100 million vehicle hours driven were calculated by driver age category, gender, time-of-day, and day-of-week. Two individual negative binomial regression models, both with a natural log link function, estimated the distance-based and time-based fatal crash risk ratios. The independent variables in each model included driver age category (coded as dummy variables for 16–24 years, 25–44 years, and 65 years or older, with 45–64 as a reference group), gender (0=female and 1 = male), time-of-day (0=daytime and 1=nighttime), day-of-week (0=weekend and 1=weekday), and quarter (coded as dummy variables for second, third, and fourth quarter, with first quarter as a reference group), and the dependent variable was the number of drivers in fatal crashes, modeled on the log scale. The two negative binomial regression models used the natural logs of vehicle miles driven and vehicle hours driven as offsets to convert the number of drivers into a fatal crash rate per vehicle miles driven and vehicle hours driven, respectively. Therefore, the estimated regression coefficients of the independent variables represent additive changes to the log of crash rate, and the exponentiation of the coefficients represents multiplicative changes of crash rate (i.e., risk ratio) associated with each specified category of age, gender, time-of-day, and day-of-week. As the seasonal quarters were included in the models as a categorical variable, the estimated risk ratios are seasonally adjusted.

When modeling the crash frequency data (i.e., counts) which are integer-valued, nonnegative, and sporadic, Poisson and negative binomial regressions are the natural modeling choices (Poch & Mannering, 1996). However, a major restriction of the Poisson distribution is that the mean and variance of the dependent variable (crash frequency) should be equal. In most crash data, the variance is larger than the mean and, in this case, the data are over-dispersed (Abdel-Aty & Radwan, 2000). Negative binomial regression can address the overdispersion issue (Shankar, Mannering, & Barfield, 1995). We started our analysis with Poison regression and found that the estimates of the overdispersion parameter for the distance-based and time-based models were 21.3 and 24.7, respectively, suggesting that our data are over-dispersed and negative binomial regression is preferable to Poisson regression. The *proc surveymeans* in SAS Enterprise Guide 7 was used to calculate the weighted estimates of vehicle miles driven and vehicle hours driven. The function *glmmadmb* in R×64 3.5.2 was used to build negative binomial regression models.

3. Results

Table 1 presents the unweighted sample sizes and the corresponding weighted estimates of vehicle miles and hours driven by driver group and driving condition with 95% confidence intervals (CIs) obtained from NHTS and ATUS. The coefficient of variation (CV) for each variable is also shown in Table 1. The CV is the ratio of the standard deviation to the mean and is positively related to the dispersion of the variable (Abdi, 2010). The small CVs for the weighted estimates suggest that our estimates for vehicle miles driven and vehicle hours driven were precise. In total, drivers aged 25–44 years had the greatest driving distance among all the age categories and drove 786,400 million miles during the 28,200 million hours over the study period (Table 1). Males drove 32% more miles and 26% more hours than females (Table 1).

The distributions of vehicle miles driven and vehicle hours driven by age category, gender, time-of-day, and day-of-week are shown in Figure 1. Overall, the distributions of vehicle miles driven and hours driven were very similar across the driver groups and driving conditions (Figure 1). The largest discrepancy between vehicle miles driven and vehicle hours driven occurred for time-of-day (Figure 1c). In total, 79.8% of vehicle miles driven occurred during the daytime, whereas 77.0% of vehicle hours driven occurred in daytime, suggesting that on average, drivers may drive at a higher speed in daytime than in nighttime. Similarly, drivers aged 25–44 years and male drivers had higher proportions of vehicle miles driven than vehicle hours driven (Figure 1a and 1b).

The fatal crash rates per 100 million miles driven and per 100 million hours driven as well as the model-based estimated fatal crash risk ratios broken up by driver age category, gender, time-of-day, and day-of-week are summarized in Table 2. Younger drivers had higher crash risks than drivers in any other age category, regardless of the exposure measure (Table 2). Compared to females, males were more likely to be involved in fatal crashes (distance-based risk ratio: 1.75, 95% CI [1.61–1.91] and time-based risk ratio: 1.75, 95% CI [1.60–1.92]). When using driving distance and the length of driving time as the exposure measures, nighttime driving had a higher fatal crash risk than daytime driving (distance-based risk ratio: 3.13, 95% CI [2.87–3.41]; timebased risk ratio: 2.83, 95% CI [2.58, 3.10]), and weekend driving had a lower fatal crash risk than weekdays (distance-based risk ratio: 0.79, 95% CI [0.73–0.86]; time-based risk ratio: 0.76, 95% CI [0.70, 0.84]; Table 2). The estimates of fatal crash risk ratios were very similar between the models that used vehicle miles driven and vehicle hours driven as the exposures (Table 2). While not equivalent to a formal statistical test, we note that the confidence intervals for distance-based and time-based fatal crash risk ratios exhibited a high degree of overlap, further suggesting that there was minimal difference between distance-based and time-based fatal crash risk ratios.

4. Discussion

Our objective was to determine if the length of driving time is comparable to driving distance as a driving exposure measure by comparing the distributions of driving distance and the length of driving time and distance-based and time-based fatal crash risk ratios by categories of driver age, gender, time-of-day, and day-of-week among U.S. drivers. The distributions of driving distance were similar to those of the length of driving time, supporting the findings of Bose and Sharp (2005) that the NHTS and ATUS data provided similar estimates for the distributions of trips between driver age category, driver gender, and time-of-crash. The similarity between the point estimates of distance-based and time-based fatal crash risk ratios for age category, gender, time-of-day, and day-of-week, along with the large amount of overlap in their confidence intervals further suggest that using driving distance and the length of driving time as exposure measures result in consistent comparisons of fatal crash risk by driver groups and driving conditions. Therefore, the length of driving time is an appropriate alternative to driving distance as a measure of driving exposure.

More importantly, starting from 2003, the yearly disaggregated estimates of the length of driving time (vehicle hours driven) by age, gender, time-of-day, and day-of-week on the U.S. national scale became available from ATUS (U.S. Census Bureau, 2017), allowing researchers to evaluate the crash risk trajectories for a specific driver group or driving condition over consecutive years. In contrast, the disaggregated estimates of driving distance (vehicle miles driven) can only be obtained in discrete periods (e.g., 2001–2002, 2008–2009, and 2016–2017). The length of time estimates of other modes of transport (e.g., walking, taking a bus, and bicycling) can also be obtained from ATUS, which provides researchers an opportunity to evaluate the user risks of other modes of transport.

The small differences between distance-based and time-based fatal crash risk ratios for time-of-day may be related to differences in driving speed between the daytime/nighttime driving conditions. With the limited visibility after dark, drivers may reduce their speed to accommodate the increased risks within the dark driving condition. Our study has identified that, compared to driving distance, a greater proportion of the length of driving time occurs at night (Figure 1 [b]), suggesting that drivers drive at a lower speed at night. Thus, for a given distance, people may drive for a longer time period at night than in daytime, increasing the denominator (the length of driving time) for the nighttime fatal crash rate. This increase in the denominator decreases the time-based fatal crash rate for nighttime, resulting in smaller a time-based fatal crash risk ratio than the distance-based one for nighttime vs. daytime.

Chipman et al. (1993) have argued that the length of driving time is not only a function of driving distance, but also a reflection of other factors (e.g., roadway hazards), and the length of driving time may be a better driving exposure measure than distance to account for those factors (Chipman et al., 1993). Chipman et al. (1993) further suggested that studies of characteristics of the time of a trip would support their arguments. The relatively smaller time-based fatal crash rate ratio for nighttime driving than the distance-based one in our study suggests that the length of driving time may be influenced drivers' perceptions to roadway risks. However, using distance as an exposure measure includes a mixture of high- and low-risk driving conditions, ignores drivers' perceptions to roadway hazards, and potentially results in overestimation to the crash risks for drivers who are more likely to be exposed in risky driving conditions (i.e., the estimated distance-based crash risk for those drivers may be mixed with the risk of the driving conditions). In relatively hazardous situations (e.g., nighttime versus daytime in this study), drivers would reduce their driving speed and have a reduced crash risk per unit time than per unit distance. As a result, the risks of the driving conditions could be partially separated from the estimated time-based crash risk for drivers who are more likely to be exposed to risky driving conditions. We believe that the length of driving time is a better exposure measure than driving distance in comparing crash risks for drivers who have substantially different levels of exposures to risky driving conditions.

There are several considerations when using the length of driving time as the exposure measure. First, basing exposure on the length of driving time may result in a paradoxical argument that for a given distance, drivers driving at a higher speed would have reduced exposure to risk, but the high speed may in turn increase the crash likelihoods and injury severities. Many previous studies have found that the increased speed limit was associated with an increased traffic fatality rate for U.S. states (Baum, Lund, & Wells, 1989; Ossiander & Cummings, 2002). Thus, drivers who habitually exceed the speed limit even possibly with reduced length of driving time are expected to have higher fatal crash risk. More importantly, if time is used to compare the crash risks between driver groups or driving conditions, the driving speed for those groups or conditions over the study period should not change substantially (e.g., no substantial change for speed limit). Second, the driving distance estimated by 2016–2017 NHTS is based on a Google API shortest path route between a geocoded origin and destination (McGuckin & Fucci, 2018), while the estimated length of driving time obtained from 2003–2018 is based on participants' estimate (U.S. Census Bureau, 2017). Thus, the driving distance may be more objective than the length of driving time. Third, the linearity between the length of driving time and crash frequency cannot be determined. A so-called "low-mileage bias" issue is associated with the using of number of vehicle miles driven as the exposure measure (Janke, 1991; Langford, Methorst, & Hakamies-Blomqvist, 2006; Langford et al., 2008). The relationship between the number of crashes and driving distance is described as a logarithmic curve (Janke, 1991; Langford et al., 2006). That is, the number of crashes increases rapidly at lower distance levels but gradually plateaus at higher exposure levels. Drivers with lower miles driven usually had a greater crash rate than drivers with higher miles driven (Janke, 1991; Langford et al., 2006; Langford et al., 2008). We are not able to determine analytically if the "low hours bias" issue also exists when the length of driving time is used as the exposure measure, as ATUS does not record their participants' crash history. The overestimation of the older drivers' crash risk per unit of distance is well documented (Massie, Campbell, & Williams, 1995; Langford et al., 2006). Since our results showed that distance-based and time-based fatal crash risk ratios for older drivers were similar, overestimation of time-based fatal crash risk for older adults may also exist.

Our study has several limitations. First, the 2016–2017 NHTS data allowed a proxy to answer for participants in some situations (e.g., participant unavailability). In our analysis, more than 30% of trips for younger drivers aged 16–24 years were answered by a proxy. In contrast, the proxy rate is less than 17% for respondents aged 25 years or older. The effects of proxy response were indeterministic (Dell et al., 2016). Second, we only used fatal crashes to determine if driving distance and the length of driving time could provide comparable risk estimates by driver age category, driver gender, time-of-day, and day-of-week. The generalizability of our results to crashes with all levels of severity is unknown.

Third, our study was also limited by the coding of time-of-day and day-of-week based on the departure time of the trips. Some trips started in the daytime but ended at night, and vice versa. Thus, some bias might be introduced into our analysis when estimating miles driven and hours driven for each category of time-of-day and day-of-week. However, as we used consistent categorization for both the NHTS and ATUS surveys, distance-based and time-based estimates should be biased in the same direction. In total, less than 3% trips in NHTS and ATUS started in nighttime but ended in daytime or started in daytime but ended in nighttime, and less than 1% trips started in weekday but ended in weekend or started in weekend but ended in weekday. As a result, our comparison should not be highly influenced by bias effects. Finally, the negative binomial regression models allowed us to model counts of the drivers in fatal crashes with the natural logs of point estimates of vehicle miles driven or vehicle hours driven as the offsets to estimate the risk ratios and the corresponding 95% confidence intervals (CIs). However, we did not account for the variances of the estimated offsets in our models. Appendix A details a sensitivity analysis in which we iteratively imputed draws from the distributions of the exposure estimates. Within each iteration, we fit negative binomial regression models with the imputed exposures as offsets. The confidence intervals for the risk ratios that resulted from pooling the between- and within- iteration variances are wider than those in Table 2. However, we reach the same conclusions as we do with the present analysis.

5. Conclusion

This study demonstrates that the length of driving time is an alternative driving exposure measure to driving distance, which is usually regarded as the “gold standard” driving exposure. However, the length of driving time has the additional benefit of being available annually starting from 2003, curtailing the discontinuity limitation of driving distance. In addition, the length of driving time can capture the drivers’ perceived risks about their driving conditions and as a result, may be a better exposure measure than driving distance in comparing crash risks between drivers whose likelihood of traveling in hazardous driving conditions (e.g., nighttime) varies substantially. A better knowledge of the availability of different driving exposures and the differences between exposure measures in evaluating crash risks can help researchers choose an appropriate exposure measure to identify at-risk driver groups or driving conditions. This understanding could, in turn, support educational efforts and other specific interventions to reduce traffic crashes and injuries and improve transportation safety.

Acknowledgements

We thank Dr. Melody Davis for her valuable comments on the manuscript. We thank the Federal Highway Administration, U.S Bureau of Labor Statistics, and National Highway Traffic Safety Administration for providing the NHTS, ATUS, and FARS to the public.

Funding sources

This research was supported by the United States National Institute of Health (R01HD074594, 2013-2022; R01AG050581, 2015-2020).

Appendix

Appendix A. Accounting for the variance of the estimated offsets via imputation.

The offsets of the models (i.e., the natural logs of vehicle miles driven and vehicle hours driven) estimated from NHTS and ATUS are not fixed and known, as they are treated in the models used in Table 2 of the main text. Rather, they are estimated and have their own variance. However, our modeling frameworks did not allow us to incorporate the variances of those estimated offsets. Therefore, we present an additional sensitivity analyses to investigate the effects of failing to incorporate the variances of offsets on our model estimates and their corresponding confidence intervals.

We performed two Monte Carlo simulations, each for 10,000 iterations. At each iteration vehicle miles driven or vehicle hours driven for each observation was imputed based on a zerotruncated normal distribution with mean and standard deviation estimated from NHTS or ATUS. In each iteration, a negative binomial regression was fit with the sampled offset, and the associated estimates of dependent variables were obtained. Treating this procedure as a form of multiple imputation of the offsets, we followed the method described in Little and Rubin (2019) to calculate the pooled mean and pooled variance of each estimate (e.g., age category and time-of-day) as follows:

$$\bar{\beta}_D = \frac{1}{D}\sum_{d=1}^{D}\hat{\beta}_d \qquad \text{equation (1)}$$

$$Var_D = Var_{within} + \left(1 + \frac{1}{D}\right)Var_{between} \qquad \text{equation (2)}$$

$$Var_{within} = \frac{1}{D}\sum_{d=1}^{D}\widehat{Var}_d \qquad \text{equation (3)}$$

$$Var_{between} = \frac{1}{D-1}\sum_{d=1}^{D}\left(\hat{\beta}_d - \bar{\beta}_D\right)^2 \qquad \text{equation (4)}$$

where $\hat{\beta}_d$ is the estimate from d^{th} iteration and $\widehat{Var}_d$ is the estimated variance for the estimate from d^{th} iteration ($d = 1, \ldots, D$). In our analysis, $D = 10{,}000$. Negative binomial regression analyses were conducted in R×64 3.5.2 with function *glmmadmb*.

Table A-1:

Pooled distance-based, time-based risk ratios, and the confidence intervals after 10,000 iterations

	Distance-based risk ratio (CI [a])	Time-based risk ratio (CI)
Age category		

	Distance-based risk ratio (CI [a])	Time-based risk ratio (CI)
16–24	2.54 (2.08, 3.10)	2.60 (1.92, 3.52)
25–44	1.33 (1.11, 1.60)	1.30 (1.06, 1.59)
45–64	-- [b]	--
≥ 65	1.50 (1.27, 1.77)	1.56 (1.22, 2.00)
Gender		
Female	--	--
Male	1.75 (1.54, 2.00)	1.74 (1.45, 2.09)
Time-of-day		
Daytime	--	--
Nighttime	3.13 (2.74, 3.57)	2.99 (2.49, 3.59)
Day-of-week		
Weekend	--	--
Weekday	0.78 (0.69, 0.90)	0.77 (0.64, 0.93)

[a] Confidence intervals;

[b] Reference group.

The results of our sensitivity analysis are shown in Table A-1. The pooled distance-based and time-based estimates were quite similar to the ones shown in Table 2. However, the pooled confidence intervals were larger than their corresponding CIs (e.g., the distance-based 95% CI for male in Table 2 is 1.61–1.91 versus the distance-based 95% CI for male [1.54–2.00] in Table A-1). It suggests that not incorporating the variances of the offsets results in underestimation of the standard errors of each estimated risk ratio and thereby, underestimation of the width of their 95% CIs. Some bias may have been introduced due to the truncation of the offset at zero. Future work should investigate practical methods for incorporating the variance of various offsets into models of crash risk.

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Highlight

- Comparison of driving time-based and population-based fatal crash risk ratios was conducted.
- Time-based fatal crash risk ratios are consistent with distance-based ones.
- Using the length of driving time as a driving exposure measure can curtail the discontinuity limitation with driving distance.

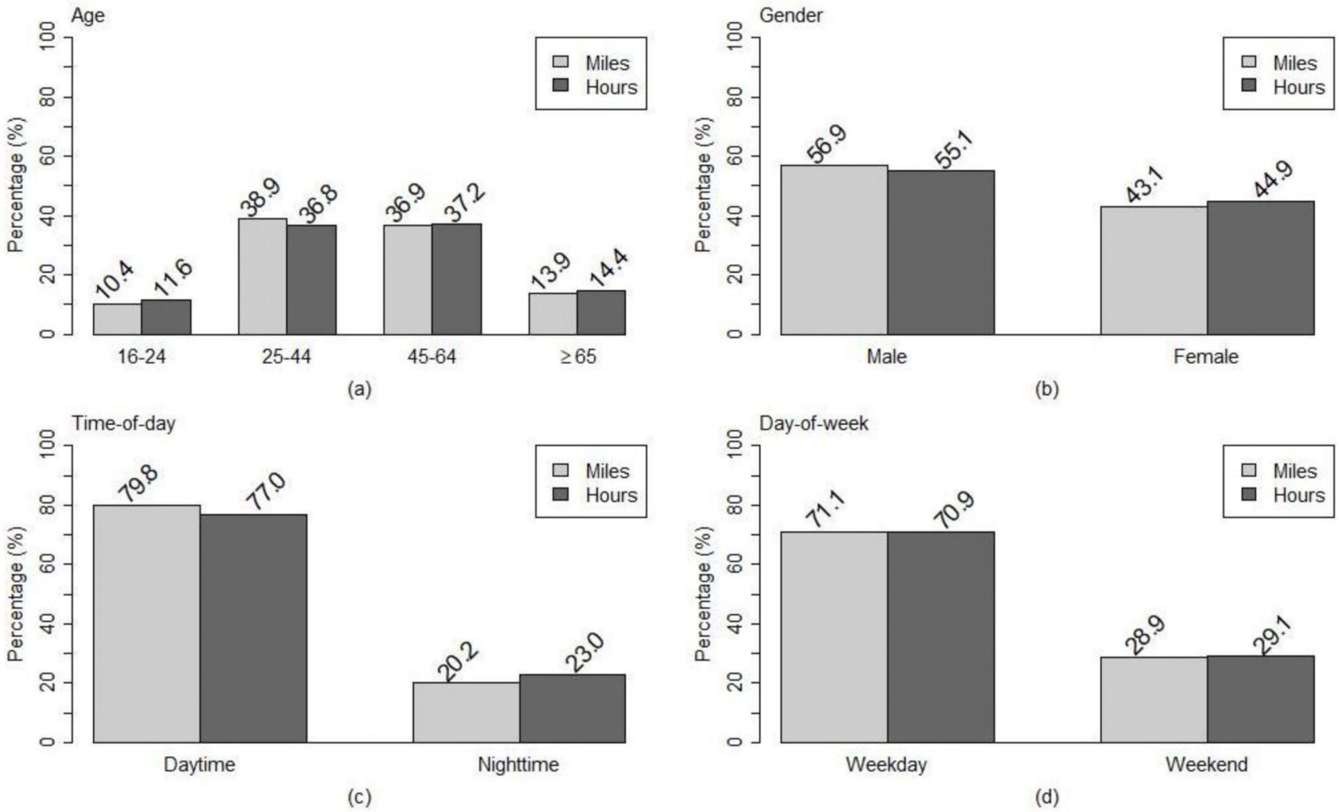

Figure 1. Distributions of vehicle miles driven and vehicle hours driven by age category (a), gender (b), time-of-day (c), and day-of-week (d).

Table 1.

Sample size and weighted estimates of vehicle miles driven and vehicle hours driven by driver age category, gender, time-of-day, and day-of-week

	NHTS [a]			ATUS [b]		
	Unweighted No. of trips	**Weighted vehicle miles driven (95% CI [c]) (100 million miles)**	**Coefficient of variation [e]**	**Unweighted No. of trips**	**Weighted vehicle hours driven (95% CI [d]) (100 million hours)**	**Coefficient of variation**
Age category						
16–24	29,615	2,096 (1,925, 2,267)	0.04	1,680	89 (78, 99)	0.04
25–44	153,968	7,864 (6,933, 8,795)	0.06	10,422	282 (268, 296)	0.06
45–64	241,854	7,453 (7,169, 7,737)	0.02	10,022	285 (272, 298)	0.02
≥ 65	171,914	2,807 (2,621, 2,993)	0.03	5,206	111 (103, 118)	0.03
Gender						
Female	299,943	8,710 (7,946, 9,475)	0.04	12,944	344 (329, 359)	0.02
Male	297,408	11,510 (11,029, 11,991)	0.02	14,389	422 (402, 443)	0.02
Time-of-day						
Daytime	495,409	16,141 (15,312, 16,970)	0.03	21,407	590 (570, 609)	0.02
Nighttime	101,942	4,079 (3,854, 4,304)	0.03	5,923	176 (167, 186)	0.02
Day-of-week						
Weekend	123,941	5,839 (5,581, 6,097)	0.02	12,613	223 (214, 232)	0.02
Weekday	473,410	14,381 (13,488, 15,275)	0.03	14,717	543 (521, 564)	0.02

[a] NHTS: National Household Travel Survey;

[b] ATUS: American Time Use Survey;

[c] The confidence intervals (CIs) of the weighted estimates for vehicle miles driven on the national scale were obtained using the Jackknife approximation method;

[d] The confidence intervals (CIs) of the weighted estimates for vehicle hours driven on the national scale were obtained using the successive differences replication method;

[e] Coefficient of variation is the ratio of the standard deviation to the mean.

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Table 2.

Fatal crash counts, rates, and distance-based, time-based risk ratios for driver age category, gender, time-of-day, and day-of-week

	No. of fatal crashes	Fatal crash rate per 100 million miles driven	Distance-based risk ratio [a] (CI [b])	Fatal crash rate per 100 million hours driven	Time-based risk ratio [c] (CI)
Age category					
16–24	9,263	4.42	2.43 (2.16, 2.74)	104.59	2.39 (2.10, 2.72)
25–44	17,075	2.17	1.32 (1.17, 1.48)	60.58	1.31 (1.15, 1.49)
45–64	12.805	1.72	-- [d]	44.94	--
≥ 65	6,714	2.39	1.49 (1.32, 1.68)	60.69	1.50 (1.31, 1.71)
Gender					
Female	13,111	1.51	--	38.14	--
Male	32,746	2.84	1.75 (1.61, 1.91)	77.55	1./5 (1.60, 1.92)
Time-of-day					
Daytime	24,011	1.49	--	40.72	--
Nighttime	21,846	5.36	3.13 (2.87, 3.41)	*V3.8’	2.83 (2.58, 3.10)
Day-of-week					
Weekend	18,512	3.17	--	82.97	--
Weekday	27,345	1.90	0.79 (0.73, 0.86)	50.37	0.76 (0.70, 0.84)

[a] The estimates were obtained through a negative binomial regression model with an offset equal to the natural log of the number of vehicle miles driven. The model included age category, gender, time-of-day, day-of-week, and quarter as independent variables and the number of drivers in fatal crashes as the dependent variable;

[b] Confidence intervals;

[c] The estimates were obtained through a negative regression model with an offset equal to the natural log of the number of vehicle hours driven. The model included age category, gender, time-of-day, day-of-week, and quarter as independent variables and the number of drivers in fatal crashes as the dependent variable;

[d] Reference group.