Urban Taxi vs Non-taxi Crashes: Implications for Automated Vehicles in the Rideshare Environment

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INTRODUCTION

One of the major benefits often cited in favor of the automated transportation is its positive impact on safety outcomes. However, measuring and comparing the actual safety benefits of automated vehicles to conventional vehicles may prove to be challenging. In addition to not having enough miles driven to make a statistically valid crash rate based comparison, a report by RAND (2018) points out that such comparisons must also be made to a crash rate for humans driving in the same or an equivalent driving environment.

Multiple simulation based research related to AV adoption suggest *shared ride* as the 'best case scenario from safety, congestion and environmental impact perspectives (Fagnant and Kockelman 2012, Fagnant and Kockelman 2015, Litman 2015). Business models related to AVs also indicate the first adoption scenarios to be through ridesharing/ridehailing systems because of high cost of ownership and trust issues (Litman 2017, Bernhart.2016). Following these hypotheses, on road testing of AVs is currently being done in urban, low-speed environments where rideshare services can be offered. To compare performance, therefore, these AVs should be evaluated against performance of ridesharing/ridehailing services operating under similar conditions. However, crash and conflict data for ridehailing services are difficult to come by and hence, we choose to use for-hire vehicle data as surrogates. We hypothesize that such vehicles operate in particular environments driven by demand, and that those environments may result in types of crashes and crash conditions that are significantly different than other passenger vehicle crashes but are similar to AVs in the ridehailing context.

METHODOLOGY

We found that Chicago police reported crash data separates taxi/for hire vehicle related crashes from passenger vehicle related crashes and thus is ideally suited for the analysis. The total number of police-reported crashes in Chicago between 2005 and 2012 was 788,392, which represents about 28% of all crashes in Illinois during the same period. About 95% of all such Chicago crashes involve at least one passenger vehicle (SUV, car, pickup or van), and 4.4% involved a taxi or for-hire car.

To test comparisons of crash characteristics for taxis vs. non-taxis involved in crashes in Chicago, we conducted a multivariate binary logistic regression to predict whether a crash-involved was a taxi or not as a function of crash characteristics. Logistic regression treats the outcome as coming from a Bernoulli distribution where the probability parameter for each case is a function of the predictors. Specifically, the logistic regression model is given in Equation 1.

$$ln\frac{\hat{p}}{1-\hat{p}} = \hat{\beta}_0 + \sum_{i=1}^{r} \hat{\beta}_i x_i \quad (1)$$

where $\frac{\hat{p}}{1-\hat{p}}$ is the predicted odds of a crash-involved vehicle being a taxi, $\hat{\beta}$'s are estimated coefficients of the linear equation, and x_i are values of the predictors in the model. The model is fit using maximum likelihood. Significance of predictors was tested using Wald χ-squared tests (α=0.05).

The predictors of the logistic regression model are selected stepwise and from analysis of effects (Table 1). Final predictors for the multivariate model include crash type (6 levels: Angle/Turn, Head-on, Ped/Cyclist, Rear-end, Sideswipe, Other), weather condition (4 levels: Clear, Snow, Rain, Other), light condition (4 levels: Daylight, Dark-lighted, Dawn/dusk, Dark-unlighted), functional classification of roads (3 levels: Interstate, Principal Arterials, Minor Arterials), weekend vs, weekday, type of traffic control (5 levels: None, Stop sign, Signal, Other, Lane), road surface conditions (4 levels: Other, Snow, Wet, Dry), alcohol/ drug involvement (yes/no) and driver distracted (yes/no).

Table 1. Analysis of Effects for Predictor Variables

Type 3 Analysis of Effects			
Effect	DF	Wald χ2	Pr > ChiSq
Weather	3	36.1204	<.0001
Light	3	1619.6705	<.0001
Functional class	2	1841.2096	<.0001
Weekend	1	10.0605	0.0015
Traffic control	4	784.5327	<.0001
Surface conditions	3	16.7102	0.0008
Driver under Alcohol/drug	1	224.9351	<.0001
Driver distracted	1	5.6926	0.017
Crash type	5	4286.9423	<.0001

RESULTS

As is seen from Table 2, as compared to clear weather, snow and sleet are significantly more likely to be associated with taxi crashes. The presence of snow and sleet increases the odds of a crash being a taxi involved crash by 9%. Taxi crashes are also significantly more associated with principal arterials rather than interstates (*increases the odds by 62%*), with weekends than weekdays (*increases the odds by 4%*), during dawn/dusk (*increases the odds by 13% as compared to daylight*) and dark, but lighted conditions (*increases the odds by 66% as compared to daylight*). Taxi crashes are significantly less likely to be associated with stop signs, driver under influence crashes, and there is no significant association between driver distraction and a taxi related crash as compared to other passenger vehicle crashes. As observed from the crash type descriptions, taxi involved crashes are significantly more likely to be sideswipe and pedestrian/bicyclist related crashes as compared to rear end crashes. The odds of a taxi involved crash also being a pedestrian/bicyclist involved crash *increases by 230% as compared to a taxi involved crash also being a rear end crash*. Similarly, the odds of a taxi involved crash being a sideswipe crash *increases by 75% as compared to a taxi involved crash being a rear end crash*. On the other hand, the odds of a taxi involved crash being *a head on crash decreases by 36% as compared to a taxi involved crash being a rear end crash*. It should also be noted that a crash involving driver being under alcohol/drug influence is significantly less likely to be a taxi crash – the odds of such a crash being a taxi crash is reduced by ~80% as compared to when the driver is not under influence.

Table 2. Results of Binary Logistic Regression Model for Taxi and Non Taxi Involved Crashes

Analysis of Maximum Likelihood Estimates							
Parameter		DF	Estimate	Std. Error	Wald χ2	Pr > ChiSq	OR
Intercept		1	-4.0122	0.0312	16513.08	<.0001	
weather	Other	1	-0.0831	0.0506	2.70	0.1006	0.920
weather	Rain	1	-0.0270	0.0168	2.60	0.1067	0.973
weather	Snow+	1	0.0880	0.0251	12.25	0.0005	1.092
weather	Clear	Base Category					
light condition	Dark	1	0.0283	0.0291	0.94	0.3312	1.029
light condition	Dawn/Dusk	1	0.1190	0.0301	15.67	<.0001	1.126
light condition	Lighted	1	0.5027	0.0123	1659.09	<.0001	1.653
light condition	Daylight	Base Category					
Functional Classification	Minor Arterial	1	-0.0427	0.0312	1.88	0.1705	0.958
Functional Classification	Principal Arterial	1	0.4835	0.0306	249.25	<.0001	1.622
Functional Classification	Interstate	Base Category					
weekend	1	1	0.0453	0.0123	13.58	0.0002	1.046
weekend	0	Base Category					
Traffic Control Type	Lane Mark	1	0.0171	0.0330	0.27	0.6040	1.017
Traffic Control Type	Other	1	0.0583	0.0451	1.67	0.1963	1.060
Traffic Control Type	Signal	1	0.2247	0.0129	304.71	<.0001	1.252
Traffic Control Type	Stop Sign	1	-0.3928	0.0243	262.09	<.0001	0.675
Traffic Control Type	None	Base Category					
Driver Under Influence	1	1	-1.6031	0.1055	230.69	<.0001	0.201
Driver Under Influence	0	Base Category					
crash_type	Angle/Turn	1	-0.0283	0.0147	3.71	0.0540	0.972
crash_type	Head-on	1	-0.4712	0.0799	34.78	<.0001	0.624
crash_type	Other	1	-0.6222	0.0213	856.64	<.0001	0.537
crash_type	Ped/Cycle	1	0.8253	0.0260	1004.43	<.0001	2.283
crash_type	Sideswipe	1	0.5563	0.0153	1329.51	<.0001	1.744
crash_type	Rear-end	Base Category					

DISCUSSION

From the findings from the Chicago crash data, it appears that taxi crashes are more likely to happen in urban arterials, during weekends, at night or at dawn/dusk, with snow/sleet/hail weather conditions. Lateral crashes resulting in sideswipes, angle, and turning-related crashes are also common in the cities explored here. The Chicago taxi data suggest that taxi drivers may change lanes more often than passenger-car drivers and end up in lateral conflicts more often (especially sideswipes). In addition, rear-end crashes are the most common crash type in all driving environments, possibly indicating driver inattention or driving faster than is safe. The crashes that taxis/for hire vehicles get into in such environment are significantly more likely to be pedestrian/bicyclist related crashes as compared to other vehicles, possibly because of both greater exposure of taxis/for hire vehicles and pedestrian/bicyclists in such environment, visibility issues and likely a conflict between under influence pedestrians and bicyclists during weekend nights. Nationally also, pedestrian and pedalcyclist conflicts are more common in urban areas than in non-urban areas (NHTSA, 2015). Taxis operate in darkness (typically, dark-but-lighted conditions) more than non-taxis, and this results in elevated risk of failing to detect pedestrians in dark and dark-but-lighted conditions (compared to daylight). That said, from this analysis, the percentage of taxi related crashes in dark-no lights condition are lower than non-taxi crashes in similar conditions (4.4% vs 5.6%), which may be again an exposure issue in that pedestrians are generally in well-lit areas. The results indicate that a significant proportion of the taxi related crashes are influenced by their most common operating environment (urban, bad weather, weekend nights) i.e., where taxis/for hire vehicles operate more frequently, and it is also the most likely environment that the ridesharing AVs will also be operating in. Therefore, when testing and comparing AVs for safety outcomes, these particular operational environmental conditions should be considered and factored in.

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