Road Safety and Simulation
International Conference
RSS2013

October 22-25, 2013
Rome, Italy

Modelling Likelihood of At-Fault and Not-At-Fault Carshare Users

Taha Hossein Rashidi

Research Fellow
University of New South Wales
UNSW, Gate 11, Botany Street, H20 CVEN, L1, Room 113
Randwick NSW 2031
Australia
Rashidi@unsw.edu.au, tel: +61 2 9385 5063, fax: +61 2 9385 6139

Vinayak Dixit

Senior Lecturer
School of Civil and Environmental Envineering
University of New South Wales
UNSW, Gate 11, Botany Street, H20 CVEN, L1, Room 113
Randwick NSW 2031
Australia
v.dixit@unsw.edu.au, tel: +61 2 9385 5381, fax: +61 2 9385 6139

ABSTRACT

Carshare systems are seen as the future for sustainable development. To promote carsharing it is imperative to make it cost effective, which includes reduction in costs associated to crashes and insurance. To achieve this goal, it is imperative to characterize carshare users involved in crashes and understand factors that can explain at-fault and not-at fault drivers. This study utilizes data from carshare users in Sydney, Australia. Based on this study it was found that experience in driving, higher insurance excess, needing car on weekends, owning a car reduces the likelihood of being in crash and being at fault. Further, the likelihood of not being at-fault reduces with higher insurance excess, not having previous instance of traffic offences, preference for luxurious cars and living near a dedicated parking. Marginal reduction in the propensity of being not-at-fault was also observed due to having a drivers license from a country having a left hand drive, similar to that in Australia. The analysis of not-at-fault drivers also provides for quasi-induced exposure methods, suggesting that when applying quasi-induced exposure methods, it is critical to control for insurance type, previous instance of traffic offences, vehicle type and what type of license the individual has. Finally, based on this study it is recommended that having higher insurance excess on risky drivers and also providing some incentives based on training and experience (based on kilometres driven), possibly on insurance excess could improve safety and reduce costs associated to crashes for carshare systems.

Keywords: carshare, safety, multinomial logit, quasi-induced exposure

INTRODUCTION

Since the 90s (Prettenthaler and Steininger 1999) innovators, industries, cities and decision makers have started to seriously consider the possibility of materializing the concept of car sharing in large cities such as Australia, Switzerland and Germany, but also on a smaller scale in Sweden, the Netherlands, Canada and the United States (Mont 2004; Steininger et al 1996). An efficiently designed carsharing system would provide an ideal alternative to private vehicle ownership, by providing users the ability to have flexibility and travel large distances while having their predominant choice of mode as public transit, walking, bicycling, taxis etc, to private vehicles. An important barrier with carsharing is the high automobile insurance costs incurred due to several members with different risk propensities using the carsharing system. Due to which overall cost of the carshare increases. To ensure the success of carsharing it is imperative to lower overall costs by reducing insurance costs. Therefore, it is critical to understand crash risks of various individuals participating in a carshare scheme.

To the best of the authors' knowledge, after an extensive review of literature, this study is the first to study crash risk of carshare users belonging to the GoGet program in Sydney, New South Wales Australia. This research studies the discrete outcomes of not crashing, crashing and being at-fault as well as crashing and being not-at-fault. Previous studies have assessed crash characteristics using discrete outcome models, such as the binary logit (Haque et al.,2009), ordered probit (Pai and Saleh, 2008), multinomial logit (Shankar and Mannering, 1996), nested logit (Savolainen and Mannering, 2007), and mixed logit (de Lapparent, 2006). Zhang (2010) identifies the assumptions and strengths of these methods.

A unique aspect of this dataset is that it contains information regarding all members, including those involved in crashes and identified as at-fault and not-at-fault drivers. This also provides an opportunity to characterize and study no-fault drivers which play an important role in crash studies utilizing quasi-induced exposure.

Characterizing cause of crashes relies heavily on normalizing occurrences of crashes based on risk exposure. Kilometres driven by a particular driver is widely accepted as a representation of this exposure. Unfortunately, crash databases do not typically contain this information making estimation and approximation of exposure rate a challenging issue. To address this issue the concept of *induced exposure* was developed by Thorpe (1967). Induced exposure was found to have typical issues associated with assigning responsibility for crash causation, which led to the development of *quasi-induced exposure* (Haight, 1971).

Quasi-induced exposure is based on the premise that not-at-fault drivers are a random sample of the driving population, which is utilized to characterize the at-fault drivers by studying the involvement ratio, i.e. the ratio of at-fault drivers to not-at-fault drivers for a certain group. An important advantage of this method is that it does not require other exogenous measures of risk exposure such as vehicle kilometres travelled, traffic volumes at a location etc., and can rely solely on the crash database to analyse crashes. Due to these advantages researchers and practitioners (Yan et al. 2005; Chandraratna and Stamatiadis, 2009; Jiang and Lyles, 2010; Mendez and Izquierdo, 2010; Jiang et al. 2012) have begun to heavily rely on quasi-induced exposure to characterize crash risks. Due to the increasing popularity of this method it has become imperative to study the validity of the underlying assumption of quasi-induced exposure regarding not-at-fault drivers being a random sample of the driving population, which also requires that crash responsibilities are correctly assigned.

Studies that have undertaken to evaluate quasi-induced exposure can be categorized into two types of studies. The first type of studies have focussed on biases associated to police officer’s judgement in assigning fault to drivers during a crash. These biases in judgements can result in violation of the assumption of quasi-induced exposure regarding not-at-fault drivers being a random sample of all drivers. DeYoung et al. (1997) identified “negative halo effect”, where in an investigating officer might assign fault to drivers’ with suspended/ revoked license, alcohol/drug use or other negative perception about the driver, despite not being objectively responsible for the crash. Kirk and Stamtiadis (2001) as well as Lenguerrand et al. (2008) found such biases in the crash data set. Rather than use the police assigned crash responsibility, the studies used exogenous methods to identify crash responsibility. Chandraratna and Stamatiadis (2009) when analysing multivehicle crashes found evidence of “negative halo effects” biasing the representation of not-at-fault drivers. Recently Jiang et al. (2012) found that hit-and run, gender, age, injury severity, and alcohol and illegal drug use significantly impacted investigating officers’ decision making.

The second type of studies can be characterized as those which compare quasi-induced exposure with traditionally used exposure metrics such as vehicle miles travelled or traffic volumes based on time of day or other disaggregate characteristics based on environmental, vehicle, roadway or driver characteristics. Lightizer (1989) was the earliest studies to compare key variables regarding crashes using the quasi-induced exposure using the Michigan crash data. The study found the assumptions of the quasi-induced exposure were met. Kirk and Stamatiadis (2001) were also able to qualitatively show the validity of the quasi-induced approach using the Kentucky crash database. On the contrary, there have been several studies that have found not-at-fault drivers to have significant under representation of vehicles (vehicles with new technologies) (Evans, 2004) and drivers (younger age group) (Kahane and Hertz, 1998) that have higher accident avoidance capabilities. Drivers having higher speed have also been found to have a higher representation (Mendez and Izquierdo, 2010) in not-at-fault drivers, mainly due to higher number of accident prone interactions (Navon, 2003) and reduced ability to avoid crashes.

Most of the previous studies relied on data from crash databases to test the validity of quasi induced exposure. This study utilizes member and crash database from the Sydney GoGet car share users to evaluate quasi-induced exposure. The purpose of this study is not only to characterize carshare users who crash and are at-fault or not-at-fault, but also to evaluate the assumption of quasi-induced exposure. This database provides a unique opportunity to explore these questions, which have not been carried out earlier. The next section describes the data used for the analysis.

DATA

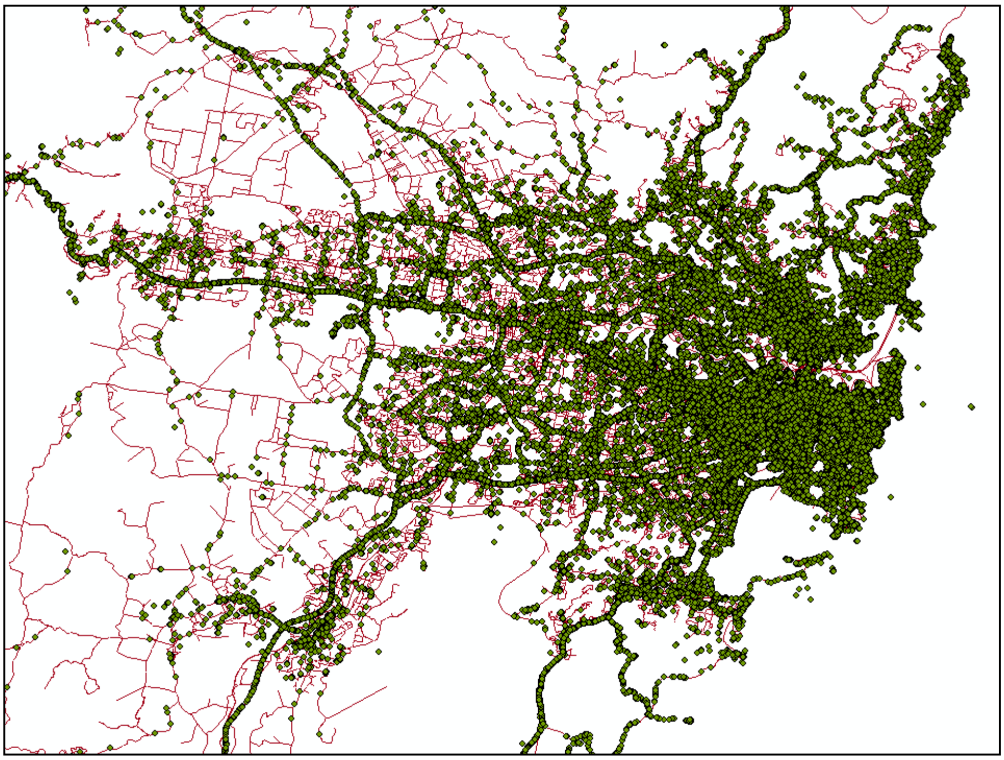

Figure 1: Extent of GoGet carshare usage in Sydney

This analysis utilizes GoGet member crash data in Sydney, New South Wales (NSW), Australia. The purpose of this study is to evaluate factors that affect the risk propensity of at-fault and not-at-fault drivers. The data was collected during the period from July 2011 to July 2012. A total of

5067 active members were part of the Sydney dataset, out of which there were 128 experienced crashes. Out of the 129 crashes 87 were at-fault drivers and 42 were not-at-fault drivers. Goget has a total of 800 vehicles located at strategic carshare locations throughout Sydney. The database contain single and multivehicle crashes. The extent of driving in Sydney, NSW during the analysis period is shown in Figure 1.

A qualitative comparison of representation of different variables between those observed in the crash database and the carshare membership database is shown in Table 1. As it can be seen in Table 1, males are more involved in accidents in the car sharing data. Though gender was not provided in the membership database, in the crash database male were found to be more likely to be in a crash. Due to lack of gender data in the membership database no meaningful comparison could be made with regard to the exposure.

Almost 67% of the crashes consisted of at-fault drivers as compared to not-at-fault. The estimates of the not-at-fault drivers will be used to explore certain assumptions about quasi-induced exposure. It was also found that the kilometres driven among those involved in crashes were systematically lower than the overall membership database, suggesting some sort of positive effect on reduction in crash likelihood due to more driving experience.

The representation of drivers having driver's licence from countries that drive on the right hand side was slightly higher in the crash database as compared to the membership database. This suggests that whether the driving license was issued in a country that has a right-hand driving style might increase the likelihood of accidents.

However it was interesting to find under-representation of drivers preferring more luxurious cars in the crashes. This suggests that such drivers might be choosing luxurious cars from the carshare pool which have better safety features, and therefore are underrepresented in the crashdata base. There is also an under representation of individuals who need to pay an excess of $1500 in the crash database, suggesting that loss aversion might be resulting in those individuals being more careful. In addition, people having a history of traffic offenses are also over represented in the crash database.

Based on Table 1, GoGet users who need the car less frequently are more likely to be involved in accidents. This finding is consistent with that observed in the kilometres driven last year, in which people who drive more are less likely to be involved in crashes. A possible rationale for this is that carshare users initially, have to use cars that are new and need to adapt to them. As the users utilize the vehicles more frequently and drive larger number of kilometres they adapt to the vehicles dynamics and are more comfortable driving, resulting in reduction in likelihood of crashes. An interesting finding is also that people who need cars on weekend are less likely to be involved in crashes. This suggests that these users utilize vehicle on weekends for recreational trips, during which the level of traffic congestion is low, and hence reducing the crash exposure.

Carshare users who do not own a car are over-represented in the crash database, while those who own cars are under-represented. A possible explanation for this is that people who do not own cars are likely to more extensively use the carshare and therefore have lower exposure to being involved in accidents.

Table 1 The impact of socio-demographic attributes on accident involvement

Variable	Categories		Accident Data	All Data
DRIVER CHARACTERSTICS				
Gender	Male		54.46%	NA
	Female		45.54%	NA
At Fault	Yes		67.44%	-
	No		38.56%	-
Kilometers Driven Last Year	0-1000		31.75%	23.50%
	1000-5000		26.98%	22.90%
	5000-10000		19.84%	21.97%
	10000+		21.43%	31.63%
Driver's License Country	Left Hand Traffic	Australia	86.06%	90.05%
		Non-Aus.	5.43%	4.78%
	Right Hand Traffic		8.53%	5.17%
Insurance that requires user to pay excess of upto $1500 in case of a crash	0		63.57%	53.70%
	1		36.43%	46.30%
Instance of Previous Traffic Offenses	0		27.13%	36.41%
	1		72.87%	63.59%
Preffered Car Class	0		81.40%	75.40%
	1		18.60%	24.60%
CARSHARE CHARACTERSTICS				
How Oftern You Need a Car	About once or twice a month		36.51%	0.91%
	About once or twice a week		23.02%	66.42%
	Everyday		0.79%	8.29%
	Most Weekdays		2.38%	6.63%
	Most Weekends		8.73%	17.04%
	Rarely		28.57%	0.71%
Vehicle Ownership	I am intending to sell my car soon		6.98%	5.43%
	I do not own a car		72.87%	54.59%
	I live in a two + car household		0.00%	2.31%
	I own a car		15.50%	32.69%
	I was intending to buy a car soon		3.88%	3.18%
	Other		0.78%	1.80%
Live Near a Dedicated Parking	0		34.00%	28.79%
	1		65.00%	71.21%
Main Mode of Transport	Bicycle		11.11%	6.46%
	Bus		19.05%	20.99%
	Car		8.73%	15.59%
	Other		2.38%	5.62%
	Train		44.44%	33.23%
	Walk		14.29%	18.11%

It was also interesting to find that presence of a dedicated parking spot near home reduces the likelihood of being in an accident. A dedicated parking spot that is well maintained also reduces the propensity of being involved in a crash due to other drivers or other environmental factors.

Percentages for GoGet users considering different modes of transport as their main mode were not very different between the crash and membership databases, except for those who consider train to be their main mode of transport. Carshare users who consider train as their main mode of transport are found to be over-represented in the crash database. This could possibly be due to lack of driving experience or unfamiliarity with routes that makes them more likely to crash.

Table 2 Comparison of not-at-fault drivers with membership data

Variable	Categories		Not-at-Fault Data	Population
How Oftern You Need a Car	About once or twice a month		40.48%	0.91%
	About once or twice a week		21.43%	66.42%
	Everyday		0.00%	8.29%
	Most Weekdays		2.38%	6.63%
	Most Weekends		11.90%	17.04%
	Rarely		23.81%	0.71%
Vehicle Ownership	I am intending to sell my car soon		9.52%	5.43%
	I do not own a car		64.29%	54.59%
	I live in a 2+ car household		0.00%	2.31%
	I own a car		21.43%	32.69%
	I was intending to buy a car soon		2.38%	3.18%
	Other		2.38%	1.80%
Age	20	25	4.76%	7.24%
	26	30	21.42%	20.62%
	31	35	28.57%	21.36%
	36	40	9.52%	17.46%
	41	45	9.52%	12.29%
	46	50	16.67%	9.30%
	51	+	9.52%	11.72%
Main Mode of Transport	Bicycle		12.50%	6.46%
	Bus		7.50%	20.99%
	Car		12.50%	15.59%
	Other		7.50%	5.62%
	Train		50.00%	33.23%
	Walk		10.00%	18.11%
Live Near a Dedicated Parking	0		42.86%	28.79%
	1		57.14%	71.21%
Kilometers Driven Last Year	0-1000		21.43%	23.50%
	1000-5000		26.19%	22.90%
	5000-10000		28.57%	21.97%
	10000+		23.81%	31.63%

To explore assumptions on the quasi-induced exposure. Table 2 presents the accident rates in different socio-demographic categories for GoGet members involved in accidents but not-at-fault and the general membership pool. A quick look at the last two columns of Table 3 reveals that lackof experience (variables: kilometres driven last year, how often you need car), not owning a car, carshare users considering train as their main mode of travel, not close to a dedicated parking are overrepresented in the not-at-fault crashes. This suggests some biases in the quasi-induced exposure. Further analysis is undertaken to characterize any systematic differences.

To control for this, covariates that describe carshare users as well as driver characteristics are included in the model. This provides theto determine which factors are able to statistically characterize carshare users that are at-fault, not-at-fault as compared to those who do not crash. Based on the above qualitative analysis factors that were thought to have a significant impact on crash propensity and being at-fault or not-at-fault were selected and summarized in Table 3.

Table 3: Variables Characterizing Driver and Carshare Usage

Variable	Definition	Variable Type	Mean / Percent	Std. Dev.
DRIVER CHARACTERSTICS				
dl_year	Number of years with Driving License	Continuous	17.08	10.00
birthage	age of the driver	Continuous	37.59	10.06
km_last_year	Kilometers Driven Last Year	Continuous	7433.70	22023.38
excess1500	Binary variable for whether the drivers have chosen an insurance with excess of	1	53.70%	-
		0	46.30%	-
ins_traffic_offense	Binary variable for whether the driver has ever committed a traffic offense	1	36.41%	-
		0	63.59%	-
CARSHARE CHARACTERSTICS				
car_class	Class of car preffered by the user. 1 indicates that user prefers luxurious cars.	1	24.60%	-
		0	75.40%	-
near_dedicated_parking	Does the user live near a dedicated parking?	1	71.21%	-
		0	28.79%	-
main_mode_auto	Is the main mode used by the person an autombile?	1	15.16%	-
		0	84.84%	-
needcarweekend	Does the person need cars on weekends?	1	17.04%	-
		0	82.96%	-
left_hand_drive	License from country with left hand drive.	1	17.04%	-
		0	82.96%	-
no_car	Does the person ***not*** have a car	1	54.59%	-
		0	45.41%	-

METHODOLOGY

This study utilizes a multinomial logit specification to study crash propensity of different carshare users. Multinomial logit (MNL) models have strict limitations regarding the IIA property. The IIA property is that the relative probability of choosing between any two alternatives is independent of all other alternatives. If there exists correlation among unobserved factors across alternatives this would violates the IIA property making the MNL model ineffective. The model was tested for this and the MNL was found to be suitable for the dataset, the discussion of this is provided in the "*Results*" section.

If *J* possible alternative consequences are possible, the utility of a particular alternative *j* for an observed event *n* is decomposed into (1) a part labelled V_{nj} that is known and observed upto some parameters, and (2) an unknown part ε_{nj} that is assumed to be random. Therefore the Utility for a particular alternative *j*

$$U_{nj} = V_{nj} + \varepsilon_{nj} \qquad \forall j$$

Assuming an identical and independent logistic distribution for each of the error terms among the alternatives, the probability of an alternative *j* can be written as:

$$P_j = \frac{e^{V_j}}{\sum_{i=\{1..J\}} e^{V_i}}$$

Assuming a base alternative k

$$P_j = \frac{e^{V_j - V_k}}{1 + \sum_{i=\{1..J\}-\{k\}} e^{V_i - V_k}} \qquad \forall j$$

Using maximum likelihood estimation $V_i - V_k$ is estimated as a linear combination of covariates.

$$V_i - V_k = \sum_m \beta_{im} X_m$$

The “mlogit” function is STATA 12.0 was used to estimate the model. The next section describes provides a qualitative and quantitative analysis to identify factors that affect the crash propensity of at-fault and not-at-fault carshare users.

RESULTS

To characterize the crash propensity as well as at-fault and not-at-fault a multinomial logit model was developed. The estimated MNL model is analysed to study the statistical significance of variables that impact the crash propensity. The results are shown in Table 4.

The model includes a categorical variable with three alternatives: 1) no crash 2) crash and at-fault 3) crash and not-at-fault. To test IIA among the three alternatives, Hausman’s specification test was conducted to test whether exclusion of one category can affect the other two. No statistical difference was found with the exclusion of not-at-fault drivers. However, due to the small number of observations for the not-at-fault drivers, the data with the exclusion of at-fault drivers was not suitable for a Hausman test. Finally to further confirm the fact that a multinomial logit can provide a suitable structure a multinomial probit was developed, the variance-covariance matrix found not to have a statistically significant different structure than a homoscedastic diagonal structure. In other words, non diagonal elements of the covariance matrix found not to be different than zero in the probit model. This suggests that the multinomial logit model would be suitable for this analysis.

Table 4 Results for the Multinomial Logit Model

Variables	Coefficients	Std. Err.	t-stat	p-value
No-Crash (base)				
at-fault				
dl_year	-5.87E-02	1.74E-02	-3.36	0.00
birthage	2.46E-02	1.63E-02	1.51	0.13
km_last_year	-4.52E-05	2.25E-05	-2.01	0.04
excess1500	-0.50	0.23	-2.19	0.03
ins_traffic_offences	-0.04	0.24	-0.18	0.86
car_class	-0.18	0.26	-0.66	0.51
live_near_dedicated_parking	0.00	0.24	0.01	1.00
main_mode_auto	-0.06	0.50	-0.11	0.91
train	0.27	0.25	1.06	0.29
needcarweekend	-0.98	0.40	-2.45	0.01
no_car	0.72	0.29	2.51	0.01
left_hand_drive	-0.42	0.44	-0.96	0.34
_cons	-3.67	0.75	-4.86	0.00
not-at-fault				
dl_year	1.25E-03	2.85E-02	0.04	0.97
birthage	5.68E-03	2.82E-02	0.20	0.84
km_last_year	-1.99E-05	0.0000244	-0.81	0.42
excess1500	-0.55	0.33	-1.67	0.09
ins_traffic_offences	1.03	0.42	2.44	0.02
car_class	-0.92	0.48	-1.90	0.06
live_near_dedicated_parking	-0.55	0.32	-1.74	0.08
main_mode_auto	0.38	0.61	0.63	0.53
train	0.60	0.40	1.49	0.14
needcarweekend	-0.50	0.48	-1.04	0.30
no_car	0.19	0.37	0.50	0.62
left_hand_drive	-0.84	0.55	-1.53	0.13
_cons	-4.58	1.08	-4.24	0.00
Observations	= 5065			
Chi-Squared (Degrees of Freedom: 24)	= 79.54			
Log-Likelihood	= -642.44			
Pseudo R-squared	= 0.0583			

The general goodness-of-fit of the model is acceptable, although the pseudo-R^2 is relatively small. However, this is because the data is heavily zero inflated. The overall results observed in Table 4 agree with the qualitative findings discussed based on Table 1.

Propensity to be at-fault

Based on the results shown in Table 4, it can be concluded that individuals who are more experienced in driving are less likely to being at-fault in accident. Among the driver characteristics this was observed in the negative coefficient for variables representing the number of years holding a driver's license (*dl_year*) and kilometres travelled in the previous year (*km_last_year*) as being statistically significant at a 95% confidence level. In addition, loss aversion among driver's were found to have a significant impact on the propensity of being at-fault, as observed by the negative coefficient for the variable representing people who selected the $1500 excess insurance plan (*excess1500*). This implies that people who have a higher excess are less likely to be at-fault as compared to those who have a lower $300 excess insurance plan.

The age of the member (*birthage*) was found to be marginally significant with a p-value of 0.13, with a positive coefficient. This suggests that older people are more likely to be at-fault and is observed in the over-representation of people in the age group of 45-50 in the crash database (Table 1). This is possibly due to larger perception reaction time and lower reflexes among the older drivers.

As observed in a qualitative analysis of Table 1, not having a car (*nocar*) increased the likelihood of being at-fault, as noticed by the positive coefficient that is statistically significant. In addition, the variable *needcarweekends* was found to have a statistically significant negative coefficient, suggesting that carshare users needing cars on weekends are less likely to be involved at-fault. Interestingly, having main mode to travel as a car (*main_mode_auto*) was not found to have any significant effect on being at-fault.

Propensity to be not-at-fault

Interestingly, loss aversion among driver's was also found to reduce the propensity of being not-at-fault, as observed by the negative coefficient for the variable representing people who selected the $1500 excess insurance plan (*excess1500*) under not-at-fault. This indicates that people who have a higher excess are less likely to be not-at-fault as compared to those who have a lower $300 excess insurance plan.

Instance of previous traffic offences (*ins_traffic_offences*) was found to have a positive and statistically significant impact on likelihood of being not-at-fault. This could perhaps be due to potential inattentiveness or slow reflexes among these drivers that might have led to earlier traffic offences, and also increases their likelihood of being not-at-fault. Another interesting finding was that people having licenses from countries that have left hand drive (*left_hand_drive*) are marginally less likely to be involved in a crash and be not-at-fault (p-value of 0.13). This can be attributed to the ability of having been trained to drive on the left hand side and therefore better ability to avoid potential crashes.

As earlier observed in Table 1, the MNL model presented in Table 4 suggests that carshare users who prefer luxurious cars (*car_class*) and live near a dedicated parking (*live_near_dedicated_parking*) are statistically less likely to be involved in a crash but be not-at-fault. As explained earlier, luxurious cars have better safety features and provide better ability to avoid potential crashes. Also living near a dedicated parking provides better protection for vehicles from other cars, and therefore are less likely to be involved in a crash and being not-at-fault. Finally, people who consider their main mode of transport to be train (*train*) are marginally more likely to be involved in crashes and be not-at-fault (p-value of 0.14). This can be attributed to these drivers not having an understanding of road network and lack of driving experience.

Though it is recognized that this analysis was carried out on a dataset of carshare users and is a biased sample of random drivers, the model estimates provide some useful insights with regard to quasi-induced exposure. Firstly, loss aversion and drivers insurance policies make a significant impact on reducing involvement in a crash even as a not-at-fault driver. This is in line with previous findings by Cummins et al. (2001) showed that the no fault system (the insurance company pays for losses regardless of who is at fault) is significantly associated to higher accident rates than a tort system (The party at fault is liable for the losses). In addition, previous instance of traffic offences increases likelihood of being not-at-fault, which hints towards over representation of inattentive drivers as well as drivers that commit traffic offenses in the not-at-fault dataset. Not-at-fault drivers might also be over-represented with people having insufficient and proper training as indicated by the observation that people given licenses in countries with left hand driving are less likely to be involved in crashes and being not-at-fault. Finally, there is evidence of people driving luxurious cars with more safety systems are less likely to be represented in the not-at-fault database due to better crash avoidance technology.

CONCLUSION

Carshare systems are seen as the future of a sustainable city. To promote cost effective carshare systems requires reduction of costs associated to crashes and insurance. To achieve this goal, it is imperative to characterize carshare users involved in crashes and understand factors that can explain at-fault and not-at fault drivers.

This study utilized carshare data from GoGet members in Sydney, NSW, Australia. The study found that experience, which is represented by kilometres driven the previous year and number of years with driving license significantly reduced the likelihood of being at-fault. Surprisingly, kilometres driven in the previous year reduces propensity to crash and be at-fault for carshare users. This suggests a different direction of relationship between kilometres driven and crash propensity from previous studies (Yan et al., 2005; Chandraratna S. and N. Stamatiadis, 2009) that find a positive relationship which is exploited and used as exposure. But the result from this study suggests that the use of kilometres driven as an exposure for carshare users would not be valid.

In addition, higher insurance excess in case of damage due to crash also reduces the propensity to be at-fault. This can be attributed to loss aversion of drivers. Reduced exposure to carshare vehicles due to owning a car and needing cars on weekends were also found to reduce likelihood of being at-fault in a crash. Increase in age was also found to marginally increase likelihood of crash and was attributed to possibly lower reflexes.

Loss aversion (excess1500), use of vehicles with better safety features (*car_class*), not having pervious instances of traffic offences and living near a dedicated parking reduced the likelihood of being in a crash and not-at-fault. Interestingly, marginal reduction in likelihood of being not-at-fault was also observed due to training and experience (*left_hand_drive*) and not having train as a main mode of travel.

Characterization of no-fault drivers also provides useful insights for quasi-induced exposure methods. As recognized earlier that though this study only uses carshare users, focussing on the driver demographics of not-at-fault drivers provides useful insights about quasi-induced exposure. This study finds that cars with better safety and crash avoidance systems are under-represented in not-at-fault drivers, this has also been found earlier by Evans (2004). The study also finds drivers with higher accident avoidance abilities due to being trained in left-hand driving as being marginally under-represented in not-at-fault drivers (also found by Kahane and Hertz, 1998). Finally, an interesting variable that has not been found earlier is that drivers having previous instances of traffic offenses are over-represented in not-at-fault drivers, suggesting that their inattentiveness or likelihood to commit traffic offenses also increases the propensity be in a crash but be not-at-fault. Therefore, it is critical to control for these variables when using quasi-induced exposure methods.

Based on this study it is possible to reduce crash propensity by having higher insurance excess for drivers highly prone to accidents, such as those with previous instances of offences and those who have no car. Additionally, providing some incentives with regard to reduction in excess based on training and experience (based on kilometres driven) could also improve safety and reduce costs associated to crashes for carshare systems.

ACKNOWLEDGEMENTS

The authors would like to thank Mr. Bruce Jeffreys and Ms. Rachel Moore from GoGet for providing data and enormous support in helping us understand it.

REFERENCES

Chandraratna S. and N. Stamatiadis (2009) “Quasi-induced exposure method: Evaluation of not-at-fault assumption.” *Accident Analysis and Prevention*, 41:308-313

Cummins, J.D., R. D. Phillips and M. A. Weiss (2001) “The Incentive Effects of No Fault Automobile Insurance” Journal of Law and Economics, Vol. 44, No. 2, pp. 427-464

De Lapparent, M., (2006) “Empirical Bayesian analysis of accident severity for motorcyclists in large French urban areas.” Accident Analysis and Prevention 38 (2), 260–268.

DeYoung, D.J., Peck, R.C., Helander, C.J., (1997) “Estimating the exposure and fatal crash rates of suspended/revoked and unlicensed drivers in California.” Accid. Anal. Prev. 29, 17–23.

Evans, L., (2004). “Traffic Safety.” Science Serving Society, Bloomfield Hills, Michigan.

Haight, F.A. (1970). “A crude framework for bypassing exposure.” J. Saf. Res. 2, 26–29.

Haque, M.M., Chin, H.C., Huang, H., (2009). “Modeling fault among motorcyclists involved in crashes.” Accident Analysis and Prevention 42 (2), 327–335.

Jiang X. And R. W. Lyles (2010) A review of the validity of the underlying assumptions of quasi-induced exposure, *Accident Analysis and Prevention*, 42: 1352-1358

Jiang X., Y. Qiu, R. W. Lyles. and H. Zhang (2012) “Issues with using police citations to assign responsibility in quasi induced exposure” Safety Science, Vol. 50, pg. 1133-1140

Kahane, C.J., Hertz, E. (1998). “The long-term effectiveness of center high mounted stop lamps in passenger cars and light trucks.” NHTSA Technical Report Number DOT HS 808 696.

Kirk, A., Stamatiadis, N., (2001) “Crash rates and traffic maneuvers of younger drivers.” Trans. Res. Rec. 1779, 68–74.

Lenguerrand, E., Martin, J.L., Moskal, A., Gadegbeku, B., Laumon, B., (2008). “Limits of the quasi-induced exposure method when compared with the standard case control design.” Accid. Anal. Prev. 40, 861–868.

Lighthizer, D.R., 1989. An Empirical Validation of Quasi-Induced Exposure. Ph.D. Dissertation, Department of Civil and Environmental Engineering, Michigan state University, E. Lansing, MI.

Mendez A. G. And F.A. Izquierdo (2010) Quasi-induced exposure: The choice of exposure metrics, *Accident Analysis and Prevention*, 42: 582-588

Mont O. (2004) “Institutionalisation of sustainable consumption patterns based on shared use” *Ecological Economics* 50, 135– 153

Navon, D.,(2003).” The paradox of driving speed: two adverse effects on highway accident rate.” Accident Analysis and Prevention 35, 361–367.

Pai C. and W. Saleh (2008) “Exploring Motocyclist Injury Severity in Approach-Turn Collisions at T-junctions: Focussing on the Effects of Driver’s Failure to Yield and Junction Control Measures” Accident Analysis and Prevention 40(2), 479–486.

Prettenthaler F. E. and K.W. Steininger (1999) “Analysis from ownership to service use lifestyle: the potential of car sharing” *Ecological Economics*, 28, pp. 443–453

Savolainen, P., Mannering, F., (2007). “Additional evidence on the effectiveness of motorcycle training and motorcyclists’ risk-taking behavior.” Transportation Research Record 2031(1), 52–58.

Schneider W. H., P. T. Savolainen, D. Van Boxel and R. Beverley (2012), Examination of factors determining fault in two-vehicle motorcycle crashes, Accident Analysis and Prevention, 45: 669-676

Shankar, V., Mannering, F., (1996). “An exploratory multinomial logit analysis of single-vehicle motorcycle accident severity.” Journal of Safety Research 27 (3), 183–194.

Steininger K., C. Vogl and R. Zettl, (1996) “Car-sharing organizations, The size of the market segment and revealed change in mobility behaviour” Transport Policy, 3(4), pp. 177-185

Thorpe, J.D., (1967) "Calculating relative involvement rates in accidents without determining exposure." Aust. Road Res. 2, 25–36.

Train, K., (2003). "Discrete Choice Methods with Simulation." first edition. Cambridge University Press, Cambridge.

Yan, X., Radwan, E., Abdel-Aty, M., (2005) "Characteristics of rear-end accidents at signalized intersection using multiple logistic regression model." Accid. Anal.Prev. 37, 983–995.

Zhang, H. (2010). "Identifying and Quantifying Factors Affecting Traffic Crash Severity in Louisiana", Ph.D. Dissertation and Louisiana state University. Accessed on: 27/04/2013 Available at: http://etd.lsu.edu/docs/available/etd-03262010-174331/unrestricted/HongZhang_Dissertation_Mar31.pdf