

**VEHICLE FOR
HIRE BYLAW
REVIEW**

Report 1: Analysis
of PTC Usage as
Recorded in the
2016 TTS

Gozde Ozonder and Eric J. Miller
April 2019

UTTRI TECHNICAL SUPPORT FOR THE CITY OF TORONTO VEHICLE FOR HIRE BYLAW REVIEW

Report No: 1

Analysis of PTC Usage as Recorded in the 2016 TTS

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April, 2019



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UTTRI

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1. INTRODUCTION

This technical report presents the work undertaken by the University of Toronto Transportation Research Institute (UTTRI) to analyze the usage of services provided by Private Transportation Companies (PTCs) as recorded in the 2016 Transportation Tomorrow Survey (TTS) in support of the City of Toronto's *Vehicle for Hire Bylaw Review*.

The 2016 TTS conducted in the fall (September-December) 2016 time period collected information on Uber trips as an explicit mode of travel (Ashby, 2018; Miller, et al., 2019). The trip records in the data have socioeconomic attributes of trip-makers (e.g., age, sex, income class, etc.), their household characteristics (household size, number of vehicles owned, etc.) and trip purposes attached (Data Management Group – Reports, n.d.). They, therefore, provide a statistically representative description of the users of the services provided by PTCs and their reasons for travel along with time and start/end locations of the trips. Despite the relatively modest market penetration of PTCs (only Uber at the time) in the City during the fall of 2016, TTS provides a considerably richer description of PTC travel and trip-makers than can be obtained from the PTC records alone, since PTC records do not have user-attributes or trip purposes attached (Miller, et al., 2019).

This report is one of the deliverables by the UTTRI team, where the main focus is on the demographics of the trip-makers and their household characteristics. PTC trip records from the same September-December 2016 time period are compared to the 2016 TTS PTC trip records to investigate both spatial and temporal usage of the services provide by PTCs in a complementary report (Project Report No. 2), hence, trips are not discussed in detail in this report.

The rest of the report is organized as follows. Section 2 reports the results of the analysis of descriptive statistics of PTC user attributes and their household characteristics, along with a concise overview on trips. Section 3 reviews three studies conducted using the 2016 TTS with a focus on PTC usage. Section 4 concludes the report with a summary of findings.

2. DESCRIPTIVE STATISTICS ANALYSIS

This study does not focus on Uber-users only, but it also includes the attribute distributions of different samples, where applicable, to allow for a more comprehensive understanding of PTC usage and comparison between different groups. The samples studied within the scope of this study are:

- (a) Complete 2016 TTS Population.
- (b) Trip-Making Population in the 2016 TTS.
- (c) Uber-Users in the 2016 TTS.
- (d) Taxi-Users in the 2016 TTS.

The trip-making population is a subset of the complete population where the individuals are 11 years of age or older and they have made at least one trip on the survey day¹. Taxi-users are explicitly studied in this investigation in addition to the first three samples, because taxi companies/drivers in the City have been raising concerns about the disruption of a level playing field with the penetration of PTCs, highlighting several issues such as their sharply reduced revenues, etc. (Powell, 2017; Moore, 2018). This study helps address these concerns by shedding light on usage patterns through detailed analysis where differences/similarities between the two user groups, i.e., Uber-users and taxi-users, are identified.

Table 1 shows the total number of individuals, households, and trips in each sample².

Table 1. Sample Totals

TTS 2016	Population	Trip-Making Population	Uber-Users	Taxi-Users
Households	162,708	143,893	1,123	1,889
Individuals	395,885	274,568	1,276	2,175
Trips	-	798,093	1,851	3,088

The number of individuals who made a taxi trip in the 2016 TTS is considerably more than the number of individuals who made an Uber trip, which might be due to the low market penetration rates of PTC services in the fall of 2016.

Note that the number of trips presented in Table 1 includes all trips, irrespective of whether at least one end of the trip, i.e., origin or destination, was within the City of Toronto.

2.1. Attributes of Individuals

In this subsection attributes of individuals from the four samples are presented and discussed.

Figure 1 shows the ratio of the respondents and non-respondents of the survey for the four samples. Usually, there is only one individual from each household who is designated as the respondent, as the survey is completed through a single person if it is a phone-survey. However, in the 2016 TTS, there are eight households, who completed the survey online, with two respondents. Taxi-users have the highest percentage of being the respondent of the survey, which might be signalling a higher probability of owning a landline phone³, which in turn might be an indicator of the age group of taxi-users.

¹ “Survey day” does not refer to the day the survey was conducted/completed, rather it refers to the travel day for which respondents have completed their questionnaires.

² The analyses are conducted using unweighted individual, household and trip numbers.

³ TTS calls are only made to landline phones, not to cell phones.

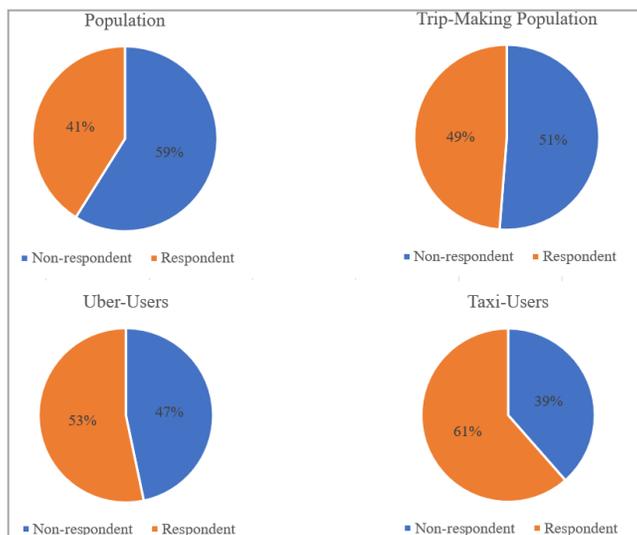


Figure 1. Respondent vs Non-Respondent

The age distributions for the four samples is shown in Figure 2. Uber-users’ age distribution peaks significantly roughly between the age range of 20 to 40, and after 40, the popularity of Uber seems to decrease, showing that Uber-user group consists of a comparatively young population in the Greater Toronto and Hamilton Area (GTHA). This might be related to Uber’s being an app-based service that can be accessed through smart-phones, which are more likely to be abundant among the young population. Further, individuals may form families, move to suburbs and own a car after 40, after having completed their education and having a stable job, which might reduce the dependency on PTC services. In addition, taxi-usage seems to be more popular among individuals older than 75. They may not prefer driving due to reduced visibility, etc., and prefer using a taxi instead, as they may not be as tech-savvy as the younger population.

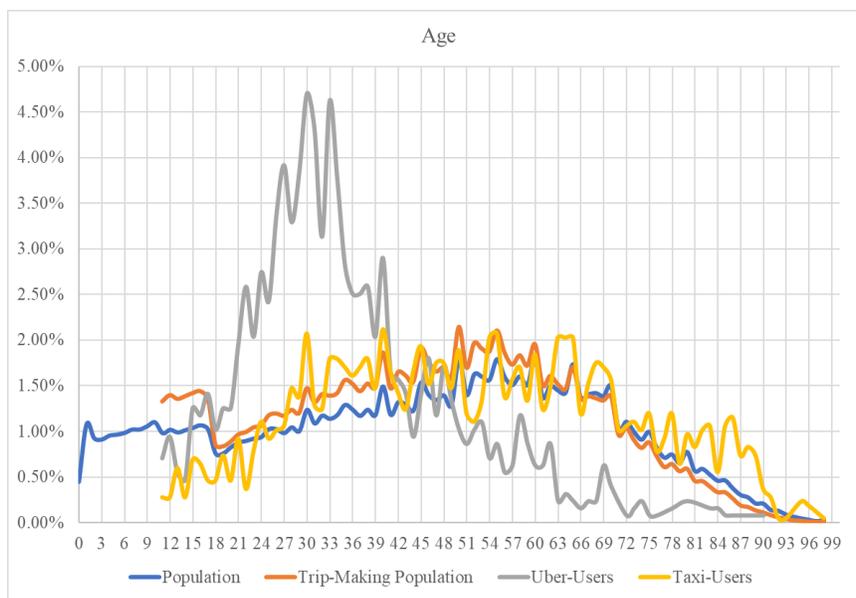


Figure 2. Age Distributions

Figure 3 shows the sex distributions for different samples, where the ratio of female to male is very similar, and close to 1. The biggest difference is observed in taxi-users, where females are relatively dominant.

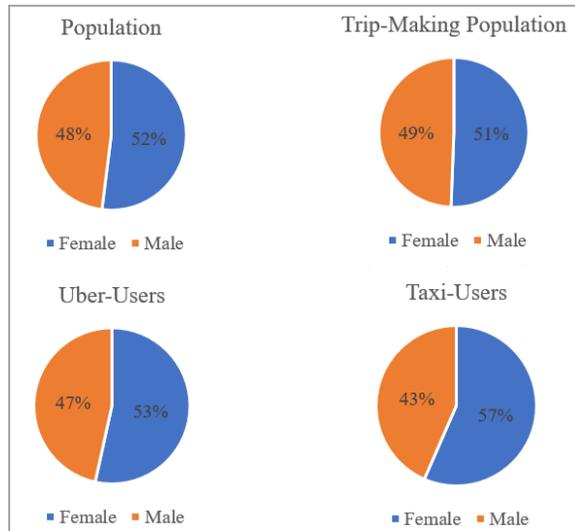


Figure 3. Sex Distributions

By comparing Figures 4 and 5, which show the age distributions of males and females respectively, it can be seen that the Uber usage patterns considering age is similar for both sexes. However, the tendency towards taxi usage is more common among females than males after the age of 75.

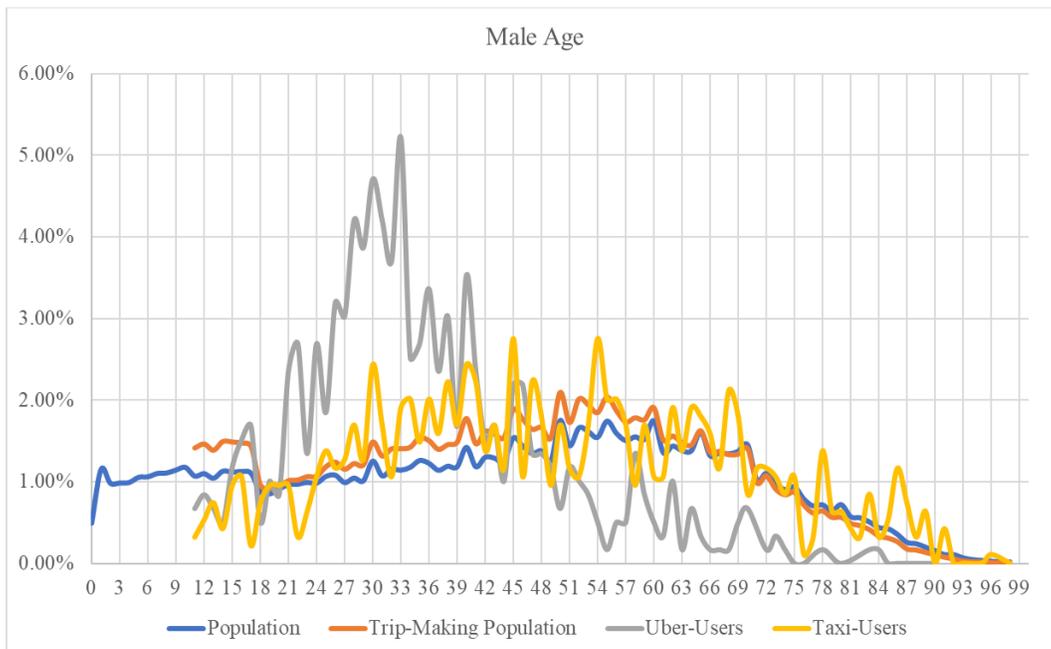


Figure 4. Age Distributions (Males)

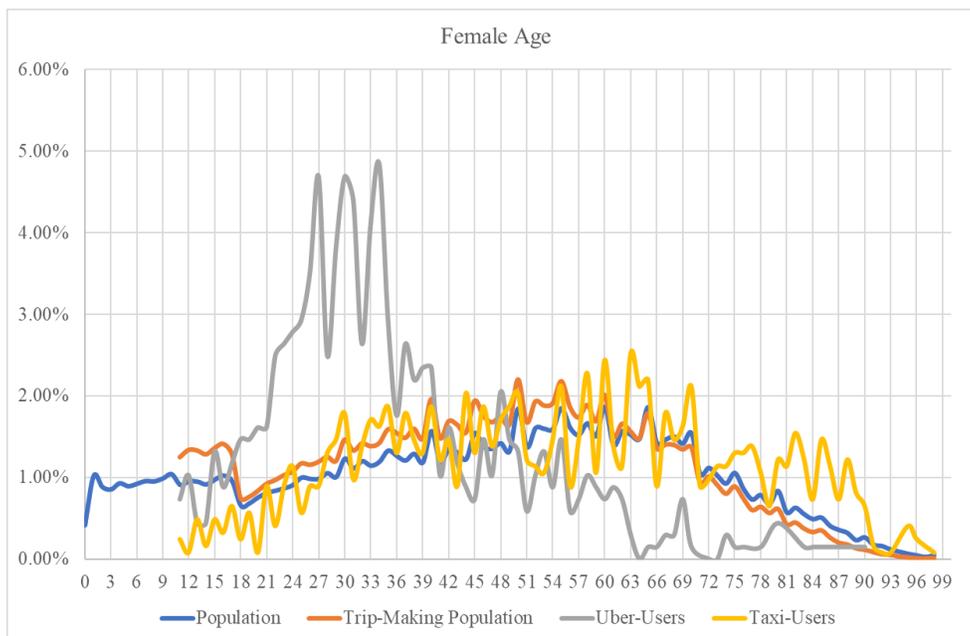


Figure 5. Age Distributions (Females)

Four employment categories are defined in the TTS (Ashby, 2018). These are full-time workers outside the home, part-time workers outside the home, full-time workers at home, part-time workers at home. Figure 6 shows the distributions of employment categories taking into account unemployed individuals. Working outside the home full-time is more common among Uber-users, particularly relative to the full-time worker population percentage. This observation also holds for part-time outside-home workers. The difference between Uber- and taxi-users is not very clear for individuals who work at home. Although, the percentage of Uber-users are more than that of taxi-users in both working-outside-the-home categories, the percentage of taxi-users are significantly higher than the percentage of Uber-users among unemployed people, which might be the case as the relatively older and/or retired population would be in the unemployed group.

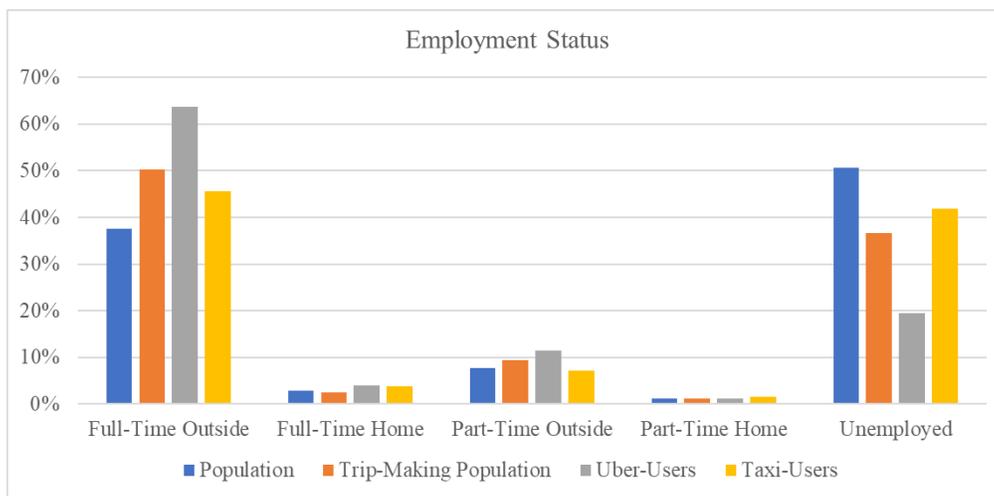


Figure 6. Employment Status Distributions

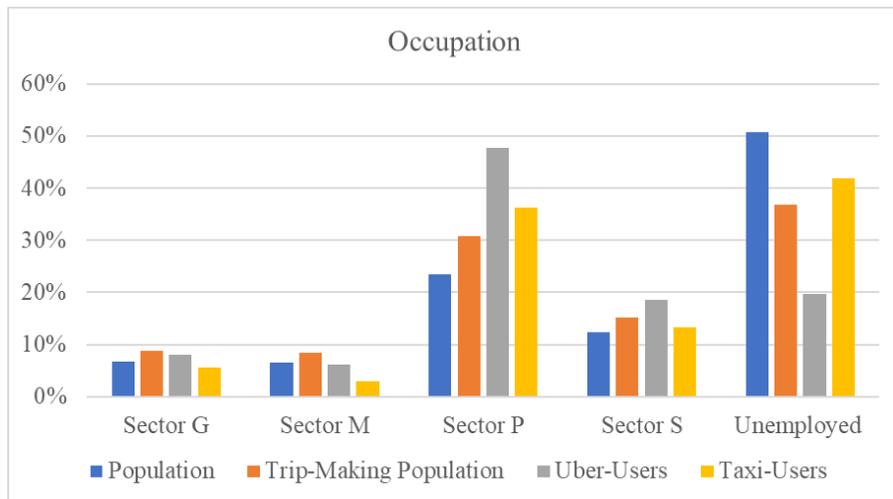


Figure 7. Occupation Distributions

There are four occupational categories defined in the TTS (Ashby, 2018): general office / clerical (sector “G”), manufacturing / construction / trades (sector “M”), professional / management / technical (sector “P”), retail sales and service (sector “S”). The occupational distributions of individuals are shown in Figure 7. Almost half of Uber-users are employed in sector “P”. Higher usage of Uber by sector “P” employees might be correlated with their income levels. In all four occupational sectors, percentage of Uber-users are higher than taxi-users’. Cross-classification of the four samples by employment status and occupation is presented in Figure 8 for further reference.

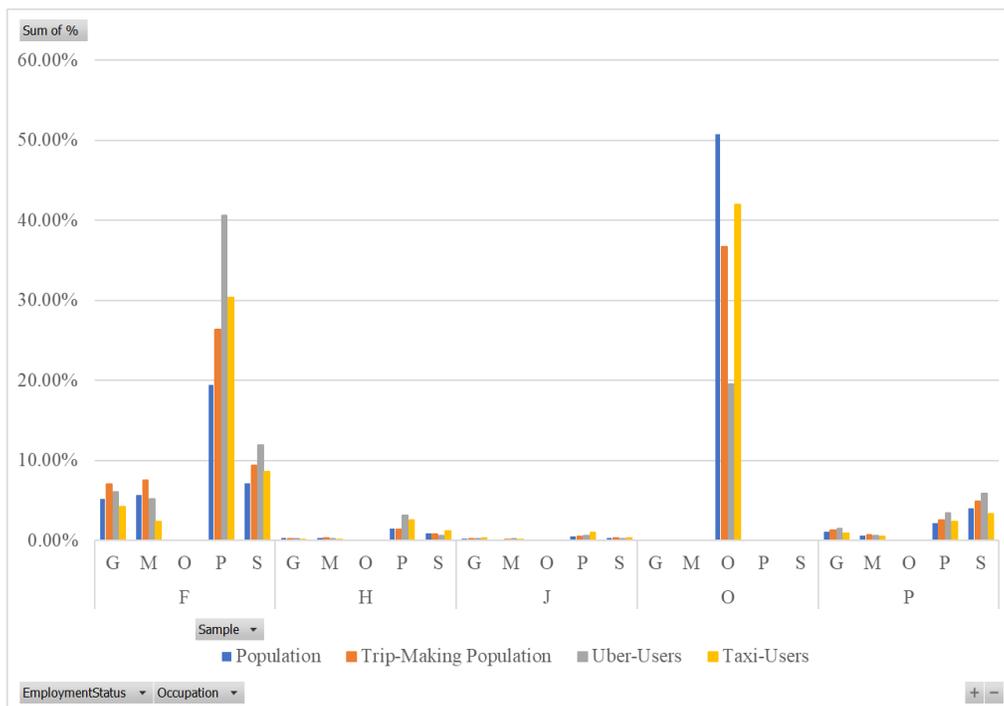


Figure 8. Cross-Classification of Samples by Employment Status and Occupation

Figure 9 shows that Uber- and taxi-users are not likely to be students, which might, again, be correlated with their income/allowance. Further disaggregation of samples of students show that if Uber or taxi service is used, it is most likely used by a post-secondary student, either full-time or part-time (refer to Figure 10). However, it can be seen that the portion of full-time post-secondary student Uber-users is more than that of taxi-users, whereas the opposite is true for part-time post-secondary students. A potential reason for this is that part-time students might also be employed, and hence, they might be more flexible in terms of transportation costs.

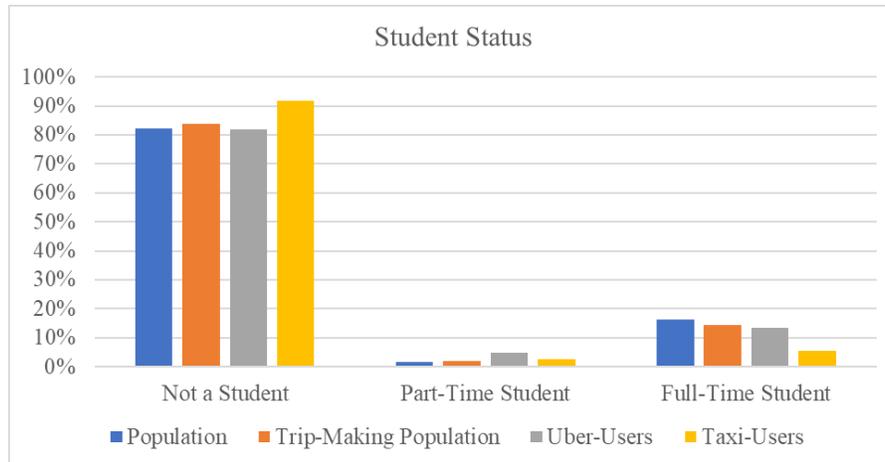


Figure 9. Student Status Distributions

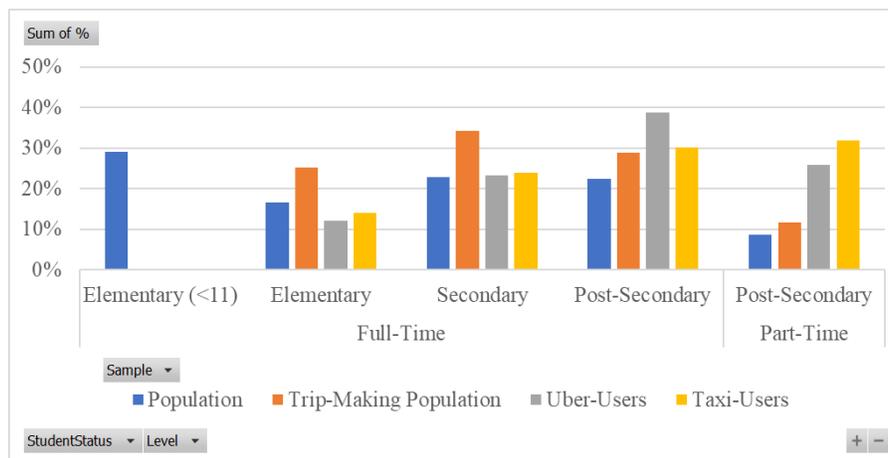


Figure 10. Students Status Distributions with Educational Levels

Figure 11 shows the distributions of driver’s license ownership across four samples. A larger portion of Uber-users have a driver’s license when compared to taxi-users. This can be attributed to the age groups of the users again. As a life skill, young individuals might get their licenses when they are eligible to take the tests and pass them, regardless of whether they own a car, but older people might not be renewing their licenses, even if they used to have one, as they have to take vision and road tests every two years after the age of 80 (Ontario, 2019). These deductions are parallel to the observations from the age distribution graphs, where a younger population chooses Uber and an older population chooses taxi.

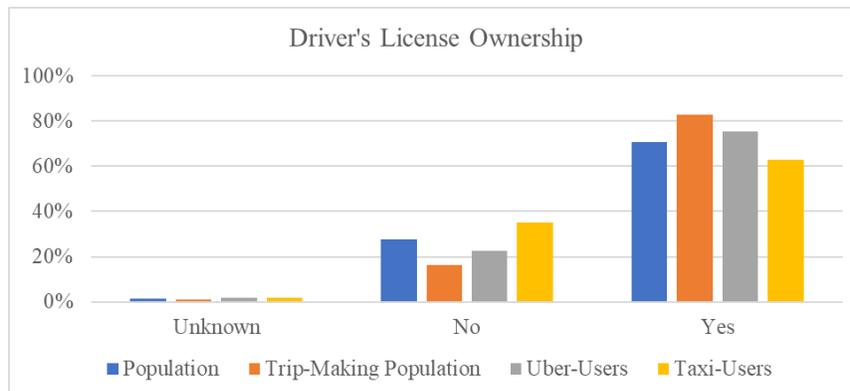


Figure 11. Driver’s License Ownership Distributions

Transit pass ownership distributions are presented in Figure 12. It can be deduced that individuals use PTC services complementary to transit service, as more than 50% of Uber-users own a transit pass. For example, they may be engaging in social activities outside the home, going to the activity location with transit but taking Uber back. This observation does not hold for taxi-users, which might hint at different purposes of use for taxi services.

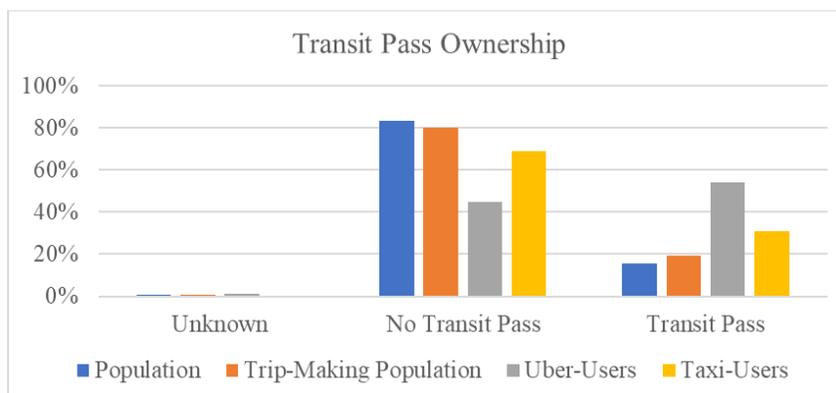


Figure 12. Transit Pass Ownership Distributions

2.2. Household Characteristics

In this subsection household characteristics of individuals from the four samples are presented and discussed.

Figure 13 shows the household size distributions for the samples. For single-person households Uber- and taxi-user percentages are much higher than the population and trip-making population percentages. This suggests that individuals who live on their own are more likely to use these modes of transportation, and the fact that there are more taxi-users than Uber-users might be because not having any dependents at home may enable individuals living on their own to be more flexible in terms of transportation budget, assuming taxi fares are usually higher than Uber fares. Also, older persons living on their own, might be the reason of the observed distribution. The highest percentage of both Uber-users and taxi-users have a household size of two. Whereas, for household sizes three and more the percentages of Uber- and taxi-users fall below survey population and trip-making population percentages. Couples with children might buy cars for convenience, and use PTC and taxi type services less, and this might explain the aforementioned trend.

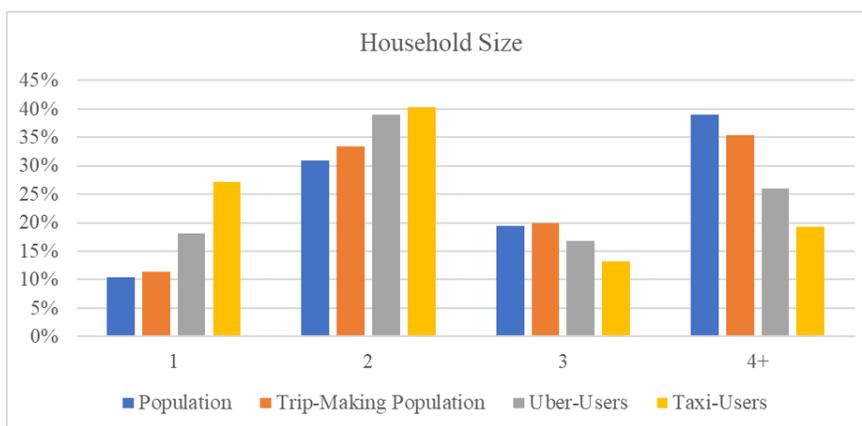


Figure 13. Household Size Distributions

In the 2016 TTS there were two methods available to complete the survey: landline phone and online. Survey method distributions across the four samples are shown in the pie charts in Figure 14. It can be seen that for the survey population, trip-making population and taxi-users 60%-70% of the surveys were completed online. The difference between online and phone surveys for Uber-users is striking. 93% of Uber-users have filled the survey online, confirming that the users of PTC services are more likely to be tech-savvy. It can also be seen that the lowest percentage of online surveys is in taxi-users group, and thus, the highest percentage of phone surveys, which strengthens the hypothesis that the likelihood of taxi-users being from an older generation, less technology-dependent individuals who own landline phones is higher.

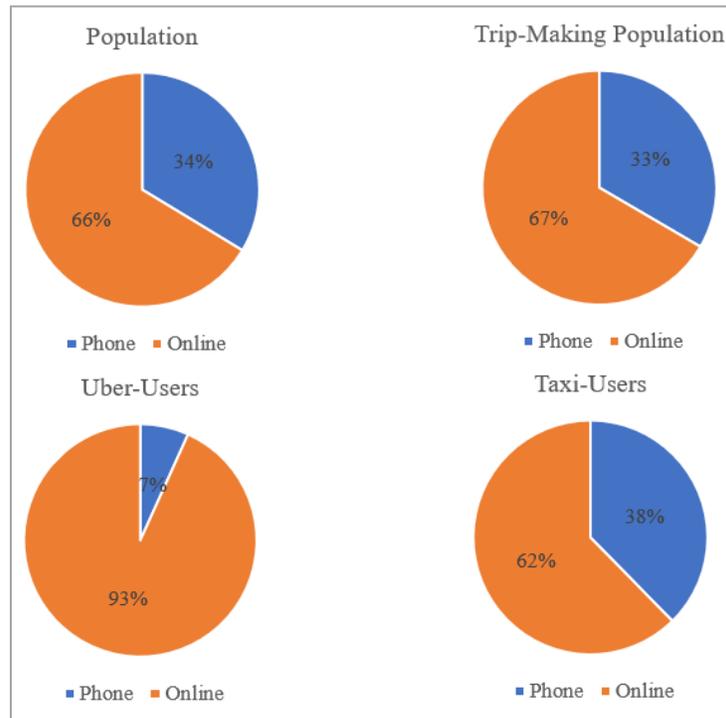


Figure 14. Survey Method Distributions

Figure 15 presents the survey day distributions. It can be seen that surveyed Uber-users were much more likely to report their trips for a Friday; only 10% of the surveyed Uber-users reported their trips for a Monday. Thursday has almost equal shares from each sample, around 25%.

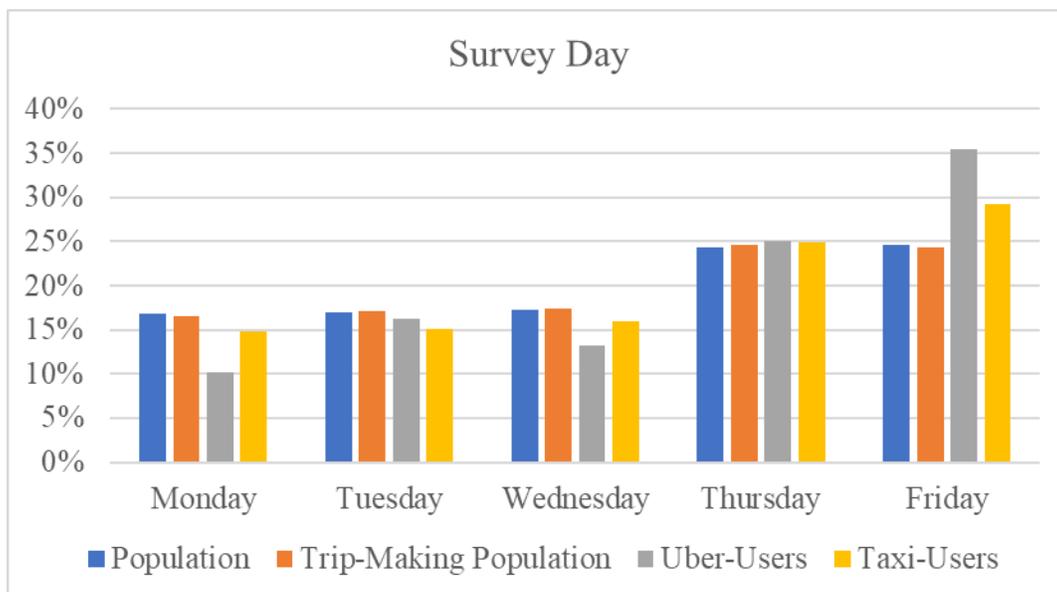


Figure 15. Survey Day Distributions

Distributions of the dwelling type for the four groups are shown in Figure 16. Almost 70% of the survey population and trip-making population live in houses, whereas living in house and apartment percentages for Uber-users and taxi-users are roughly equal. The fact that the percentage of Uber- and taxi-users residing in apartments is much more when compared to the survey and trip-making populations can be correlated with them being mostly single- or two-person households, and thus, not needing living areas as big as larger families (three or more person households) need.

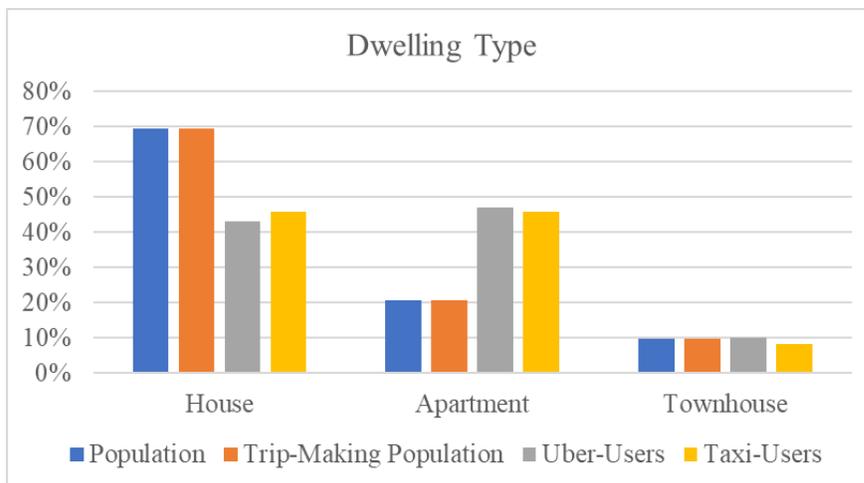


Figure 16. Dwelling Type Distributions

In the 2016 TTS, households’ total annual income class data were collected for the first time (Ashby, 2018). Figure 17 shows the income class distributions. Taxi-user percentage is higher than the remaining three samples for the first two lowest income groups. As a use case to support this trend, one can think about low income households who prefer going to relatively affordable grocery stores for weekly/monthly needs, that may not be within walking distance, and taking taxi back to avoid carrying the bags inconveniently. The highest percentage of Uber-users is, not surprisingly, in the highest income class. It can be seen that 15%-20% of all the samples have either declined to report or did not know their household income, except for Uber-users, for whom this rate is slightly less than 10%.

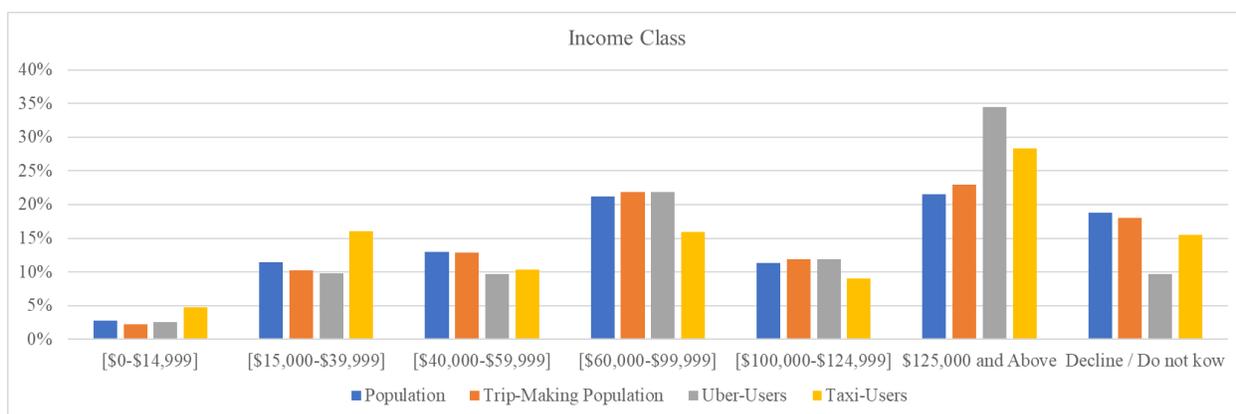


Figure 17. Income Class Distributions

Distributions of auto ownership levels are presented in Figure 18. The percentage of taxi-users declines with an increase in the number of vehicles owned by the household. The percentage of Uber-users is the highest for single vehicle households. If one thinks of a two-person household, for instance, it might be the case that one individual takes the car for the day, and the other one might need to use PTC services.

Conceptually, there is a big difference between owning a single car and two or more cars in a household, when you consider households with sizes of two or more. Owning a single vehicle potentially constrains individuals much more than the other cases. With two or more vehicles one might expect more redundancy and hence less dependency on PTC or taxi services.

It can be noted that the percentage of both Uber-users and taxi-users are very high when compared to the other two samples for the case in which the household does not own any vehicles, which makes sense, since these services are available anytime (day/night) and they do not require any capital, maintenance, insurance, etc. cost, and thus, might be preferred by the individuals who do not have any cars.

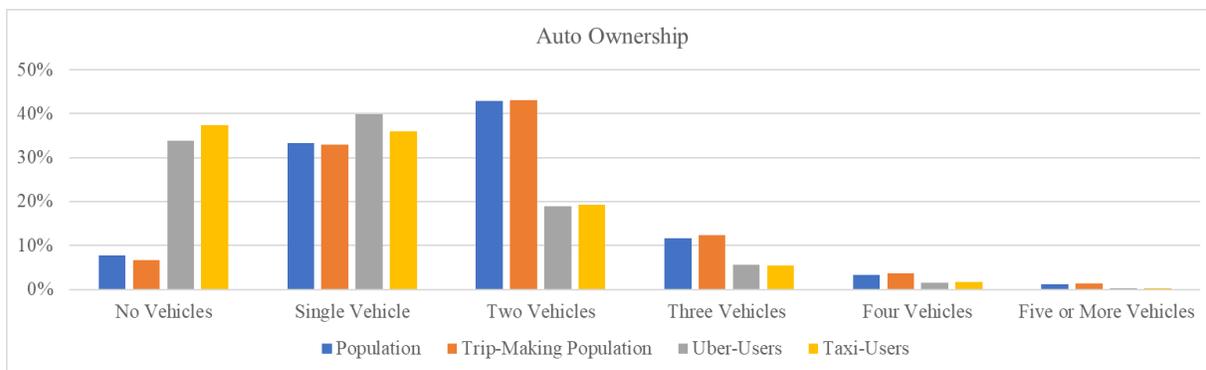


Figure 18. Distributions of Auto Ownership Levels

Table 2 quantifies a comparison of a household characteristic (number of vehicles owned) and an individual-level attribute (driver’s license ownership) through cross-classification. Although the highest percentage of individuals falls into the “license owner and two or more vehicle-owner household” category for the survey population and trip-making population, it is observed that for Uber- and taxi-users, the highest percentage of individuals are found in the “license owner and a single vehicle-owner household” category. This finding is similar to previously discussed aspects.

Table 2. Cross-Classification of Driver’s License Ownership and Vehicle Ownership

	Population			Trip-Making Population			Uber-Users			Taxi-Users		
	No Veh.	1 Veh.	2+ Veh.	No Veh.	1 Veh.	2+ Veh.	No Veh.	1 Veh.	2+ Veh.	No Veh.	1 Veh.	2+ Veh.
Unknown	0%	0%	1%	0%	0%	0%	1%	0%	1%	1%	0%	1%
No License	4%	9%	14%	3%	6%	7%	9%	8%	5%	21%	9%	5%
License	3%	24%	44%	3%	27%	53%	24%	31%	20%	15%	27%	21%

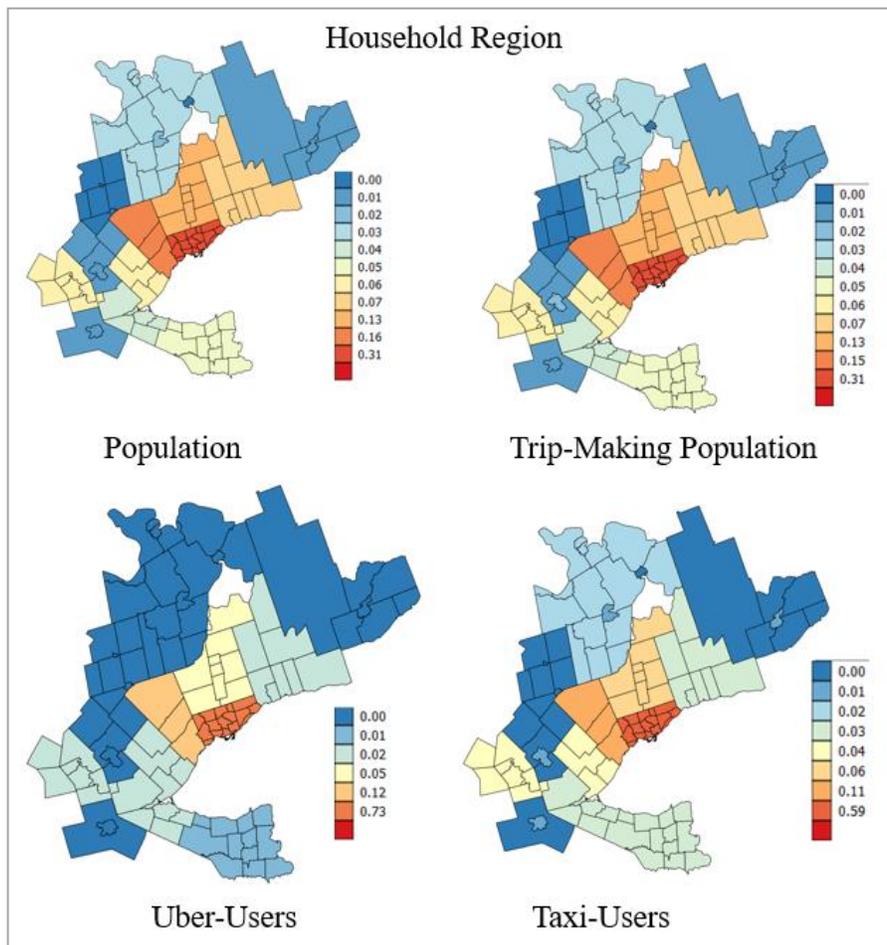


Figure 19. Maps of Household Regions

Residential regions of the households of the four samples are plotted in the maps shown in Figure 19. More than half of Uber- and taxi- users reside in the City of Toronto: 73% of Uber-users; 59% of taxi-users. The residential distribution of the survey population and trip-making population is quite similar to each other, with few regions that have very low values of residence (e.g., County of Dufferin) (See Figure 20 for detailed region names). However, this observation does not hold for Uber-users and taxi-users. There are more regions with very low residence values, e.g., City of Kawartha Lakes, County of Peterborough, County of Brant, County of Wellington, etc. A very large portion of Uber- and taxi-users’ households are either in the City of Toronto or the neighbouring regions (e.g., Region of Peel, Region of York, etc.). A higher percentage of taxi-users reside in the Region of Niagara when compared to Uber-users. Figure 21 is provided for a more direct and easier comparison of household regions of different samples.



Figure 20. Map of Regions in Survey Area - Source: (Ashby, 2018)

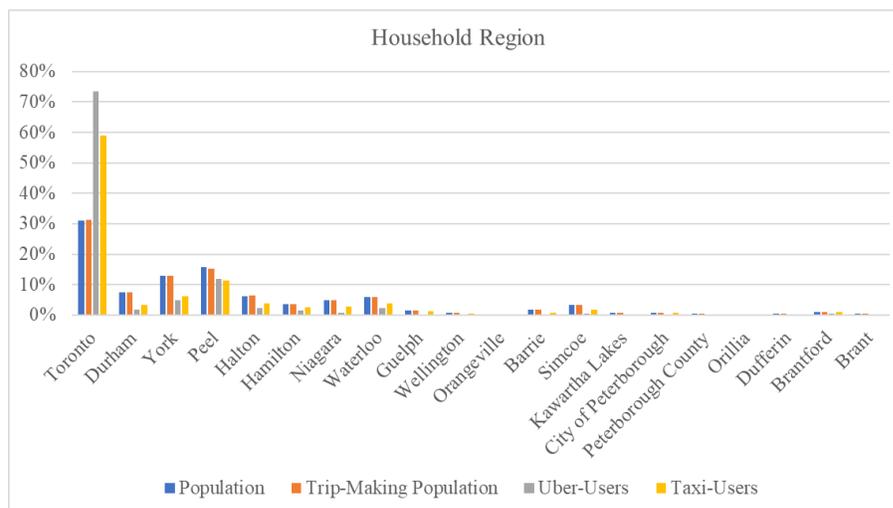


Figure 21. Distributions of Household Regions

Household residential planning districts within the City of Toronto are mapped for the four samples in Figure 22. Again, the survey population and trip-making population display a similar distribution. However, it can be seen that the percentages⁴ of Uber- and taxi-users are much higher (almost thrice) than the survey/trip-making populations’ in Planning District 1 (PD1), downtown Toronto.

⁴ These percentages are conditional on the household’s region being Toronto, i.e., percentages are calculated only considering Toronto residents. 10% for a certain PD means, 10% of the individuals with households in Toronto reside in PD1.

Some neighbouring PDs (e.g., PD2, PD4, PD6) (See Figure 23 for detailed PD labels) also have higher percentages of residence when compared to the survey/trip-making population for both Uber- and taxi-users. Figure 24 is provided for a more direct and easier comparison of household planning districts of different samples.

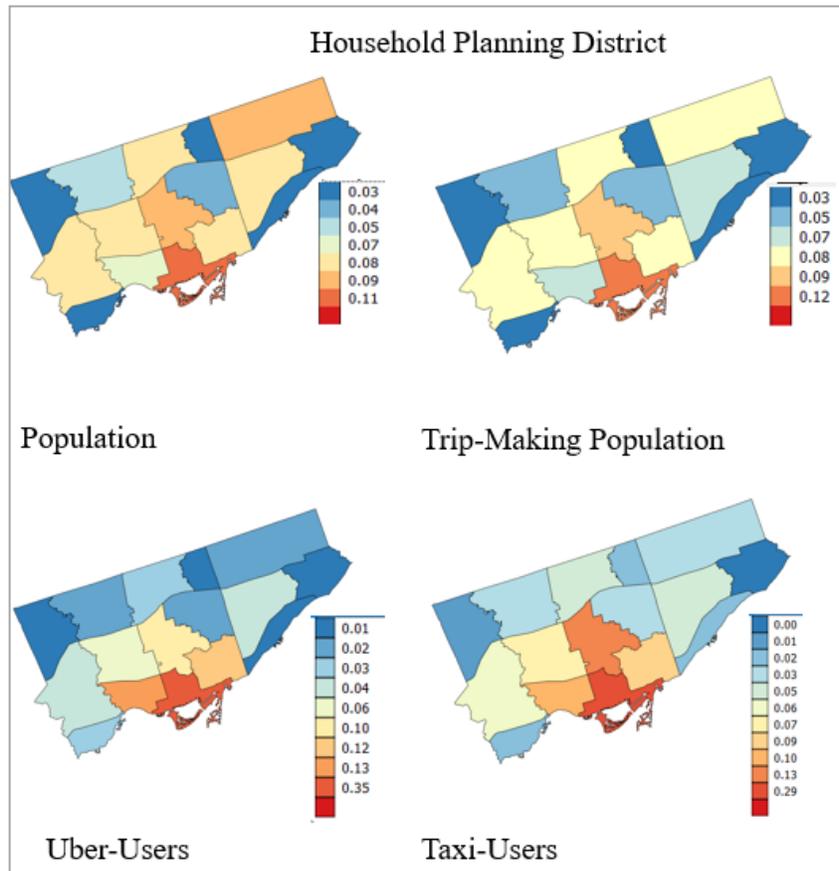


Figure 22. Maps of Household Planning District within the City of Toronto

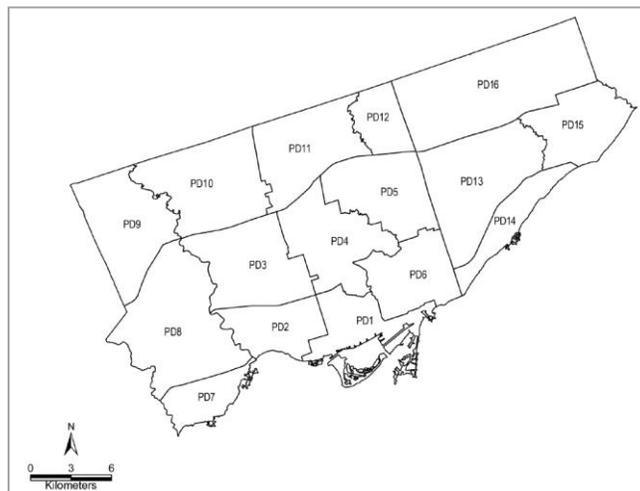


Figure 23. Map of Planning Districts in the City of Toronto - Source: (Ashby, 2018)

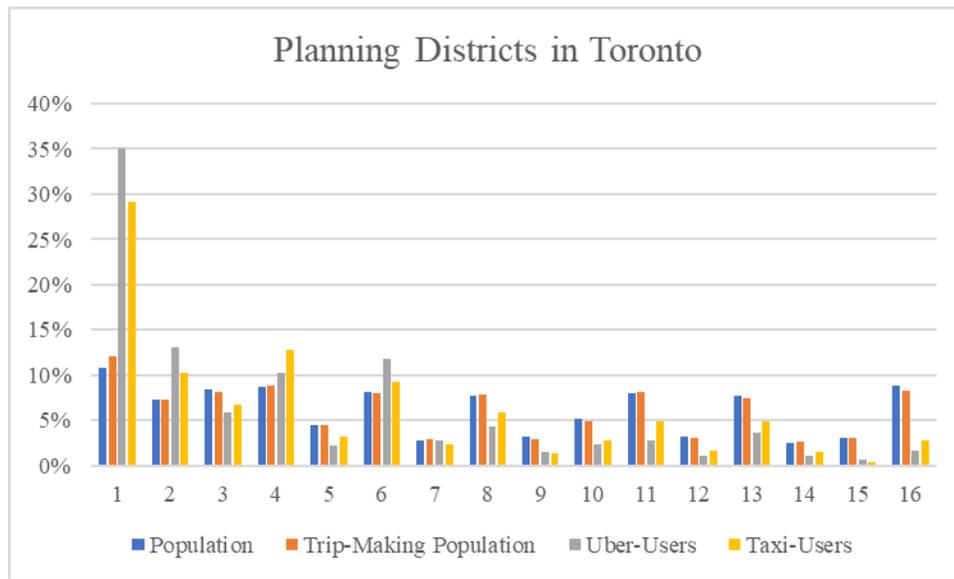


Figure 24. Distributions of Household Planning Districts

2.3. Trips

In this subsection trip attributes made by Uber- and taxi-users are discussed very briefly.

Figure 25 shows the trip frequency distributions by day. It can be observed that the trip percentage of Uber-users is the highest on Friday, slightly over 35%. This observation also holds for taxi-users, but their percentage is around 30%. The lowest trip frequency of Uber-users is on Monday. For taxi-users Monday, Tuesday and Wednesday have very similar percentages, where the percentage increases going from Monday to Friday.

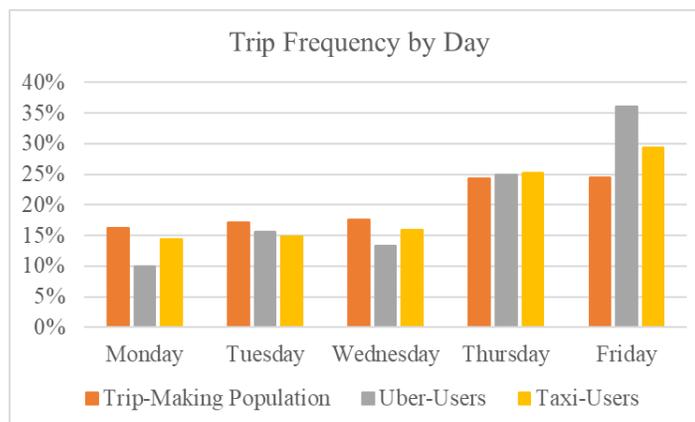


Figure 25. Trip Frequency Distributions by Day

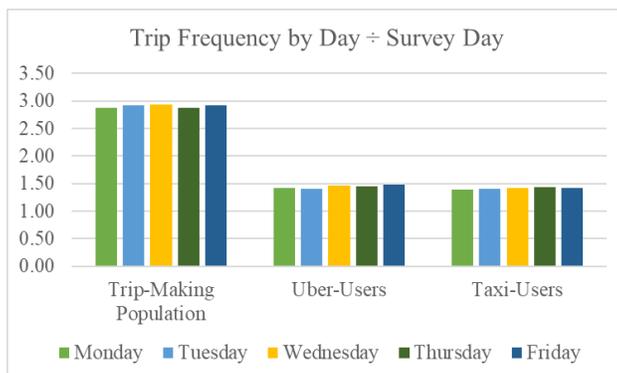


Figure 26. Trip Frequency by Day Divided by “Survey Day”

However, looking at trip frequency distributions only can be misleading. Figure 26 shows the trends of trips per survey day for three trip-making samples. Only analyzing Figure 25, one might think that Uber-users make most of their trips on Fridays, however, since they have also completed the survey more often for Fridays, the number of trips per day gives a better understanding of the behaviour, which shows that the five days are not significantly different. This holds for taxi-users as well.

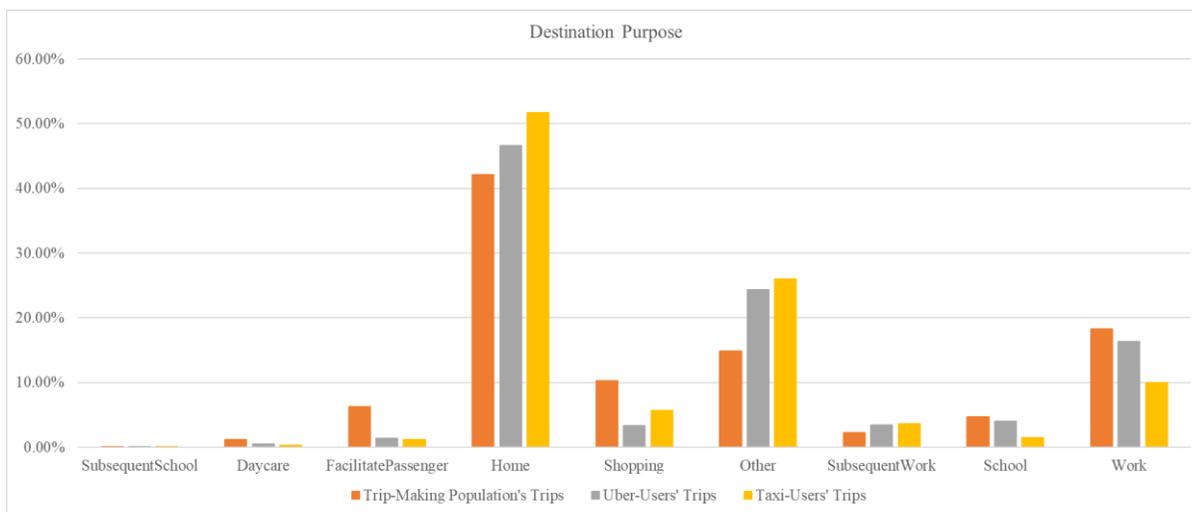


Figure 27. Distributions of Destination Purpose

Distributions of the activity purposes at the destination of trips are shown in Figure 27. A majority of Uber and taxi trips were made to home (more than half for taxi trips, more than 45% for Uber trips). This is not surprising, especially when you consider home-based tours, one leg of the tour will always be return home, despite various activities that might be engaged in in the other legs of the tour. Uber and taxi services were also used considerably for “other” purposes, i.e., for anything other than work, school, daycare or facilitating a passenger, which would involve, for instance, going to/getting back from restaurants, bars, museums, concerts, etc., i.e., social events, entertainment. Figure 28 is provided for more direct comparison of destination purposes between Uber and taxi trips. For shopping purposes taxi trips have a higher percentage, although the value is around 6%, which is rather small.

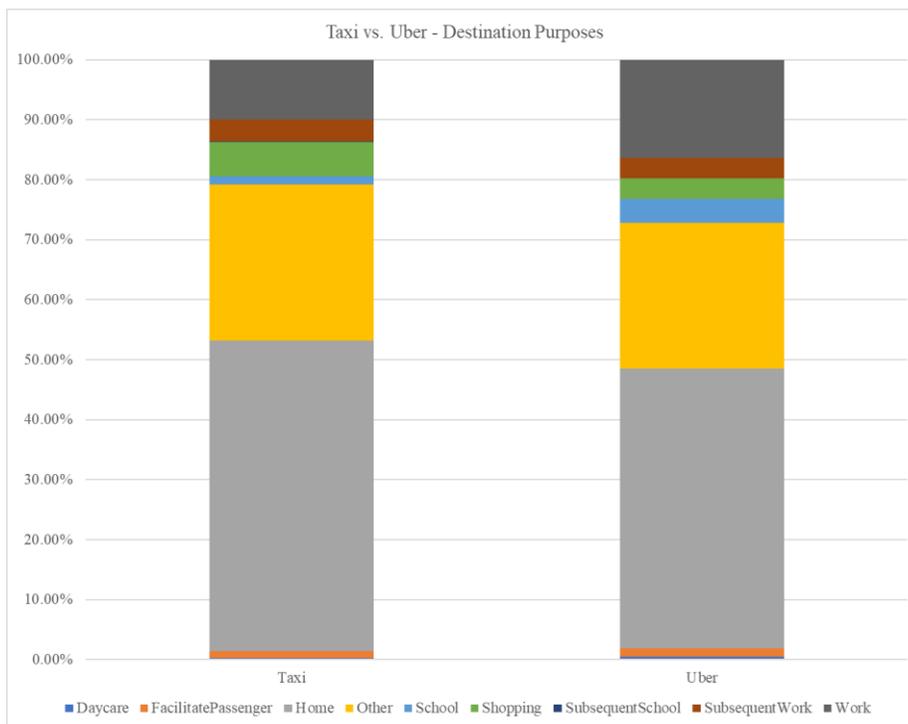


Figure 28. Comparison of Uber and Taxi Trips considering Destination Purpose

It can also be observed that more than 15% of Uber-users’ trips were made for work purposes, which is not negligible. Figure 29 presents more disaggregate distributions of work-related trips. 70% of the work-related Uber trips were made to the usual workplace of the employees as the first work trip of the day. Hence, this shows that Uber is mainly used for commuting purposes, rather than for going to a business meeting within the day. Taxi usage is similarly high for first work-related trip of the day to individuals’ usual workplace.

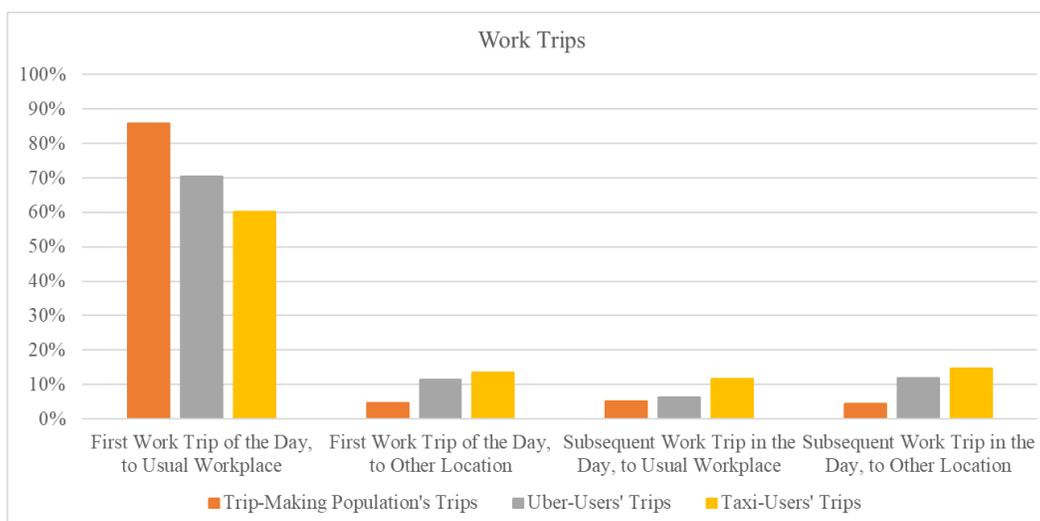


Figure 29. Work-Related Trips

A combination of two individual attributes, driver’s license ownership and availability of free parking at the usual workplace, and a household attribute, vehicle ownership, is considered in Figure 30, which shows the percentages of the day’s first work-related trips that were made to the employees’ usual workplace in each scenario. Figure 30 shows that Uber is used the most, above 30%, despite the availability of a driver’s license, a free parking spot at usual workplace and at least one vehicle owned by the household. On the other hand, taxi service is used the most, 19%, when the individual does not own a driver’s license, although his/her household owns at least one vehicle and s/he has a free parking spot at the usual workplace.

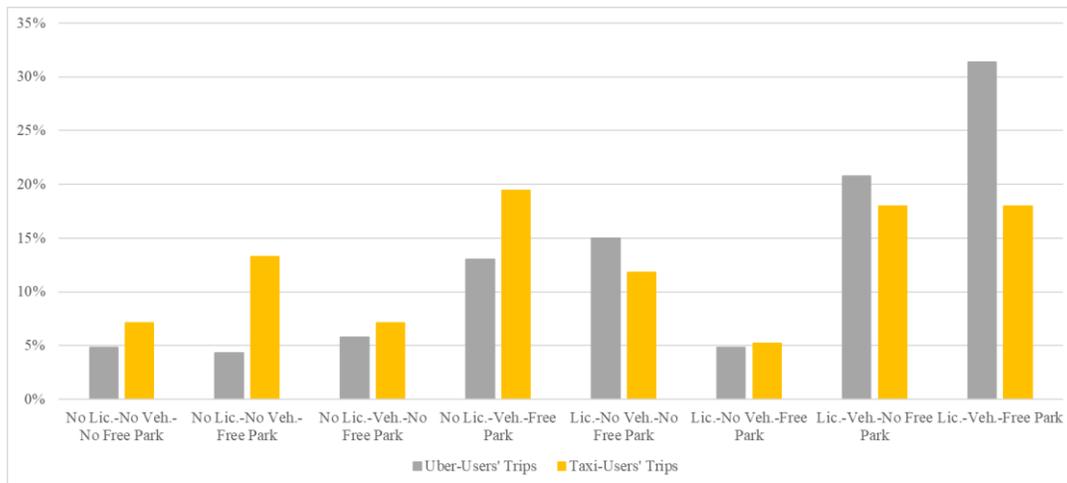


Figure 30. First Work-Related Trip of the Day to Usual Workplace

When the second/subsequent work-related trips of the day to one’s usual workplace are examined (see Figure 31), it is seen that both Uber and taxi services are preferred the most, around 45%, when the individual owns a driver’s license, his/her household owns at least one vehicle, but s/he does not have free access to a parking spot at the usual workplace. These results clearly underline the perceived importance of free parking at a workplace.

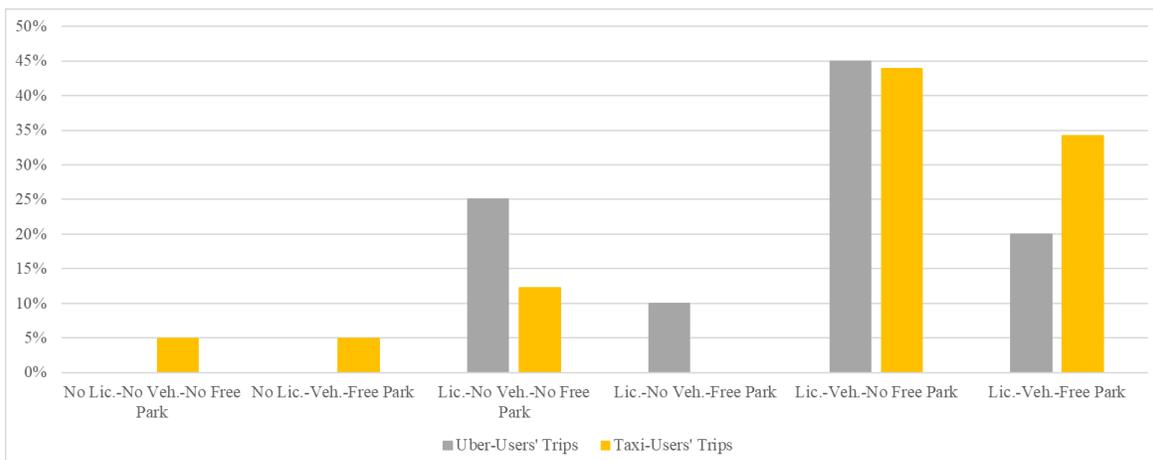


Figure 31. Second/Subsequent Work-Related Trips of the Day to Usual Workplace

Figure 32 shows the mode shares considering all the trips reported in the 2016 TTS. It can be seen that auto drive category, which includes motorcycling, is very dominant, 66%. Shares of Uber and Taxi trips are as low as 0.23% and 0.39% respectively.

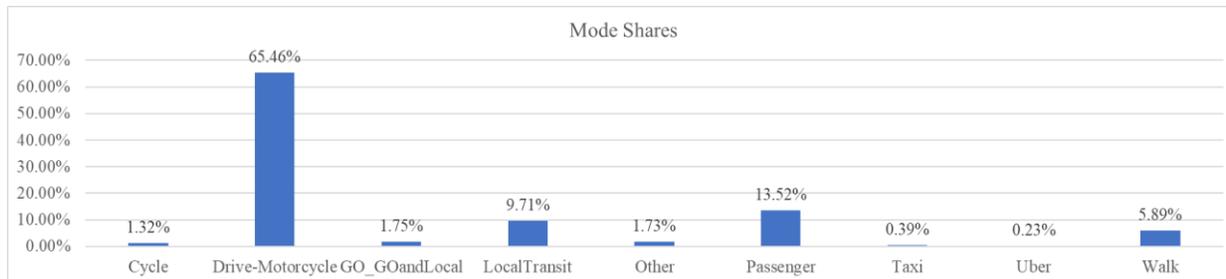


Figure 32. Mode Shares

Figure 33 shows mode shares by income classes. Auto drive and motorcycle mode is dominantly used by members of relatively higher income households. Due to the small mode shares of taxi and Uber, Figure 34 is prepared to facilitate the comparison between the two modes, which shows that Uber is preferred more by individuals from the three highest income classes, whereas the opposite is true for taxi-users. The orange line is below the blue line until the middle income class (\$40,000-\$59,999), then it surpasses the blue line, i.e., the percentage of taxi trips are higher until the middle income class, after that point the percentage of Uber trips become higher. This is similar to the trends observed in Figure 17.

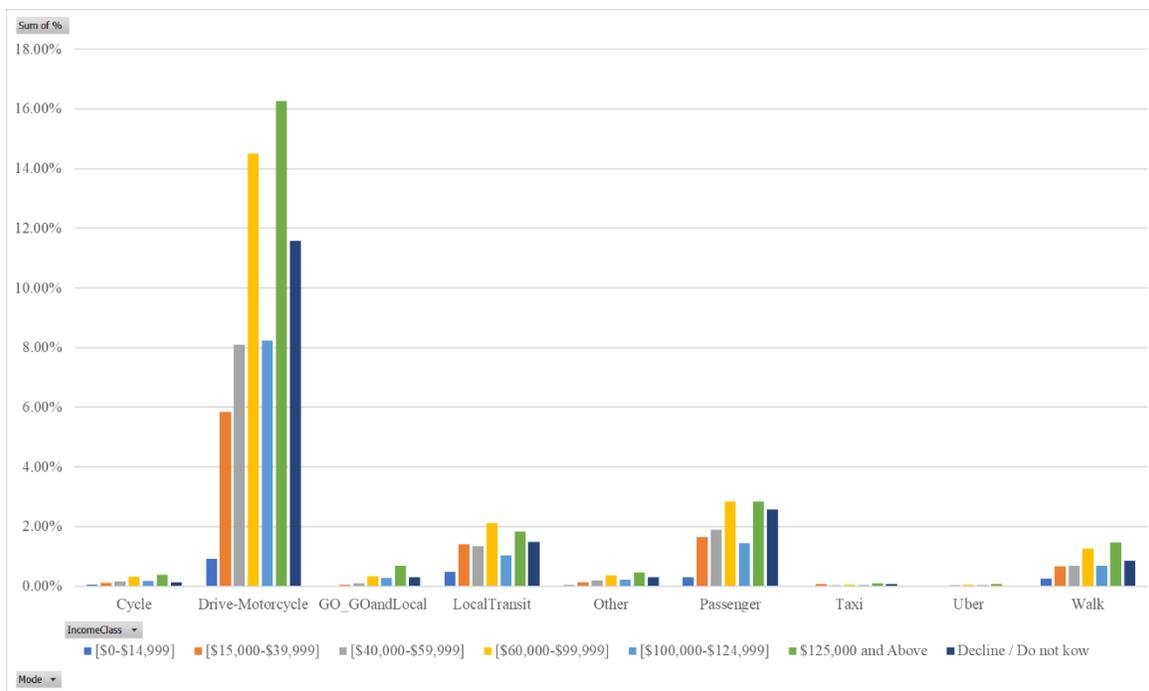


Figure 33. Mode Shares by Income Class

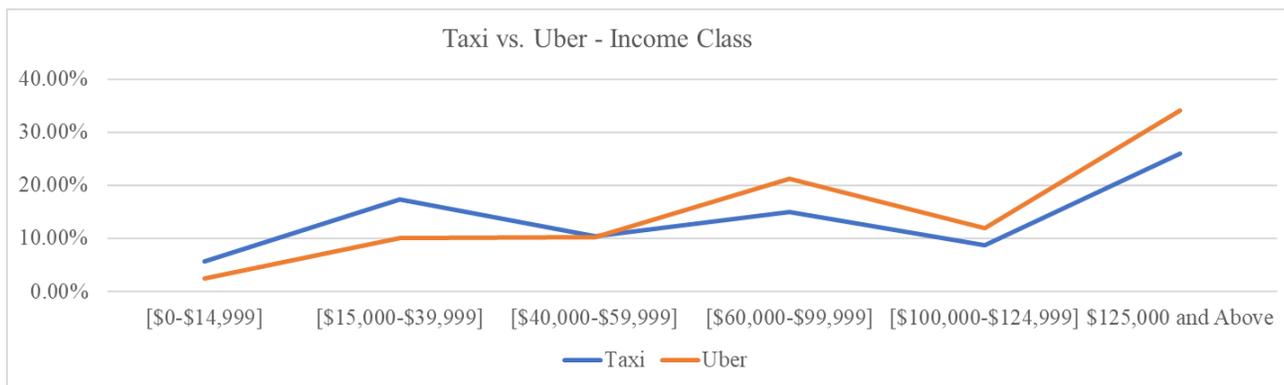


Figure 34. Taxi vs. Uber Trip Percentages by Income Class

Spatiotemporal patterns associated with Uber trips is discussed in Report No. 2, which includes a comparison between PTC data provided by the City and the 2016 TTS Uber trips, and thus, these patterns are not discussed here.

3. OTHER STUDIES

Three important studies conducted by the UTTRI researchers which focus on investigating different aspects of PTC usage as recorded in the 2016 TTS are summarized in this section. The study by Young and Farber (2019) focusses on answering three questions related to Uber usage in Toronto: the “who”, “why” and “when” (See Section 3.1). Calderon and Miller (2019) mainly analyze spatiotemporal patterns of Uber trips (See Section 3.2), whereas Habib (2019) reports the results of a new choice model structure which includes Uber as an explicit mode (See Section 3.3).

3.1. The Who, Why, and When of Uber and Other Ridesourcing Trips: An Examination of a Large Sample Household Travel Survey (Young and Farber, 2019)

Young and Farber (2019) compare socioeconomic attributes of Uber-users and their trip characteristics to that of users of other modes using weighted records from the 2016 TTS with the objective of better understanding the effect of the PTC services on urban transportation systems and cities. They only include individuals living within the six central PDs of the City, PD1-6, in their analysis. Nonetheless, this represents over 50% of all Uber trips.

In reference to the title of the paper, the answer to the “who” question is individuals younger than average, most often aged between 20 and 39 years old, belonging to the Millennials generation, as also discussed earlier in this report. The researchers note that this is probably because of the prevailing digital divide between younger and older generations. They also find that Uber-users are also likely to be employed full-time and to be wealthy, earning over \$125,000 annually. Uber-users also tend to own a transit pass but not a car, however, the authors note that this might also be correlated with their study area, vehicle ownership is relatively low among the residents of PD1-6. These findings are very similar to the observations reported in this document (See Section 2).

In response to the “when” question, Young and Farber (2019) indicate that Uber usage is more common in the evenings (7-11pm) and nights (11pm-5am), when the public transit ridership appears to be at its lowest. Thus, the authors indicate that this finding can either be used to support the claim that Uber is taking riders away from public transit or provide evidence that PTC service is complementary to public transit service, as the former is used the most when the latter is at its lowest.

In response to the “why” question, while the primary reason for using each mode of travel is returning home, it is shown that “other” purpose category is the second most popular reason for choosing Uber, as reported in Section 2.3 of this document. “Other” purposes combined with relatively young age group of travellers, travelling between 11pm-5am might be an indicator that these trips are likely to be associated with entertainment related activities.

The authors also investigate whether Uber usage impacted shares of other modes. Hence, they examine mode shares from several years, including the 2001, 2006, 2011 TTS data to their analysis of the 2016 TTS data. However, they note that it is not possible to draw strong conclusions due to the minuteness of Uber data available, which is additionally possibly under-reported. Nevertheless, they underline that with the introduction of Uber mode, taxi ridership has fallen, and active mode shares have risen in specific market segments.

The researchers also point out that they believe, based on the characteristics of users and their trip purposes (e.g., dominance of “other” purposes), Uber usage might effectively reduce drunk-driving, and that in the future, services provided by PTCs will have a much more pronounced effect on the level of ridership of other modes.

The analysis carried out by Young and Farber (2019) provides important insights for design of policies for our cities, which are needed to accommodate foreseeable changes imposed by the services provided by the PTCs.

3.2. A New Outlook on Ridehailing: Spatiotemporal Patterns and Commuting Analysis from the Greater Toronto and Hamilton Area (Calderon and Miller, 2019)

In their paper on the spatiotemporal patterns and commuting analysis related to Uber usage in the GTHA, Calderon and Miller (2019) conduct an explanatory analysis of the Uber trips recorded in the 2016 TTS data which serves as a first step towards incorporating services provided by the PTCs into an activity-based travel modelling system. They investigate vehicle occupancy, trip rates, and temporal and spatial patterns associated with Uber trips in the GTHA, along with providing useful considerations for future models to be developed.

In their analysis, they first convert the person-trips into vehicle trips accounting for multiple individuals sharing a vehicle from the same household. The researchers assess vehicle-sharing based on an examination of locations of trip origins and start times, and they find an average occupancy of 1.07 passengers per vehicle. In their study, mainly unweighted records of trips are used.

When they investigate the distribution of Uber trip start times by different time intervals (e.g., 1 hour, 30 minutes, 15 minutes, 5 minutes), they mainly observe a bimodal temporal distribution (with morning and afternoon peaks), though with an extended afternoon peak which leads to a third peak at night. Regardless of the afternoon and night peaks, it is concluded that the considerably large peak observed in the morning supports the argument that Uber is used as a commuting mode. This finding is parallel to the observations in Section 2.3 of this report.

The authors underline the importance of temporal granularity of the demand for PTC services, since it is a fundamental consideration when determining how models should deal with “time” dimension. They also indicate that the PTCs’ operational decisions depend heavily on how trip requests naturally aggregate in time, in particular for demand-supply matching processes, since efficient fleet management requires having a “sufficiently large” number of trips to be served.

In the study, it is deduced that roundtrip patterns are generated in the suburbs, i.e., more balanced trips are observed in the suburbs when origins and destination distribution of Uber trips is considered. Through rigorous analysis, it is also found that TTS provides a representative spatial coverage of Uber trips in the GTHA.

Calderon and Miller (2019) conclude that a considerable portion of Uber usage is for commuting purposes. They note that the demand for PTC services is higher in the Central Business District, but also highlight that the demand is widely spread throughout the GTHA at the same time. These findings reinforce the need to include PTC services as an explicit mode in travel demand forecasting models.

3.3. Mode Choice Modelling for Hailable Rides: An Investigation of the Competition of Uber with Other Modes by Using an Integrated Non-Compensatory Choice Model with Probabilistic Choice Set Formation (Habib, 2019)

Habib (2019) formulates a new theoretical approach to assess the competition of Uber with other modes in the GTHA in his paper. In his model, Uber is explicitly considered as an alternative mode, with the objective of capturing the motivation behind the choice of Uber for a trip. The author considers taxi as Uber’s closest competitor, noting that the PTC services might be emerging as an alternative to “regulation-trapped taxi services” in many big cities, including the City of Toronto, in addition to underlining that PTC services has faced opposition from the taxi companies in the City (Peticca-Harris, et al., 2018, as cited in Habib 2019).

Habib (2019) identifies trips that could have been made by an Uber or a Taxi, by looking at the origin-destination pairs of Uber and taxi trips present in the 2016 TTS data, but made with other conventional modes, and names them as “hailable rides”. He combines Uber and taxi trips with these trips and obtains his data set to be used in the analysis. He cleanses the data before estimating models to filter out incomplete observations.

As discussed in this report, and in Young and Farber (2019), Habib (2019) notes that Uber trips are used largely for social, recreational, personal maintenance and other discretionary activities (i.e., “other” purposes in the TTS), and also for returning home from these activities. The author suggests that Uber might be complementing auto drive and passenger modes in the return home trips. He deduces that Uber is, perhaps, not used as a regular mode for activities such as work, which contradicts the observations in this report and Calderon and Miller (2019). However, this might be due to conducting different analysis using different sub-samples of Uber trips. Habib underlines that the majority of Uber trips are made in the evening time, as noted in Young and Farber (2019). Further, based on the trip purpose and time-of-day distributions of Uber trips in the 2016 TTS data, he believes that Uber service tends to fill the gap in transit service, again, as suggested by Young and Farber (2019), and by this report.

The author develops a new approach to understand mode choice behaviour because he believes comparing all alternatives in a choice set against each other (i.e., fully compensatory choice), as done in classical discrete choice models, is not suitable for the current modelling exercise. Thus, he proposes a new random utility-based maximization structure which jointly models probabilistic choice set formation and conditional semi-compensatory choice, to evaluate to what extent travellers compare all alternatives that are feasible when choosing a mode for hailable trips in the region. Detailed model formulations are not discussed in this report; the interested reader is referred to the original paper.

His proposed model performs better than a couple of other specifications tested, and it is reported that his model has a very good fit. The model results show no clear competition between Uber and the private car, public transit, or non-motorized modes. Rather, it seems to fill the gap when the transit service is relatively poor. The model reveals that taxi is more likely to be Uber’s main competitor, but Habib (2019) indicates that there are notable differences in socio-demographic profiles of users of taxi and Uber. As previously discussed in this report, and also reported by Young and Farber (2019), he notes that taxi is preferred by older people, whereas Uber is preferred by younger people. Additionally, he underlines that there is no gender difference in such a pattern.

The model results also indicate that Uber-users are the least sensitive to travel time when the users of all other modes are considered. Taxi- and Uber-users both seem to be sensitive, taxi-users more than Uber-users, to cost per unit distance (kilometre) of travel rather than the total cost of the trip. Total cost, on the other hand, is found to have a significant impact on the choice of auto drive, passenger and transit modes. For the active modes, walk and cycle, total travel distance is found influence the choice significantly. It is also useful to note that, the study revealed that parking cost at the destination is the strongest deterrent to the choice of auto drive mode.

When the choice set consideration aspect of his proposed model is considered, Habib (2019) highlights that car passenger mode has the highest impact of the choice set considerations on choosing it as a mode, meaning if an individual finds car passenger as a definitely feasible mode, then there is a very high chance (80%) that s/he will choose that mode, without comparing it to any other mode. On the other hand, he notes that taxi is potentially feasible for everyone in any context, and hence, its impact of choice set consideration in the choice of taxi for a trip is low. But since Uber is a relatively new option and it requires a smart-phone to book a trip, and an electronic

payment system, there might still be some barriers in having Uber as a “feasible-for-all” mode in all contexts. Nevertheless, the empirical model reveals that if Uber is considered as an alternative, then this highly influences choosing it while comparing it with alternative modes.

Habib (2019) emphasizes that this study serves as a preliminary investigation. He notes several important questions that should be addressed in the future to improve transportation system performances and sustainability in transportation. These questions are: how PTC services affect mobility tool ownership; how they influence short-term trip destination choice and long-term home/work location choices?

4. CONCLUSIONS

This report contributes to understanding the characteristics of users of PTC services, Uber in particular, and associated trip attributes through analyzing the 2016 TTS data and reviewing three important studies conducted using the same data set, in addition to comparing Uber usage to taxi usage to be able to address raised concerns in the City.

Even though, both taxi and Uber can be considered as close replacements for an owned vehicle, in terms of convenience, comfort, travel time, etc., through rigorous analyses it has been shown that their user groups display distinct characteristics. Uber-users tend to be younger when compared to taxi-users. In addition, they are members of relatively high-income households, unlike taxi-users. The online survey ratio, age category, etc. all hint towards Uber-users’ being more enthusiastic in technology (e.g., using smart-phones, app-based services). It is seen that the percentage of Uber-users decreases as the number of vehicles in their household decreases, this observation also holds for taxi-users, although there are less Uber-users with no vehicles owned by their household compared to Uber-users with a single vehicle owned by their household. Highest percentage of both Uber- and taxi-users have a household size of two. Trends in taxi usage over time are examined in more detail in Project Report No. 3 by the UTTRI team.

A major portion of Uber-users recorded in the 2016 TTS, more than 70%, reside in the City of Toronto, i.e., within the GTHA, the City has the highest share of Uber-user residents. Among the ones residing in the City, 35% live in PD1, where PD2, PD4 and PD6 each embody around 10% of Uber-users. It is observed that Uber is mainly preferred for returning home, accessing activities with “other” purposes (social, recreational, etc.), and going to work. Taxi is also mainly used for these activities.

Both the analyses conducted in this report, and the studies reviewed suggest that Uber usage might in fact complement public transit service, rather than reducing its demand. This observation is based on multiple aspects: high transit-pass ownership of Uber-users, temporal patterns of Uber usage (when transit service is not available), etc. However, it is also important to note that, as indicated in Young and Farber (2019), potential transit-users might be switching to using Uber when the transit service is low. This issue is examined in detail in Project Report No. 4 by the UTTRI team, which specifically focusses on comparing public transit and Uber.

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It is crucial to note that the analyses in Section 2 of this report and the studies reviewed in Section 3 all make use of data that are from a moment in time which can be considered as the early days of Uber usage in the City of Toronto, with a very low mode share (less than 1%). The next cycle of the TTS, the 2021 TTS, is expected to provide a more comprehensive understanding regarding Uber-users, their trip patterns and purposes. The 2021 TTS will also facilitate the comparison between mode shares (taxi, transit, auto drive, Uber, etc.) and enable researchers to assess the changes/stabilities while determining the factors that have an impact on these changes/stabilities. Nonetheless, the observations and findings reported in this document are of critical importance to policy-makers and planners until more detailed analyses can be conducted using data from more recent years.

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