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MASTER'S THESIS

The Impact of TNC Services on Urban Mobility

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Date of Submission: 2019-05-27

Abstract

Transportation Network Companies (TNCs) growth over the past few years have impacted urban mobility in numerous ways. Despite widespread claims about the benefits of such services, limited research is available on this topic. This study assesses the willingness of Regional Munich transportation users to pay for TNCs. Realizing the difficulty to obtain data directly from TNCs, a stated preference survey was designed. The dataset includes mode choice preferences regarding TNC and its similar modes: car and transit, and socio-demographic attributes from 500 surveys. Survey results indicate TNCs popularity among larger household sizes and households with fewer cars.

To examine the impact of TNCs, an incremental logit approach was used for the existing MATSim model, run for the Munich region. With modal splits and penetration rate influenced by the introduction of TNC fleets, changes to quality of traffic flow, and level of service were observed. The results indicate insignificant changes on congestions. A large fleet size of 10,000 vehicles compared to a fleet of 2,500 vehicles, had no impact on the in-vehicle trip time but improved the waiting time by 65%. However, the smaller fleet was more efficient in handling requests during peak times where 90% of the fleet was busy compared to 20% with the larger fleet. Although the research focused on the Munich region, the results provide insight into the impacts of TNCs

Acknowledgements

I would like to express my deepest gratitude to Dr. Ana Tsui Moreno Chou for her continuous advice and support throughout the past six months. Dr.Ana’s extensive knowledge and expertise in the field, continuous mentoring and steady availability provided me immense support throughout all the stages of my thesis.

I am also very thankful to Dr. Rolf Moeckel for accepting to support my thesis topic and Dr. Carlos Llorca Garcia for his assistance with MATSim.

Many thanks go to all other colleagues at the Chair of Modelling Spatial Mobility and my friends who helped me with the distribution of the survey. Special thanks to each of the respondents who responded to my survey.

I dedicate this work to my dad and mum, who instilled in me the unmeasurable value of education and have always provided me with unconditional support. Also special thanks to my siblings: Haitham, Hossam and Dana, who are my everyday inspiration with their accomplishments.

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List of Abbreviations

CPUC	California Public Utilities Commission
DRT	Demand Responsive Transit
HBW	Home-based Work
HBE	Home-based Education
HBS	Home-based Shopping
HBO	Home-based Other
IPF	Iterative Proportional Fitting
MiD	Mobilität in Deutschland
MNL	Multinomial Logit
MMR	Munich Metropolitan Region
NOETS	New Online Enabled Transportation Service
SCN	Scenario
TNC	Transportation Network company
VOT	Value of Time
VKT	Vehicle Kilometers travelled
VMT	Vehicle Miles Travelled

1. Introduction to Transportation Network Companies (TNCs)

The past few years have witnessed a significant growth of gig-companies, operating on-demand and app-based, prearranged services known as TNCs, which are also referred to as ridehailing, ridesourcing and ridematching (Rayle et al. ,2016). The original term used for such services was the New Online Enabled Transportation Service (NOETS). The definition of TNCs varies across literature but for the purpose of this study, it shall be referred to as defined by the California Public Utilities Commission (CPUC) “an online platform that connects passengers with drivers that are driving around with their personal, non-commercial vehicle”. The GPS capability of the online platform allows the driver to determine the passenger’s pickup location and keeps the passenger updated about the driver’s location and arrival time.

2. Problem statement

Current studies on TNCs reflect their impact on urban mobility through measures such as: mode shares, vehicle occupancy, vehicle miles travelled (VMT), deadheading miles and quality of traffic. Literature review of the available work reflected the struggle to acquire data from TNC companies about the vehicles, drivers and passengers. Several authors tried different approaches to acquire adequate and reasonable TNC data using surveys and, interviews. An innovative approach to dissect the market was performed by (Henao & Marshall, 2018) where one of the authors personally drove for two TNC companies. Despite the general consensus that TNC services are more efficient than their mutual modes, literature on the topic is quite limited. The available research stresses the importance of data to study the impacts of such rapidly growing services. To fill the gap in academic literature and aid in studying the impacts of TNCs, a survey that understand how commuters in the Munich Metropolitan Region value their time when using TNC services shall be designed. Studying the influence of TNCs using the value of time (VOT) addresses the willingness to pay by different income groups, which was a limitation by several published work. This study will help the local region and policy makers understand the impacts of TNCs when making policy decisions and engineering developments.

3. Objectives

The main goal of the thesis is to predict the level of service of TNCs, their influence on modal split and the quality of traffic in the Munich Metropolitan Region based on the subjective perception of commuters.

To accomplish the main objective, a survey was developed and distributed to transportation users in Munich region, to study the willingness to use TNCs. The survey responses will provide a prediction about the probabilities of TNC use and the new mode shares using an incremental logit model. The new mode shares will allow for computer model simulations to estimate the traffic situation influenced by TNCs.

In working towards the main objective, the following research questions are answered:

1. How can a survey be adequately designed to fill in the gap about the willingness to pay for TNC services based on the subjective perception of people?
2. Which TNC service attributes can fluctuate the demand for TNC and available transportation modes?
3. What characteristics of commuters can influence their choice to use TNC services?
4. What effect can the subjective perception of survey respondents to TNCs have on modal shares?
5. How can various TNC fleet sizes impact the quality of traffic flow?
6. How can various TNC fleet sizes impact the level of service of TNC services?
7. Which TNC fleet size can reasonably satisfy the study area?

4. Hypotheses

In working towards the main goal of the research and developing a reasonable model that reflects the attitudes of the region towards TNC services, several hypotheses are developed based on the published work:

Hypothesis 1: Demographic attributes affects the Multinomial logit (MNL) model fitness and can produce weighted estimations.

Hypothesis 2: Travel time influences the use of TNC services.

Hypothesis 3: Travel cost influences the use of TNC services.

Hypothesis 4: Higher income groups are more likely to use TNC services.

Hypothesis 5: Destinations other than work have a higher demand on TNC than work destinations.

Hypothesis 6: Younger age groups are relatively more likely to use TNC services.

Hypothesis 7: Individuals with fewer or no cars in their household are more likely to use TNC services

5. Literature review

In this chapter, previous work and research that has been conducted in the same field has been reviewed to gain a deeper understanding of the topic and develop methodologies to identify the gaps and fulfil the research objectives. This chapter is divided into three sections: Section 5.1 defines TNCs and their way through the market during establishment and expansion. Section 5.2 covers the acceptance of TNCs and their use across different geographical locations. Sections 5.3 discusses their impacts through city-wide simulations.

5.1. TNCs establishment and expansion

(Kauffman, 2018) narrates the timeline of TNCs when they were first established in San Francisco in 2011, Sidecar started first as a shared-ride service and its application allowed drivers to carpool, with other people travelling on the same route, while sharing the trip costs. The nexus was the availability of an app that can be accessible by almost everyone. However, drivers started utilizing such a service by working like taxi services, driving around to find passengers that they could benefit from. Prior to Sidecar, Uber was launched in San Francisco in 2010 (McAlone 2015), also using an online-enabled platform as a private black-car limousine operated by licensed drivers. Another shared-ride service named Zimride, launched in 2007 on Facebook, allowed drivers to sell their empty car seats through Facebook (Lawler, 2014). Zimride later hosted a hackathon which gave birth to Lyft. Similar to Sidecar, Lyft offered TNC services to passengers and both companies were competing together, but Lyft had better funding and operations. By mid-2012, the competition (Sidecar terminated its operation by end of 2015) was joined by Uber when they launched their "UberX" – the standard Uber service available nowadays. UberX in comparison to Uber cars when it first started, now doesn't require its drivers to hold a professional license or a certain vehicle type. UberX is very similar to its competitors "peer-to-peer" on-demand services (Gannes, 2012)

In attempts to boost passenger rides to its services, Uber has continually cut base rates on its UberX since 2014, which it says has brought about higher profits for the drivers, and launched its cheapest ridesharing service, UberPOOL (Uber Newsroom, 2014). Towards the end of 2015, the number of drivers driving for the two top TNCs, Uber and Lyft, were almost the same as the amount of taxi drivers and chauffeurs nationally. (Cramer and Krueger 2015)

While TNCs usually operate with the drivers own personal non-commercial vehicle, they are often criticized for not being responsible for the vehicle's maintenance, insurance and depreciation (CBI insights, 2019). In places where car ownership is unaffordable by most people such as Singapore, TNC leases some of its own vehicles for use by drivers (Lin, 2017). As a matter of fact, TNCs are cooperating with vehicle manufacturers to develop their personal sustaining fleet of autonomous vehicles (Jawkins, 2018).

An important distinction of TNCs to some other ride-sharing services is that it is commonly available as a door-to-door service meaning that passengers are picked up or dropped off to the closest point accessible by car. Other ride-sharing services such as Via for example, operates at a zone-to zone level (Whiney, 2016). Zone-to-zone means that passengers will usually walk a couple of blocks to their ride (pickup) or a couple of blocks to their destination (dropoff).

TNCs such as Uber for example succeeded to grow and amplify its existence in a brief period of time. Although the novelty behind its concept is not very complicated, its violent market entrance, bulldoze-style promotion mentality and persuading many venture capitalists to invest into it are a few of the factors that accelerated its growth. Figure 1 illustrates Uber's fast rising growth in comparison to its rival, Lyft. Uber is considered to be the largest TNC in terms of operational locations and market valuation. As of 2018, Uber operates in 600+ cities and 80+ countries at a valuation of around fifty billion dollars (Muchneeded, 2018).

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Figure 1: Fast Rising Apps in the U.S. (*ComScore Media Matrix, June 2017, U.S.)*

Although it seems like Uber has a very wide reach, different countries had different responses to such services. In the US for example, local areas can have different service types but UberX is almost always present. The service survived in some middle-income and developing countries in Europe but not in richer democracies, as it died after some time in Sweden (Thelen, K., 2018). Berlin and Munich accepted Uber as a service to its population in Germany, but if you live in other cities chances are you will have to travel a lot to your nearest driver.

Germany and the United States (US) response to Uber's arrival was not easily welcomed, but rather resisted by their local transportation authorities. In Stockholm however, the head of marketing at its oldest taxi company gladly welcomed Uber with a message reflecting how such a service is great for the market by pushing the industry to utilize a new technique, a new platform (Thelen, K., 2018).

In Germany, Uber began its operations during early 2013 in Berlin – capital city. The services appeared to work for some time until a year later when its cheap options started emerging, Berlin's taxi companies reflected their ferocious resistance with legal action. Meanwhile, Uber kept proceeding with its expansion plans reaching to operations in Hamburg, Cologne, Stuttgart, and Duuseldorf. (Thelen, K., 2018). However, after several claims and legal suits filed against Uber citing them as an unfair market player, Uber representatives gave up on the German market after being banned in several cities. Berlin and Munich are its only operational grounds now with limited services to allow its operation while complying with the German laws. Besides Uber, other ride sharing services such as Cabify and BlaBlacar or car sharing such as Car2Go, DriveNow and ZipCar are the TNC companies in operation in Munich or most German cities today. Car2Go and DriveNow were developed by top German car manufacturers Daimler and BMW, around 10 years ago (Firnkorn, 2012). These services are considered to be the first of its kind because they offer one-way carsharing as compared to traditional carsharing services where users have to return the vehicle to its checked-out station.

5.2. TNCs acceptance and use

Once TNCs were accepted to the market and demand on such services started increasing, studies revealed that the trip purposes of TNC users are mostly used for social and other purposes but rarely for work purposes, when compared to transit (Murphy & Felgon, 2016). Returning back home, and destinations that fall under trips other than work such as social, shopping, entertainment etc., appear to be the popular reasons for commuters choosing TNC (TTS, 2016). In other studies, TNCs satisfied faster commuter demands during unpredictable weather conditions, using surge pricing to increase its supply (Brodeur & Nield, 2016). (Clewlow and Mishra, 2017) found that TNCs provide unprecedented level of convenience and the surveyed responses showed that 37% would choose TNC because of the struggle to find a parking, 33% would do so to avoid drunk driving.

To determine TNC users market segment, (Farber & Young, 2018) found that in Toronto, people mostly using TNCs are age groups between 20 and 39 years old with only 2% of its users aged 60 years. Majority of the trips took place from a late-night time until 5am. The same study found that households with higher earnings use TNC (54%) as compared to low income groups (2.6%). (Nielsen Company, 2012) also found similar results for the market segment demand which is explained by the common use of technology among younger age groups.

Drivers operating their own vehicle for Uber were studied in the US by (Hall and Krueger's, 2016). Only 24% of the drivers relied on Uber as their sole source of income. 85% of Uber drivers are part-time (meaning they work fewer than 35 hours a week). Most drivers work less than 10 hours a week, using the platform to fill gaps in employment or to substitute wages from other part-time or full-time occupations (Mishel, 2015; Caldwell, 2017)

In a report published by the transportation research board (TCRP 195, 2018) focused on understanding the interaction between different transportation modes, mainly TNCs while addressing the common obstacle with research on TNCs when it comes to gathering of essential and suitable information. The study area of the research comprised of the five regions (Chicago, Los Angeles, Nashville, Seattle and Washington D.C.). TNC trip data was provided by a major TNC company and San Francisco County Transportation Authority (SFCTA). 10,000 users were surveyed in eight metropolitan areas and administered by transit agencies. The key findings include:

1- Highest use of TNC occurs during late hours of the day and weekends.
2- Majority of TNC trips are short and taking place in urban cores.
3- No relationship exists between TNC use in peak-hour and longer-term alterations in transit use.
4- TNCs are used irregularly by people who routinely use transit or drive solo.
5- Top concerns for users who would shift from transit to TNC were transit travel and waiting times.
6- TNCs are used by all income groups.
7- The use of TNCs is impacted by the decrease in car ownership with its frequent users reporting no cars per household.

5.3. Impact of TNCs

The effect of TNCs entrance to the market on other modes of transport is noteworthy. When comparing TNC vehicles to traditional taxis, research by (Cramer & Krueger, 2016) in five cities in the US found that TNC vehicles have a higher efficiency rate in terms of the trips performed compared to taxis. (Li & Hong & Zhang, 2016) has found that with the capacity utilization of TNCs leads to a significant decrease in congestions and exhaust emissions. In San Francisco, taxi trips dropped by 65% from 2012 to 2014 (Yıldızgöz K., Çelik H.M. ,2019). Three years after the entrance of Uber to the market, New York city taxi rides per hour decreased by around 8% (Brodeur & Nield, 2016). In the same city, TNC ridership doubled annually over last three years to 133 million passengers in 2016, approaching yellow cab ridership (local taxis). TNCs also generated 31 million trips and 52 million passengers since 2013 (Yıldızgöz K., Çelik H.M. ,2019). (Jiang et al., 2017) conducted a study in Beijing that found that from 2012 to 2015, the average passenger-delivery trip number per day per taxi dropped by 18.08% and the average daily profit per taxi dropped by 19.29%. The study was based on GPS trajectories over three time periods. Dubai taxis lost 15% of their trips to Uber and Careem TNC’s after their entrance to the market (Yıldızgöz K., Çelik H.M. ,2019).

Studies in major American cities found that TNCS are responsible for 6% reduction in transit use (Clewlow and Mishra, 2017). 21% use TNC for commuting and a larger portion using transit for commuting, with TNCs popularity higher in late evenings and night and less frequently in morning and evening rush (Murphy, 2016). Prior to arrival, Uber had: complementary effect on transit cities with low transit ridership and substitution effect in cities with high transit. This is due to Uber's ability to provide additional flexibility in when transit supply was insufficient (Hall et al. ,2018)

The effects of TNC services has been studied from different viewpoints with simulation results presenting potentials, but also limitations of such services (Guasch et al., 2014; Hussain et al., 2015), with the main issue of efficiently supplying the service to demand at the right time.

In Toronto, (Farber & Young, 2018) found that Uber costs less than taxi ($7.20 per 6km trip) but more expensive than transit ($3.25). The analysis of the changes in mode shares after the introduction of TNCs from 2011 to 2016 shows that TNC changed from 0% to 24.1%, taxi (22.8% to 5.2%), transit (16.3% to 20.3%), auto (44.6% to 21.4%), active modes (16.3% to 29.1%)

In Berlin, (Bischoff & Maciejewski & Nagel, 2017) tested the potential for shared rides using MATSim with Demand Responsive Transit (DRT) extension with a taxi fleet of capacities between 2 and 4. The shared taxis were distributed city wide, but their operations were focused in the city's center and airport. They found a reduction of 15-20% on the vehicle kilometers travelled (VKT), with the travel time increases not exceeding 3 minutes per passenger. Their study also reveals that taxis that are occupied with two requests are satisfying demand up to 50% of the time and 10% of the time is satisfying three requests. Chances of handling four requests seem to be significantly low, given the time constraints.

Table 1 summarizes the findings of more authors on the impacts of TNCs in different study areas. The methodology and limitations of studies are also presented.

Author	Study Area	Methodology	Findings	Limitations
Rayle et al., 2016	San Francisco	Survey-based study conducted in three spots in the city.	If TNC doesn't exist: • 8%: won't conduct the trip • 39%: would use a taxi • 33%: would use public transit • 10%: would walk/bike	Unclear impacts on overall vehicle travel.
(Alonso-Mora et al., 2017)	New York city	Mathematical model for sharing rides	Demand satisfied by 14,000 taxis can be replaced by 2,000 ten-seat vehicles, with most demand being satisfied.	Not considering the passengers willingness to share a ride
(Xiao & Lees & Knoll, 2013)	Singapore	Algorithm to simulate shared taxis by matching customers in same sub-set of partitioned road network	Ride-sharing potential between 15 and 20%, when the detour per passenger doesn't exceed 5 minutes.	Not considering the passengers willingness to share a ride
(Cramer and Krueger, 2016)	Few US cities	Studied the efficiency of taxis and UberX using the capacity utilization rate	Percent of work hours with a passenger: - Taxi: around 41% - UberX: around 50.2% Percentage of miles driven with a passenger: - Taxi: 39.9% - UberX: 59.7%	Not including the time Uber drivers spend on the road, after signing out of the application.
(Henao & Marshall, 2018)	Denver, Colorado	Survey based approach by the author driving around for Uber and Lyft.	Deadheading miles: 40.8% Avg vehicle occupancy: 1.4 passengers/ride TNC vehicles lead to VMT increase of 83.5%	Sample size, study region and the use of one driver to provide data.

Table 1: Summary of research on TNCs impacts

6. Data and methodology

The present research mainly uses secondary data (revealed preference surveys) and base MASTim model for the Munich region from the Chair of Modelling Spatial Mobility at Technical University of Munich (TUM). The current model was built from the daily trip data collected through the German national household travel survey, Mobilität in Deutschland (MiD, 2008). MiD conducted the survey over an entire year to detect daily travel behavior of people and households. Although seven competitive modes (auto driver, auto passenger, bus, tram/metro, train, bicycle and walking) were considered, the focus of this research is primarily on the modal share of TNCs. To address subjective perception of commuters and estimate the variations on mode choices due to TNCs, a survey was conducted.

The incremental logit (or pivot point) model is used to forecast revised travel behavior on the foundation of present travel forms and projected or predicted changes in utility experienced by the commuter. The following section describes the incremental logit model, survey design with the alternatives and attributes that were certain for the assessment along with the rationalization for the inclusion of such variables.

6.1. Study area

Figure 2 presents the entire catchment area for the Munich Metropolitan region (MMR) in Southern Germany. The network modeled includes main streets, arterial streets, middle and small sized streets. The grey cities in the map (Munich, Augsburg, Ingolstadt, Landshut and Rosenheim) were found by (Moeckel & Nagel, 2016) to be the five main core cities in the region with high commuter flows among each other.

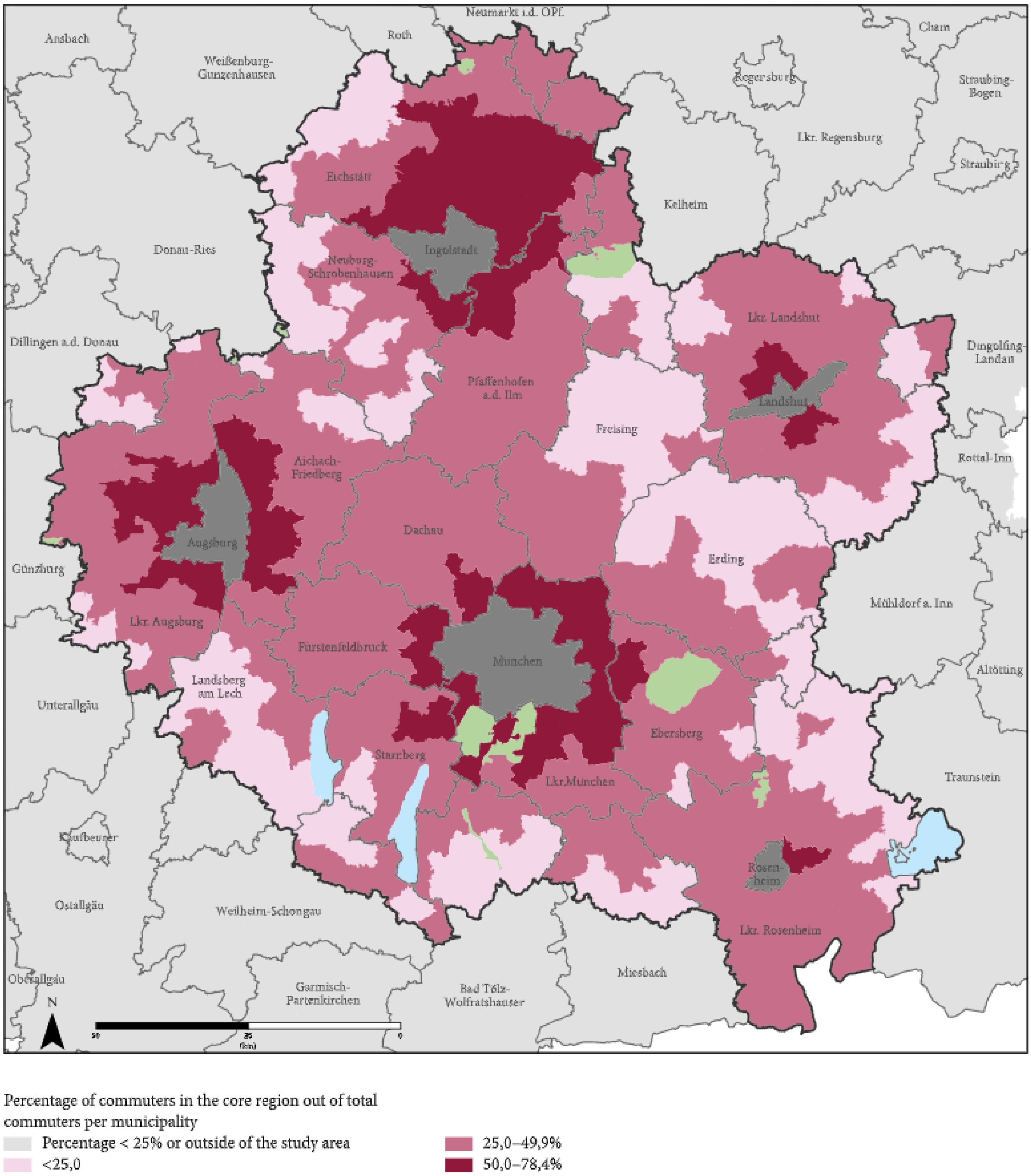


Figure 2: Map of the Munich Metropolitan Region

6.2. Online survey

An online survey was designed using limesurvey (limesurvey.org), an online statistical survey application. Four groups of questions were constructed. The first group about general questions contains demographical information such as gender, age, area type, occupation, residence period in Munich, number of cars/people/workers/children in a household, distance to nearest stop, driver license ownership and household income. The second question group starts with a brief introduction to TNC services and a question about the choice set of the different modes (private car, car/ride share, bicycle, bus, train, tram/metro, walk) typically used for trips originating from home and destined to work, education, shopping or other. This question group also includes three stated choice scenarios within the purpose of home to work/education, to estimate the value of time for respondents from a mode choice set of private car, public transport and car/ride sharing. These three scenarios are hidden for respondents with an occupation outside work/education. The third group of questions includes the same scenario set with a trip purpose from home to other activities. The last group of questions asks the frequency with which respondents use the available modes. Comments box was also added for respondents to reflect their opinion on the survey and TNCs in Munich. While the last group of questions is not directly beneficial for the developed model, it will be helpful for future research on the topic.

The survey was constructed with English and German language options, to address the two commonly used languages in Munich, especially the only German-speaking locals.

The survey question groups were designed in the format of socio-economic questions followed by the mode choice questions to follow the theory of discrete choice to calculate the utility of an alternative (Hensher & Greene, 2003). The socio-economic questions were adapted from the attributes that were used to assess the utilities of each mode in the base model. The mode choice questions design is described in section 6.2.1.

6.2.1. Mode Choice questions

While there is a wide choice set of transportation choices available for commuters in Munich, it is critical to compile the wide set in a universal but finite list to fulfil the global utility maximizing rule (Hensher et al., 2015). Figure 3 presents the nested model structure with blue representing the current model nest and orange representing the updated model nest to accommodate the introduced mode, TNC. The updated structure includes TNCs in the Auto and Transit nests since the majority of car/ride sharing service users would substitute such a service to auto or public transport (Clewlow and Mishra 2017).

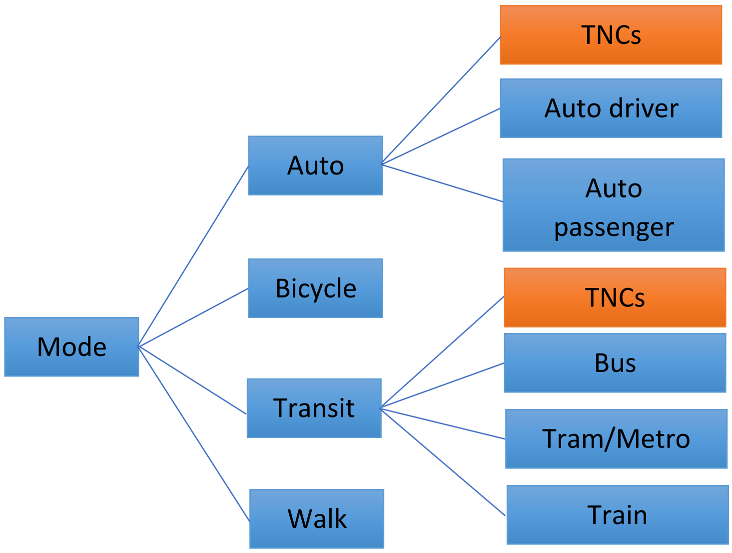


Figure 3: Nested Model Structure of available modes

Although 28% of trips completed in Munich are done by walking (Landeshauptstadt München, 2010), walking and cycling were omitted from the choice sets developed in the survey because the choice sets were based on a distance which is uncomfortable to commute by both modes in terms of effort and time spent travelling.

Although increasing attributes associated with each alternative can better reflect the complex process to select an alternative, the degree of difficulty to respond also increases so limiting the attributes keeps the experiment controllable and preserves the quality of data (ChoiceMetrics, 2018). To construct an efficient and sensible choice set scenarios that can yield outcomes with high rationality, attributes were selected in such a way that variations can marginally influence the respondent's response. All attributes included along with their levels will be described for each mode in section 6.2.2.

6.2.2. Attributes and Levels

The key objective of the scenarios presented is to acquire a confident measure of the demand for TNCs and the respondent's value of time in comparison to its mutually exclusive alternatives (private car and public transport). The baseline modal share used in the study is consequential to the model established by the Chair of Modelling Spatial Mobility. Then, the outcome of incremental variations in explanatory variables is computed by means of the incremental logit model. TNCs being the subject of study, are the only mode with varying attribute levels.

- Attribute 1: In-Vehicle Travel Time

Travel time is an important attribute that is included in all transportation choices and usually refers to the door-to-door time spent in travelling from origin to destination which can include the walking time to vehicle, waiting time, in-vehicle travel time, walking time to destination, transfer time and parking search time.

<u>TNC</u>

Since the most common form of TNC in Munich is Uber, a simple trip (usually uncomfortable to accomplish via bicycle or walking) was estimated using Uber (Uber App, 2019) and the time taken to travel was used as the reference time. +10% and +20% are the levels of the extra scenarios presented to determine the value of time of respondents. The added time levels are due to the ride being shared with more than one passenger. The (+10%) level is time added to the in-vehicle travel time while the (+20%) level is time added to waiting and in-vehicle travel time, since commuters can sometimes consider time spent out of a vehicle more onerous than in-vehicle (4).

<u>Car</u>

The same trip was searched through Google Maps app (Google Maps, 2019) and the time taken to travel was used as the reference time. The reference time remains the same in all scenarios since the interest is to study the impact of value of time variations in TNC only in comparison to its mutually exclusive modes. Figure 4 presents an example of the route and time estimated by the app.

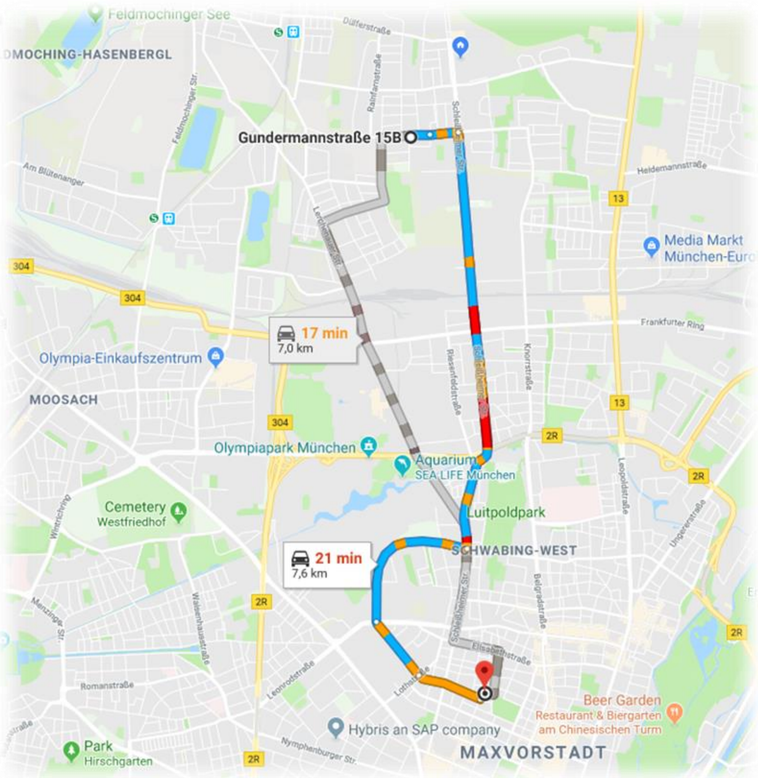


Figure 4: Google Maps App trip time estimation for auto

Public Transport

The same trip was searched through Münchner Verkehrs- und Tarifverbund (MVV App, 2019) and the time taken to travel was used as the reference time. The reference time remains the same in all scenarios since the interest is to study the impact of value of time variations on TNC only in comparison to its mutually exclusive modes. Figure 5 presents an example of route, time and cost estimated by the app.

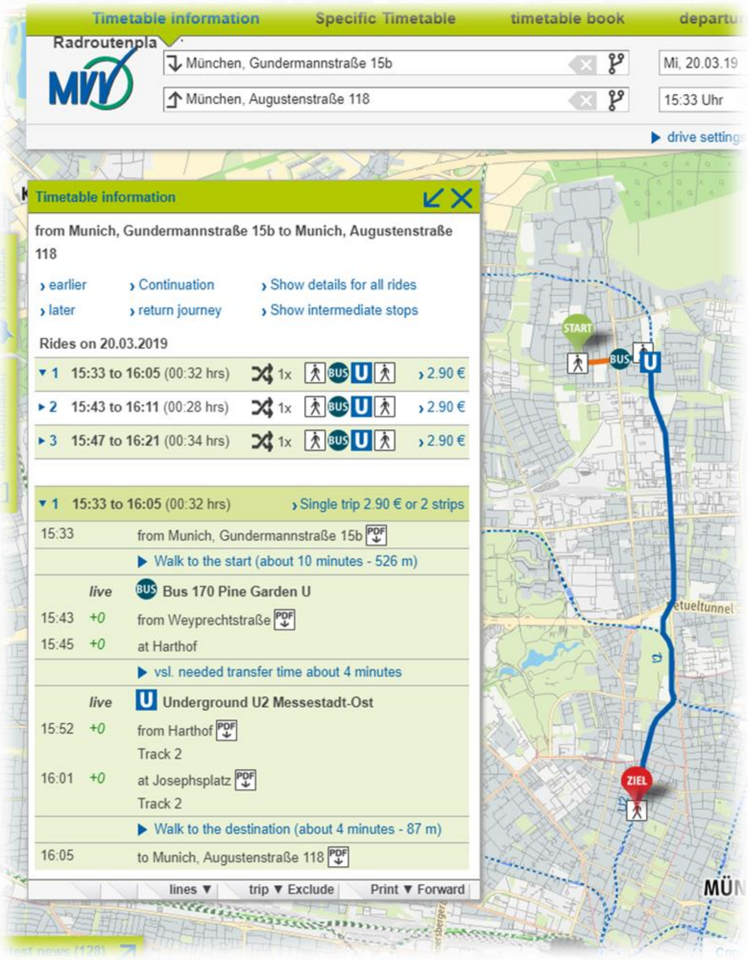


Figure 5: MVV App trip time and cost estimation for transit

- Attribute 2: Walking and Waiting Time

As mentioned in the previous subsection, commuters consider walking and waiting time more onerous than in-vehicle time (Iseki, Taylor & Miller, 2006), the inconvenience caused by walking to a vehicle or waiting for a vehicle (TNC) was also included in the scenarios based on the time calculated from the Uber and Google Maps App. In the third scenario (+20% level), the additional time is added to walking/waiting time to include the additional time during Uber pool.

For Public Transport, 5 minutes is the average waiting time considering the headway of public transport services in Munich and the total walking and waiting time is around 8 minutes according to (Moovit Public Transit Index, n.d.) which is valued based on the average walking distance and speed.

For Car, 2 minutes of walking time was set assuming that cars are usually parked very close to the housing location. Waiting time is set at 0 since the car user does not have to wait.

- <u>Attribute 3: Travel Cost</u>

Like travel time, travel cost is also a main attribute that is included in the majority of mode choice studies since it's a very critical factor on selecting a transportation mode. Regarding travelling by a private car, an all-inclusive cost for travelling was included at 0.53 € /km which includes fixed maintenance costs, insurance and taxes, depreciation per km and fuel (Twaddle, 2011). The cost variable was further modified to accommodate fuel costs during congestions (fueleconomy, n.d.). Travel cost remains the same in all scenarios since the interest is to study the impact of value of time variations in TNC only in comparison to its mutually exclusive modes. For Public Transport, the cost of a single trip ticket for one or two zones at around 3 € was used.

When it comes to the price of a car/ride share, the reference scenario used a value of 12 € as calculated by the Uber App, presented in figure 6. The cost was halved in the following scenarios since they are based on the ride shared with an additional passenger.

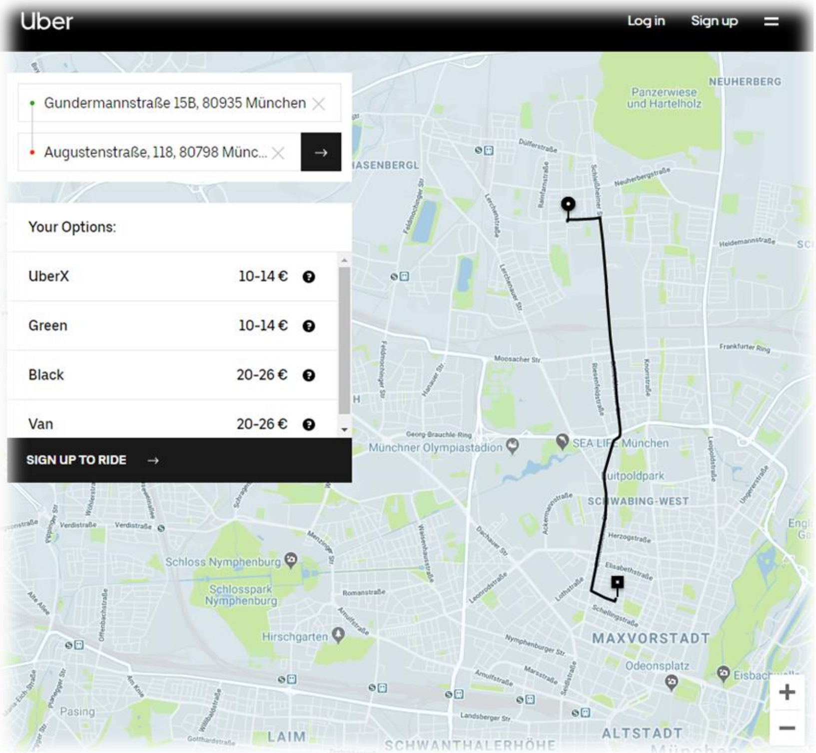


Figure 6: Uber App trip cost estimation for TNC

- <u>Attribute 4: Parking fee</u>

Parking fees are considered to be an influential attribute across mode choice sets (Vrtic et al., 2009; Ortuzar et al., 2000). The cost of parking in Munich's city center is around 50 cents per 15 minutes. Depending on the trip purpose and time spent on the activity, such a cost can strongly dominate if included at an assumption of the time spent parking. To mitigate this issue, an absolute value of 2 € was used.

Table 2 summarizes the included attributes for each mode choice and the attribute levels for the TNCs time and cost.

Alternative	**Attribute**	**Attribute levels**	**Source**
Private Car	Walking time to vehicle	2 min	Self-created
	In-vehicle travel time	25 min	Google Maps
	Parking search time	6 min	Self-created
	Walking time to destination	2 min	Self-created
	Travel Cost	6 €	(Twaddle, 2011)
	Parking Cost	2 €	(Axhausen & Polak, 1991)
Public Transport	Walking time to transit	3 min	Moovit PT index
	Waiting time	5 min	Moovit PT index
	In-vehicle travel time	32 min	MVV App
	Walking time to destination	3 min	MVV App
	Travel Cost	3 €	MVV App
TNCs	Walking time to vehicle	4 min	Uber App
	Waiting time	2 min, 5min	Uber App
	In-vehicle travel time	25 min, 29 min	Uber App
	Total Travel Time	35 min, 39 min, 42 min (0%, +10%, +20%)	Uber App
	Walking time to destination	4 min	Uber App
	Travel Cost	12 €, 6 €, 6 € (0%, -50%, -50%)	Uber App

Table 2: Summary of the Attributes and Attribute levels by transportation mode

All survey participants have to respond to the demographic background questions. Each survey participant with an occupation of work or education receives three scenarios for home-based work trips three scenarios for home based other trips. Each survey participant with occupation other than work or education receives only three scenarios for home based other trips. An example of one of the scenarios is presented in Figure 7. Full survey is attached in the appendix.

*Scenario 1: Imagine the following modes of transportation are available from your **home to work/education.** The trip duration and cost using each one are as presented below. Please mark below which of them would you prefer?

	Car/ride sharing	Public Transport	Private Car
Walking time to the vehicle	4 min	3 min	2 min
Waiting time	2 min	5 min	0 min
Travel time in-vehicle (without the parking search time)	25 min	32 min	25 min
Parking search time	-	-	6 min
Walking time to the destination	4 min	3 min	2 min
Travel cost	12 €	3 €	*6 €
Parking cost	0 €	-	2 €

All inclusive cost (fixed & maintenance costs of the car)

Choose one of the following answers

This question is mandatory

Car/ride Sharing | Public Transport | Private Car

Figure 7: Sample of questionnaire scenario

6.2.3. Survey Distribution

On the 11th of March 2019, a test version of the survey was released to 20 respondents. The majority of the respondents commented on the difficulty of selecting a choice alternative when navigating through the different attributes and values of different scenarios. Highlighting the value changes between scenarios/attribute levels with **bold** made it less tedious for respondents to make a choice.

For two weeks starting from the 11th till 25th of March 2019, the survey was activated online to the public and distributed via an online link that was emailed to several students at different universities, employees at different companies and Facebook groups. Additionally, 500 flyers were printed in German and English with the survey barcode for easier access via smartphones and distributed around the city center of Munich.

The survey was distributed in online form only to keep the anonymity and reduce the time and work load in comparison to paper-pencil or personal interviews. Availability of the survey online only makes it inaccessible to respondents who don’t use the internet, so some statistics might not be entirely illustrative of the whole population.

6.2.4. Response Bias

A response bias can be defined as the tendency to answer certain questions based on some basis rather than the specific item content (Paulhus, 1991). One of the strong impact classes on the validity of surveys is the response styles of respondents (Furnham, 1986; Nederhof, 1985).

Humans responding subjectively rather than passively to a stimulus, integrating multiple sources of information to shape their response, causes response bias (Orne, 1962).

The bias types that may occur in the research’s survey include:

1. Careless response style: The tendency to inattentively choose choices randomly.
2. Social Desirability Bias: The tendency to choose choices inline with social norms and expectations. (Paulhus, 1984, 2002)
3. Non-Response Bias: The systematic difference in characteristics of the respondents and non-respondents.
4. Sampling Bias: The over or under-representation of certain groups.

Careless response style can occur at any of the questions in the survey due to the respondent being inattentive or misreading the question and choosing a random choice to quickly finish the survey. This leads to bias in the answers because it’s not a reflection of the actual choice (Meade & Craig, 2012). Social Desirability bias is different from careless response style in the fact that the respondent reads and understands the question and answers but decides to give positive self-descriptions (Paulhus, 2002). Such bias can be expected in all question groups within this survey such as choosing a generally acceptable occupation or selecting a certain mode within the presented scenarios based on its sustainability in todays world to project an image of being environmentally conscious. While “I prefer not to answer" options are provided in most cases, Social Desirability bias can still occur. Non-Response bias is the bias that occurs within a certain response group. For example, an age group of (18-24) within the survey might be well representative of the population in terms of its ratio. However, there is a high possibility that such an age group is dominated by students with high educational background which leads to different perceptions in responses. In general surveys are prone to non-response biases due to the limitation of the available characteristics of the population and the extent of questions that can be questioned but minimizing such a bias is possible by gathering high response rates (Sedgwick, 2014). Sampling bias is also another common type of bias in surveys where an over-represented group can influence survey results but minimizing such a bias is possible by using iterative proportional fitting (IPF) to weigh surveyed individuals across different constraints of which population aggregated values are known.

Besides the gathering of high response rates and the use of IPF, mitigation of survey bias can be done by conducting a follow up survey and including incentives to incentivize the respondent to respond honestly. Moreover, the careless response bias can be mitigated by comparing the time spent on a survey by respondents to average time taken to complete the survey. Discrepancies between both times can help identifying the responses that were influenced by random selection. Data cleaning is a critical process in preliminary analysis of survey results that shall be discussed further in the survey results section.

6.3. Incremental Logit Model

The work flow in applying the incremental logit technique starts with establishing (Pi), the original probability of choosing between modes. ΔUj, the incremental change in utility is then estimated while considering the variations of the explanatory variables' coefficients. Explanatory variables consider cost, travel time, household size, income, car ownership, trip purposes…etc. Time and cost are alternative specific variables that are specific to each mode, meaning that the marginal effect on the commuter's indirect utility from fluctuations in cost or travel time on a certain mode is not equal to the marginal effect on an alternative mode. Once Pi and ΔUj are estimated, the new probability of choosing mode i can be calculated.

Since a fully built model is already available for the study area, the incremental logit technique will be used to predict the changes in the utility by commuters for TNCs. This technique uses a similar basic utility function as in binomial or multinomial logit function. Benefits of using an incremental logit model in the study is that research thorough current utility on all relevant alternatives available to a trip maker is not needed; only estimates of projected variations to modal disutility are essential (Zupan et al., 2011). Based on the values of the coefficients of travel time and cost, variations in modal disutility can be calculated. The expression of the incremental logit model is described as (Clark and Lam, 1990):

$P'i = \frac{(Pi * \exp(\Delta Ui)}{\sum_{j=1}^{J} Pj \exp(\Delta Uj)}$

Where

$P'i$ = revised probability of choosing mode i,

Pi = baseline probability of choosing mode i, and

Uj = utility of mode j in the choice set j (j = 1,2,3,..., j).

The VOT to be calculated is used to predict the new mode shares using the nested incremental logit approach. The calculations are based upon the existing mode shares and changes due to the addition of TNC. |The following different cases to increment the new mode shares can be calculated (Koppelman, 1983):

1- Improvement of an existing mode service
2- Introduction of a new service which replaces an existing service
3- Introduction of a new service in addition to existing services

While there are several approaches available to increment the exisiting mode shares, I shall be using the third method "Introduction of a new service in addition to exisiting services" shall be used and all available transportation modes is incremented since literature reflects that availability of TNC influences the motorized and non-motorized transportation modes.

To account for the case where similarity exists among auto, transit and TNC and where no changes are made to the other similar modes, future mode shares of TNC will be more attracted from auto and transit services than from other modes. The calculation procedure proposed by (Koppelman, 1983) is followed using the following formulas:

- To predict the total auto ridership share when a new auto mode (TNC) is added:

$$P'A = \frac{P\,XA\,(e^{\left(\frac{S'NA - S\,XA)}{\delta}\right)} + \left(\frac{S'XA - S\,XA)}{\delta}\right))^{\delta}}{P\,XA\,(e^{\left(\frac{S'NA - S\,XA)}{\delta}\right)} + \left(\frac{S'XA - S\,XA)}{\delta}\right))^{\delta} + (1 - PXA)}$$

Where

$P \; and \; P' = base \; and \; future \; shares$

$P \; (NA \; and \; XA) = base \; and \; exisiting \; Auto \; share$

$S'(NA \; and \; XA) = mathematical \; functions \; that \; describe \; the \; new \; and \; existing \; Auto \; modes$

$\delta = nesting \; coefficient$

- The shares for the new Auto and exisiting Auto alternatives are calculated using:

$$P'NA = \frac{e^{\left(\frac{S'NA - S\,XA}{\delta}\right)}}{e^{\left(\frac{S'NA - S\,XA}{\delta}\right)} + e^{\left(\frac{S'XA - S\,XA}{\delta}\right)}} * P'A$$

$$P'XA = \frac{e^{\left(\frac{S'XA - S\,XA}{\delta}\right)}}{e^{\left(\frac{S'NA - S\,XA}{\delta}\right)} + e^{\left(\frac{S'XA - S\,XA}{\delta}\right)}} * P'A$$

- The shares for other modes are calculated using

$$P'O = PO * \frac{1 - P'A}{1 - PA}$$

Where

$O = other\ modes$

The previous equations were provided as an example for the Auto nest and were also used for the Transit nest. The nesting coefficient δ ranges from zero to one, accounting for the similarity (0) or dissimilarity (1) between the available alternatives. Complete similarity at zero assumes that the best available mode is based upon the mathematical functions that describe the mode characteristics. (Sobel, 1980) found values less than 0.5 for similarity between auto modes using data from the Netherlands. Thus, a coefficient of 0.25 is used.

6.4. Simulation

To simulate the impact of TNCs on the study area, Munich Metropolitan region, an agent based simulator MATSim is used (Horni & Nagel & Axhausen, 2016). The basic concept used by MATSim is simulating people along their daily plans. Realistic simulation of TNCs is possible using MATSim because of its ability to simulate millions of agents (fast queue-base traffic simulation) and its ability to develop trip plans using a rich behavioral model (Maciejewski et al., 2016). Through the iterations performed agents alter their plans using co-evolutionary algorithm to improve their scores until equilibrium is reached. The extension used for the simulation of the TNC fleet is Dynamic Vehicle Routing Problem (Bischoff & Maciejewski, 2016). The extension handles the passenger requests, TNC vehicles locations and arrival and departure times to efficiently process demand. It also dispatches nearest TNC vehicle to a passenger during (fleet oversupply or non-peak times) or nearest passenger to TNC vehicle (fleet undersupply or peak times) as thoroughly described in previous research (Maciejewski & Bischoff, 2015; Maciejewski et al., 2016). These strategies optimize the use of TNC fleets to minimize waiting times.

7. Results and analysis

7.1. Online survey

This section includes a description of the preliminary data analysis, providing input for value of time estimations, and further modelling using MATSim. Subsection 7.1.1 presents the results of the survey and processing of absent data choices. For complete understanding of the respondent's responses, a detailed analysis is followed.

7.1.1. Survey Results

Once the survey was deactivated to the public on 25th of March 2019, the data cleaning and preparation process for the model started. A total of 878 responses were received but 366 of them were discarded since they were incomplete and the remaining 512 full responses were used for the cleaning process. Analysis of the incomplete responses shows that respondents stopped responding once they reached the revealed preferences section for the different scenarios, which might have been perceived by such respondents as a tedious question.

- Data Cleaning

The data cleaning process has been conducted in two stages:

- Stage 1:
  - Removal of unused categories
- Stage 2:
  - Removal of the NA or "no answer" values
  - Removal of Unreasonable responses

<u>Stage 1: Removal of unused categories</u>

Since they are not required for analysis, the following three categories were deleted from the responses excel sheet exported from lime-survey:

1. Seed
2. Date started
3. Date last action

<u>Stage 2: Removal of the NA or "no answer" values</u>

Table 3 summarizes the percentage of "no answer" values per each variable. Since percentages are very small and the sample size is already large enough (512 responses), 12 responses were removed from the survey to ensure complete answers within the remaining dataset. The number of responses mentioned in Table 3 is higher than 12, because of the categorization of variables.

Variable	Answer	Number	Percentage to full responses
Gender	I prefer not to answer	6	1.17%
Age	I prefer not to answer	5	0.98%
Period living in Munich	No answer	10	1.95%
Occupation	Other	11	2.15%

Table 3: Summary of the responses removed from the dataset

Stage 2: Removal of Unreasonable responses

In this step responses that match the following two conditions are eliminated:

1. Total time spent on survey is less than three minutes, since it is unrealistic that someone might have completed the survey twice as fast as the average respondent (median)
2. The answer to the household size question is less than the sum of answers to household workers and household children.

Table 4 shows the distribution of the survey completion time (mins).

variable	n	mean	median	min	max
Total survey time	500	7.56	5.11	1.92	312.78

Table 4: Analysis of the survey completion time

The extremely high response time can be explained by respondents who don't complete the survey in one go. Regarding the minimum and all other respondents up to 2.55 mins (half the median), their responses were analyzed thoroughly to ensure logical response to the second condition mentioned to eliminate responses.

The total remaining respondents after the two stages of the data cleaning process were applied are 500 responses.

7.1.2. Research Sample

This subsection introduces the respondent's composition. The sociodemographic characteristics were compared to the data used in the base MATSim model (2011 census data), to correctly reflect the population. Categories such as gender, age groups, occupation and household size were used for comparison. Table 5 summarizes the main survey dataset categories compared to the population data.

N = 500		Survey	2011 Census
Gender	Male	45.00%	48.6%
	Female	55.00%	51.4%
Age	<18	0%	16.56%
	18 – 24	19.52%	8.01%
	25 – 29	30.88%	7.14%
	30 – 39	37.45%	14.58%
	40 – 49	8.17%	17.16%
	50 - 64	3.78%	18.18%
	>65	0.20%	18.37%
Occupation	Employed	67.80%	87.10%
	Student	27.20%	10.00%
	Unemployed	5.00%	2.90%
Household size	1	33.80%	34.36%
	2	34.80%	32.78%
	3	14.20%	15.26%
	4 or more	17.20%	17.59%
Income	>5600€	20%	4220€ per household
	1500€ - 5600€	57.00%	
	<1500€	23.00%	

Table 5: Summary of the unweighted survey and population characteristics

Age and household size categories seem to be well represented while categories such as age and occupation seem to be less representative of the population. Income category “1500€ - 5600€” has the largest share of survey respondents which is within the same group of the average monthly disposable income per household in Munich. However, it is not entirely possible to say that it is well represented since it’s a range category in the survey.

The dominant survey respondent groups are ages younger than 39 years old and working and student groups in comparison to the population data which can be explained by the way the survey was distributed and considering that older age groups don’t have the same access to the internet (Dillman, Smyth, & Christian, 2014). While an iterative proportional fitting (IPF) procedure is applied in the next step, it should be important to realize that the gaps within the socio-economic factors and the attempts in cleaning the dataset do not completely clear the biasness from the survey results.

7.1.3. Iterative Proportional Fitting (IPF)

This section demonstrates how the IPF was performed for the data using the ipfp package in R software. IPF is the most widely used mature deterministic method to allocate individuals by calculating a series of non-integer weights that represent how representative each individual is of each constraint (Lovelace and Dumont, 2016).

IPF works as a weighting system where the survey individuals table (original data) values are adjusted constraint by constraints through multiple iterations to fit the row and column constraints of another dataset. The resultant data is obtained when probabilities are convergent within an acceptable limit (Birkin, 1987; Bishop et al., 1975)

The IPF algorithm proceeds constraint by constraint. Each individual starts with an initial weight representative of the constraint. The weight matrix will then have the dimension (number of individual * number of constraints). “w(i,t)” corresponds to the weight of the individual ‘i’ during step ‘t’. The weight matrix to each constraint ‘c’ is initialized with a full matrix of 1, and for each step ‘t’. ‘ind(i,c)’ is the category of individual ‘i’ for the variable ‘c’ and the denominator is the sum of the actual weights of all variables having the same category in this variable as ‘i’. The weights are redistributed so the data follows the constraint concerning this variable (Lovelace and Dumont, 2016). The formula can be expressed as :

$$w(i, t+1) = w(i, t) * \frac{const\_t(x, ind(i, c))}{\sum_{j=1}^{n\ ind} w(j, t) * I(ind(j, c) = ind\ (i, c))}$$

IPF in the research demanded two input datasets: individual-level data where rows represent individuals and columns represent categories, and population data where rows represent population and columns represent category constraints. The model will weight individuals based on age, gender, occupation and household size and the code used was adopted from RStudio’s library.

Since the age group (<18) was not considered in the survey sample, its value from the population was distributed proportionally over the other age groups with respect to their weights. (>65) age group in significantly small in my survey which could disrupt the weighting system, so it was grouped with its preceding age group, (>50).

An initial run of the input data was tested and found to have a correlation of 0.686, and a plot of the model output (individual-data) vs constraints (population-data) is shown in Figure 8.

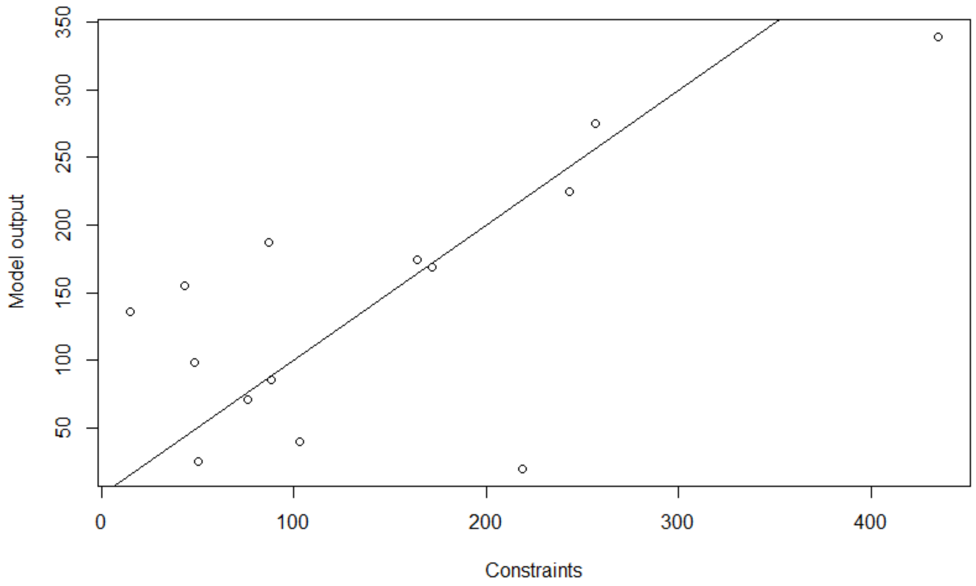


Figure 8: Survey and population data correlation - Input

Once the IPF procedure was run fully for all four constraints, the correlation was improving from one constraint to the next which reflects the robustness of the IPF method. The new correlation after reweighting was calculated across all constraints was found to be 0.998, and a plot of the model output (individual-data) vs constraints (population-data) is shown in figure 9.

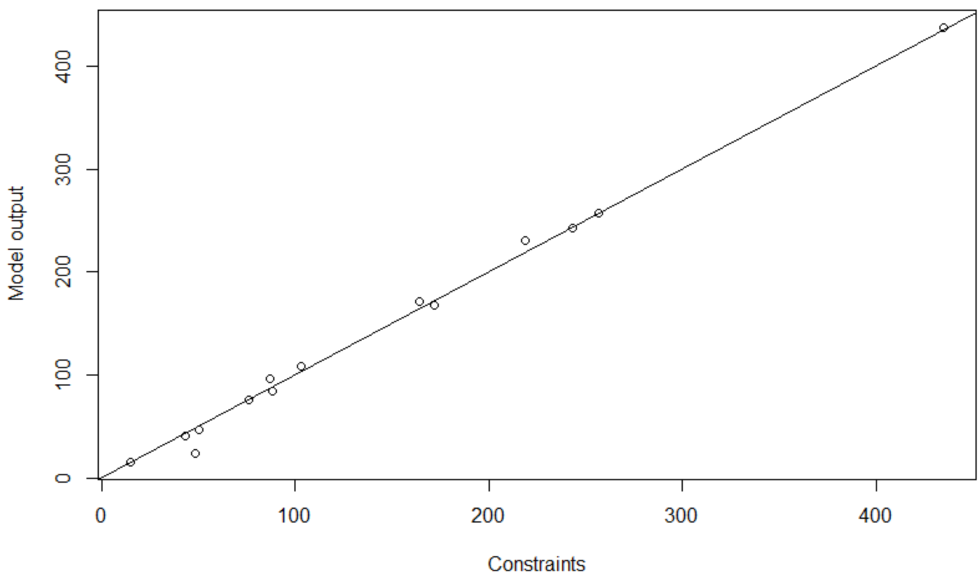


Figure 9: Survey and population data correlation - output

A sample of the output weighted individuals is presented in Table 6:

```
    weights5[, 1]  id age         hh occupation sex
1      0.52829928   1  35          1          e   m
2      0.37732406   2  27          2          e   f
3      7.39857120   3  55 4 or more          e   m
4      2.10969049   4  45          3          e   m
5      0.04538303   5  27 4 or more          s   m
6      0.63278385   6  35          2          e   f
7      0.63278385   7  35          2          e   f
8      0.05503022   8  27          3          s   m
9      0.55618277   9  20          1          e   m
10     0.11254443  10  20 4 or more          s   f
```

Table 6: Sample of (IPF) output

Table 7 presents an updated comparison between the weighted survey dataset and the population data.

N = 500		Survey	2011 Census
Gender	Male	48.60%	48.6%
	Female	51.40%	51.4%
Age	<18	0%	0%
	18 – 24	4.84%	9.60%
	25 – 29	8.14%	8.55%
	30 – 39	19.30%	17.48%
	40 – 49	21.60%	20.56%
	>50	46.11%	43.80%
Occupation	Employed	87.42%	87.10%
	Student	9.40%	10.00%
	Unemployed	3.18%	2.90%
Household size	1	33.68%	34.36%
	2	34.22%	32.78%
	3	15.21%	15.26%
	4 or more	16.89%	17.59%
Income	>5600€	34.09%	4220€ per household
	1500€ - 5600€	61.95%	
	<1500€	3.96%	

Table 7: Summary of the weighted survey and population characteristics

7.1.4. Descriptive analysis

Before the scenarios were questioned in the survey for respondents to state their preferences, they were asked to choose the most common mode they typically used with respect to trips originating from home and destined to work, education, shopping and other. Car/ride sharing, and bus seemed to be the least used modes in comparison to Tram/Metro which were the most used modes to work and education, and private cars were most frequent in other trips while walking seemed to have the highest preference when it comes to shopping. Figure 10 presents the mode shares as typically used by respondents for home-based work (HBW), Home-based education (HBE), Home-based shopping (HBS), Home-based other (HBO).

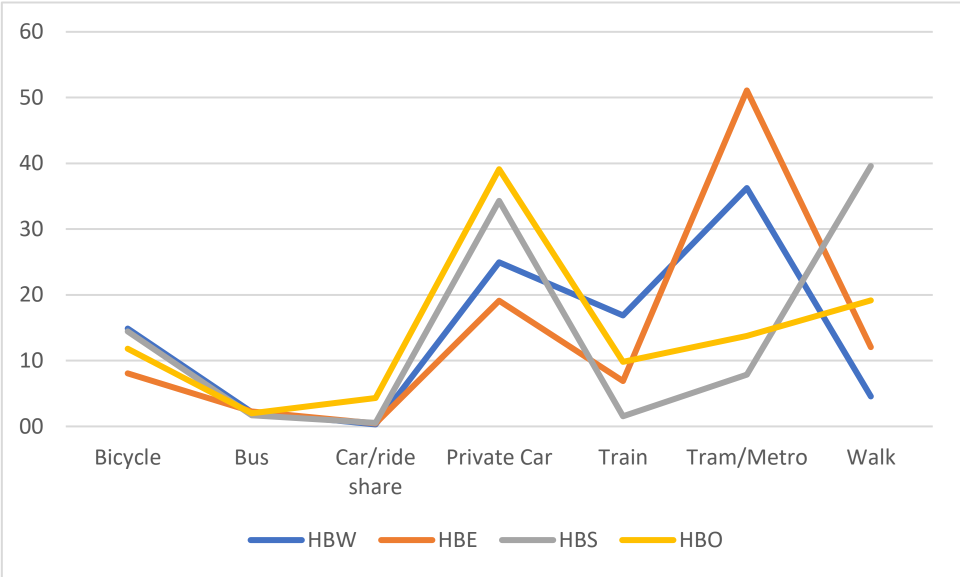


Figure 10: Typically used mode by trip purpose.

Figure 11 represents the mode share distribution across different scenarios. The first set reflects the HBO scenarios while the second set reflects the HBW scenarios. As the scenarios are the same in both sets, Car/ride sharing seemed to have a higher preference when commuting to trips other than work. Scenarios 2 (SCN 2) with the shortest time and least cost had the highest preference in both sets. Table 8 presents the changes across scenarios.

TNC CHANGES

SCN 1	TT, C
SCN 2	1.1TT, 0.5C
SCN 3	1.2TT, 0.5C

Table 8: Summary of TNC attribute changes

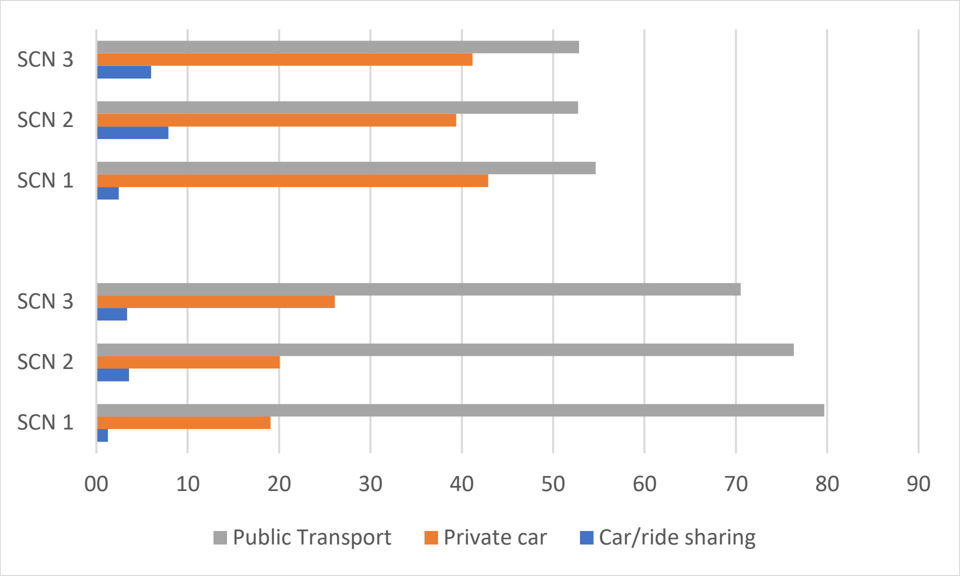


Figure 11: HBO and HBW Modal split across scenarios

To analyze the mode share fluctuations across scenarios and the percentage of users shifting from a particular mode to another in each scenario change, Figure 12 and Figure 13 present the changes from scenario 1 to 2 and scenario 2 to 3 for HBW/E and HBO scenario sets.

From scenario 1 to 2, TNC seemed to be the biggest winner in terms of gaining choices followed by private car, gaining the choices from public transport. Scenario 2 to 3 shares the same changes but with private car gaining the most. Although changes across scenarios are only happening to TNC, it seems that private car use was highly triggered in response to changes happening to TNC.

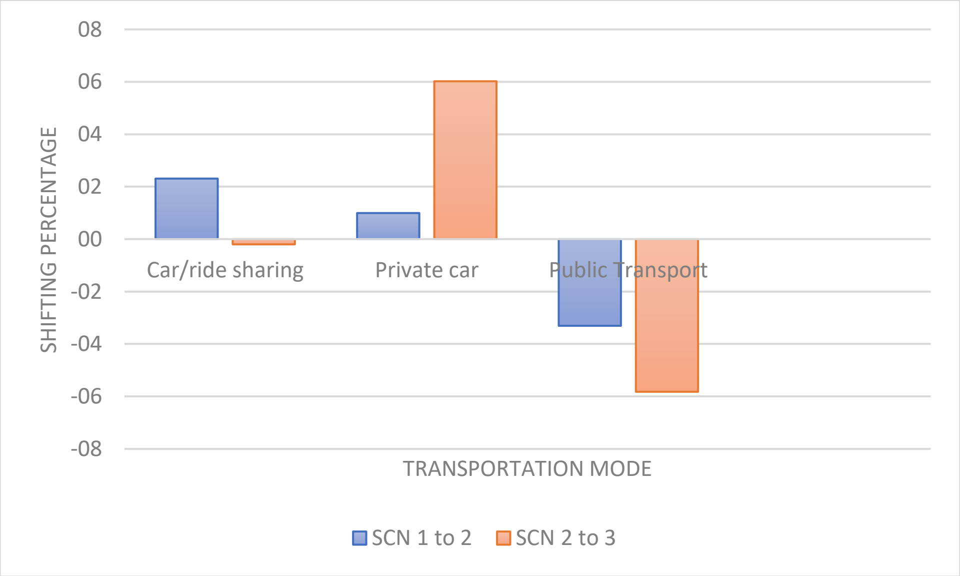


Figure 12: HBW/E Mode share fluctuations

From scenario 1 to 2, TNC seemed to be the only winner in terms of gaining choices, gaining more choices from private car than public transport. However, in scenario 2 to 3 private car gained the most choices from TNC. Although changes across scenarios are only happening to TNC, it again seems that private car use was highly triggered in response to changes happening to TNC.

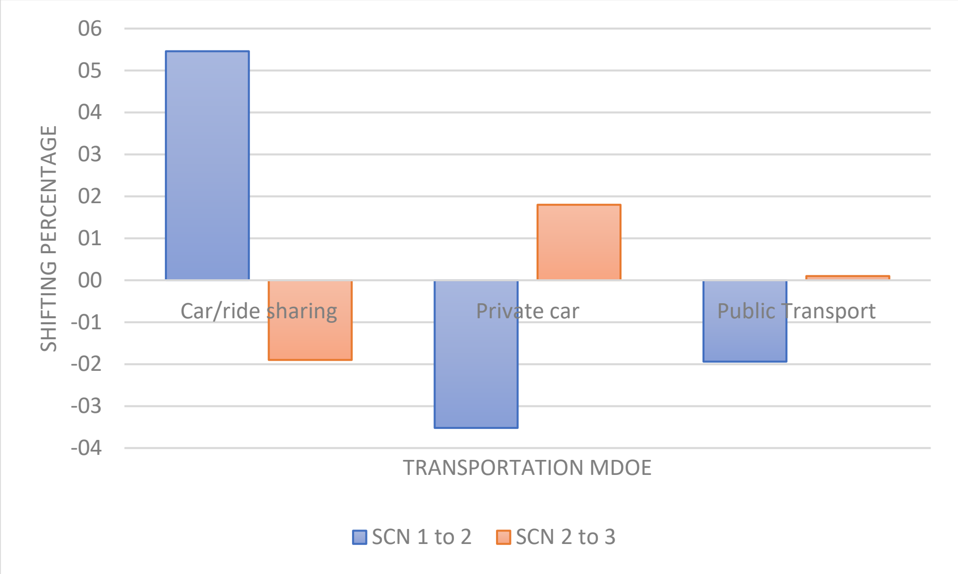


Figure 13: HBO Mode share fluctuations

An additional question was added towards the end of the survey to determine the frequent use of the available transportation modes by respondents and the responses are presented in Figure 14. While walking and public transport seemed to be the most frequently used modes, TNC services seem to be the least used mode with more than 60% of respondents never using it and around 30% using it few times a year – the highest percentages compared to any other mode.

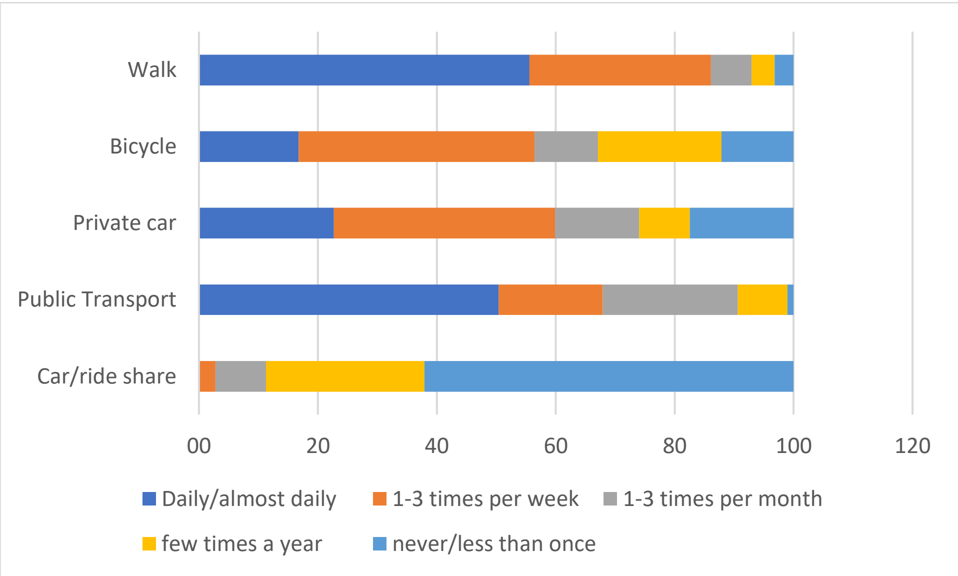


Figure 14: Frequency of Mode use

7.2. MNL Model estimation

As mentioned in section 6.3 about the Incremental logit, the probabilities of the new mode shares are predicted based on the concept of utility maximization. Since Value of Time (VOT) of different income groups is the reference attribute from the base model, to predict the revised modal shares of the introduced TNC mode, VOT of TNC for different income groups is estimated from the survey.

The constructed model adopts the discrete choice modelling framework, where the individual's choice in the survey is modelled using the concept of utility maximization (Ben-Akiva & Lerman, 1985). Meaning that the choice providing the highest utility to respondents is the chosen choice in comparison to other lower utility choices. Utility expressed in terms of the choice attributes such as (travel time, cost…etc.) is the attracting force of the choice. Its important to note that this concept expects logical response from respondents, providing complete data about all choices with similar and joint choice set which is not usually the case.

Mutlinomial logit model (MNL) being one of the most common choice models in predicting travel demand (Munizaga & Ortúzar, 1999) has been used for the estimation of VOT using the coefficients of time and cost.

7.2.1. Dataset

The model's dataset is extracted from the online stated preference survey that was conducted earlier this year. The explanatory variable used along with the full and restricted MNL models developed are presented in the following sections.

7.2.2. Explanatory variables

The survey developed earlier this year and fully completed by 500 respondents (post-cleaning) captures the socio demographic attributes and the respondent's sensitivity to TNC services in comparison to their mutually exclusive modes. Sensitivity or VOT calculated from the time and cost coefficients is governed by various explanatory variables which can be classified into the following categories (Ortúzar & Willumsen, 2011):

1. Individual characteristics, e.g. socio-economic variables
2. Transport characteristics, e.g. time, cost, comfort, safety, etc.

A summary of the used explanatory variables for my MNL model is presented in Table 9.

Category	Explanatory variables	Type of Variable
Individual characteristics	Gender	Categorical
	Age	Categorical
	Area type	Categorical
	Residence period in Munich	Categorical
	Occupation	Categorical
	Household size	Continuous
	Household workers	Continuous
	Household children	Continuous
	Household cars	Continuous
	Distance to nearest transit stop	Continuous
	Driver’s license availability	Categorical
	Household Income	Categorical
Transport characteristics	Total travel time	Continuous
	Total cost	Continuous

Table 9: Explanatory variables considered in the model

7.2.3. Explanatory variables correlation

Discrete choice modelling demands variables to be mutually independent so a test for the correlation between all the input variables was conducted to ensure that the results make sense. The correlation output is presented in Figure 15. Generally, correlation didn’t exceed an absolute value of around 0.5 except with the student and age and working categories. The student variable which had a high correlation (-0.59) with age – a higher age means an absence of a student status, and even higher correlation (-0.89) with working – a working status means an absence of a student status. These high correlations were enough to remove the student status variable from the estimation. During estimation, each of the variables available were tested once at a time to build a reasonable model.

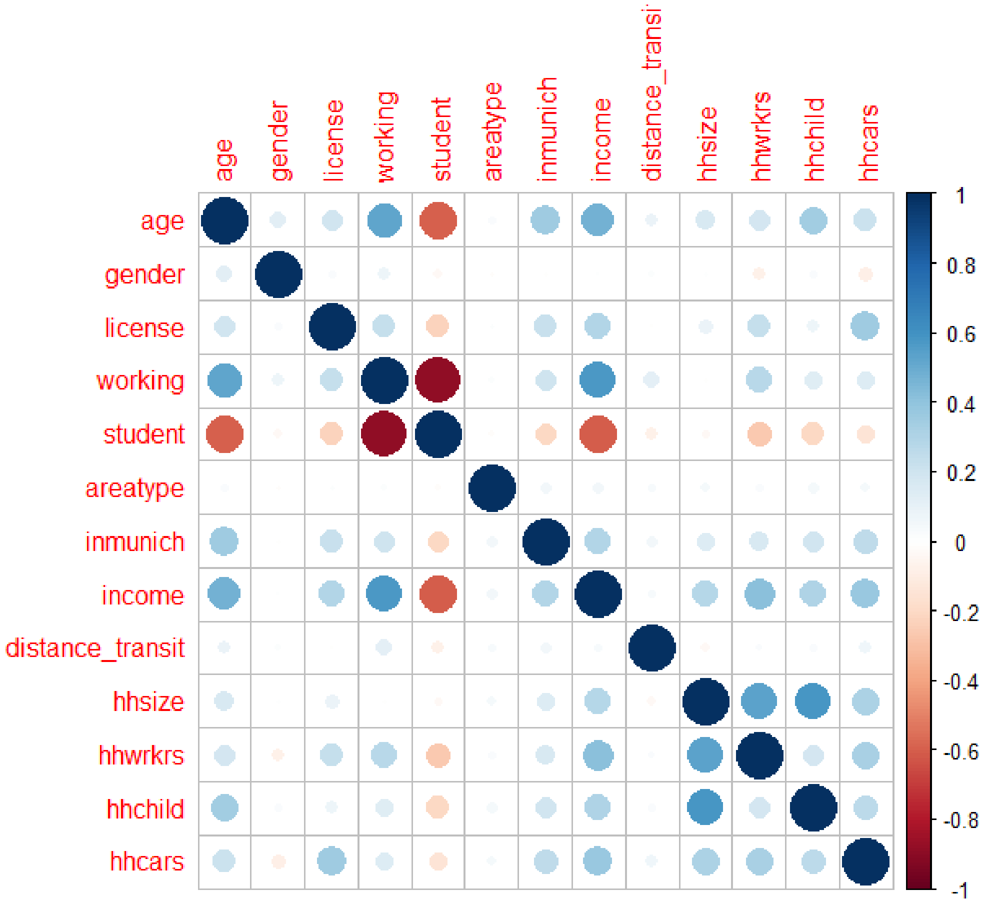


Figure 15: Correlation Matrix

7.2.4. Model Estimation using R package mlogit

The model is estimated using the package for multinomial logit models, mlogit or gmnl, developed by (Yves Croissant, 2015). The package allows the implementation of maximum likelihood method for the estimation of multinomial logit models with random coefficients.

7.2.5. Data format

The package accepts data in two different formats. "long" format presents the dataset with one row for each alternative while "wide" format presents the dataset with one row for each choice. I have used the "wide" format as it is easier to read and implement, so there will be nine rows for each individual (three choices for each of the three scenarios).

7.2.6. Model function

The gmnl function accepts a formula and a dataset. The function then outputs the estimated coefficients and statistical measure of each estimated coefficient and of the whole model. A full model was created for each of the purposes HBW and HBO. A restricted model was then created after removing the insignificant variables (general to specific approach in models building). In the process of building a working reasonable model, different variable combinations were tested one by one. Figure 16 and Figure 17 present the model developed for HBW and HBO, respectively.

HBW

```
Call:
gmnl(formula = choice ~ cost:IncomeClasses | ttime + AgeClasses +
    distance_transit + hhsize + hhcars, data = data_table, weights = data_table$weights,
    method = "nr")

Frequencies of categories:

    auto      tnc  transit
0.168421 0.057544 0.774035

The estimation took: 0h:0m:8s

Coefficients:
                            Estimate  Std. Error  z-value  Pr(>|z|)
tnc:(intercept)          -1.4212e+01  3.5249e+02  -0.0403  0.967839
transit:(intercept)       1.3427e-01  1.7060e+04   0.0000  0.999994
cost:IncomeClasses€1500  -2.9613e-01  1.6352e-01  -1.8110  0.070144 .
cost:IncomeClasses€3000  -2.1509e-01  1.3541e-01  -1.5884  0.112194
cost:IncomeClasses€6000  -1.5231e-01  1.3728e-01  -1.1095  0.267231
tnc:ttime                -2.1903e-02  1.2213e-01  -0.1793  0.857669
transit:ttime             1.8768e-02  3.9674e+02   0.0000  0.999962
tnc:AgeClasses18-24       1.3679e+01  3.5246e+02   0.0388  0.969041
transit:AgeClasses18-24  -1.2071e+00  4.2336e-01  -2.8512  0.004355 **
tnc:AgeClasses25-29       1.4589e+01  3.5246e+02   0.0414  0.966983
transit:AgeClasses25-29  -1.0279e+00  3.3197e-01  -3.0965  0.001958 **
tnc:AgeClasses29-39       1.4560e+01  3.5246e+02   0.0413  0.967049
transit:AgeClasses29-39  -1.0945e+00  2.3591e-01  -4.6397 3.489e-06 ***
tnc:AgeClasses40-49       1.4050e+01  3.5246e+02   0.0399  0.968202
transit:AgeClasses40-49  -9.7192e-01  2.2084e-01  -4.4010 1.078e-05 ***
tnc:distance_transit      9.3088e-03  3.3270e-02   0.2798  0.779634
transit:distance_transit -1.1732e-01  4.2258e-02  -2.7762  0.005500 **
tnc:hhsize                2.2769e-01  2.4639e-01   0.9241  0.355426
transit:hhsize            1.1295e+00  1.1064e-01  10.2089 < 2.2e-16 ***
tnc:hhcars               -1.2903e+00  3.0793e-01  -4.1901 2.788e-05 ***
transit:hhcars           -1.9085e+00  1.4850e-01 -12.8514 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Optimization of log-likelihood by Newton-Raphson maximisation
Log Likelihood: -632.55
Number of observations: 1425
Number of iterations: 17
Exit of MLE: successive function values within tolerance limit>
```

Figure 16: Estimated coefficients and model information for HBW

HBO

```
Call:
gmnl(formula = choice ~ cost:IncomeClasses | ttime + AgeClasses +
    hhsize + hhcars + Area, data = data_table, weights = data_table$weights,
    method = "nr")

Frequencies of categories:

    auto      tnc  transit
0.263333 0.084667 0.652000

The estimation took: 0h:0m:6s

Coefficients:
                           Estimate  Std. Error  z-value  Pr(>|z|)
tnc:(intercept)         -1.1946e+01  3.1500e+02  -0.0379 0.9697492
transit:(intercept)      2.4231e-02  1.4533e+04   0.0000 0.9999987
cost:IncomeClasses€1500 -5.0682e-01  1.2956e-01  -3.9120 9.154e-05 ***
cost:IncomeClasses€3000 -2.3158e-01  9.4797e-02  -2.4428 0.0145718 *
cost:IncomeClasses€6000 -4.9275e-01  1.0051e-01  -4.9024 9.470e-07 ***
tnc:ttime               -1.0695e-01  8.7459e-02  -1.2229 0.2213665
transit:ttime            4.8387e-02  3.3797e+02   0.0001 0.9998858
tnc:AgeClasses18-39      1.5920e+01  3.1498e+02   0.0505 0.9596895
transit:AgeClasses18-39  2.1635e-01  1.6499e-01   1.3113 0.1897546
tnc:AgeClasses40-49      1.5814e+01  3.1498e+02   0.0502 0.9599576
transit:AgeClasses40-49 -5.7752e-01  1.8055e-01  -3.1986 0.0013808 **
tnc:hhsize               4.8145e-01  1.3236e-01   3.6375 0.0002753 ***
transit:hhsize           8.0415e-01  7.2047e-02  11.1615 < 2.2e-16 ***
tnc:hhcars              -1.2589e+00  2.1767e-01  -5.7837 7.306e-09 ***
transit:hhcars          -2.3546e+00  1.4099e-01 -16.7006 < 2.2e-16 ***
tnc:Areasuburban        -1.4247e+00  1.0645e+00  -1.3384 0.1807754
transit:Areasuburban    -2.7747e+00  3.6890e-01  -7.5213 5.418e-14 ***
tnc:Areaurban           -9.4551e-01  1.0438e+00  -0.9058 0.3650268
transit:Areaurban       -3.2859e+00  3.6144e-01  -9.0912 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Optimization of log-likelihood by Newton-Raphson maximisation
Log Likelihood: -925.79
Number of observations: 1500
Number of iterations: 17
Exit of MLE: successive function values within tolerance limit>
```

Figure 17: Estimated coefficients and model information for HBO

Table 10 presents the log-likelihood and Mcfadeen's R^2 for the MNL model done for HBW and HBO trips.

	HBW	**HBO**
Log-likelihood	-632.55	-925.79
Mcfadeen R^2	0.29	0.22

Table 10: Model fit test, by trip purpose

The indexes of Mcfadden R^2 is used to test to fitness of the model or in other words the explainable degree of the model on the differences of the added variables. The higher the index, the better the model fitness. Values of 0.29 and 0.22, indicates that independent variables explain 29% and 22% of the differences of the explained variables. Although the indexes are not very high, they are acceptable.

In the process of developing the MNL models, few tests were done to assess the reasonableness and accuracy of the estimations. The signs of the coefficients were of costs for all income groups was negative implying that the utility of mode will decreases as its cost increases. The sign of the coefficients for time with respect to TNC is also negative implying that the utility of TNC will decrease as the mode becomes slower or its time increases. However, the time coefficient for transit wasn't negative but also very insignificant. This can be explained by the fact that the attribute levels across scenarios are only changing for TNC while remaining the same for car and transit.

In the restricted HBW model, the coefficient of cost with respect to the different income groups didn't seem to have a significance on the choices (confidence level < 95%). This low significance was also obvious with the travel time for TNC. This can be due to the low share of respondents that selected TNC choice (varying attribute levels) among the other choices (consistent attribute levels). This suggests that the effect of income groups on the utilities of TNC may not differentiate them from the reference mode (car). An alternative could be to combine two income groups together, but for since my goal is to obtain the VOT for each income group it was decided to retain them as such. While the significance of the used coefficients is low, rather than discarding them, it can be interpreted that the used variables provide little information towards the stated mode.

On the other hand, the restricted HBO model had significant (confidence level > 95%) for the coefficients of cost but low significance for time using TNC. This can be due to the higher share of respondents selecting TNC for destinations other than work, which are more influenced by the cost changes rather than the changes in time.

Demographic Attributes

For HBW, the relationship between all the age groups, distance to the nearest transit station and household size and the propensity to use TNC services had non-significant coefficients and thus are equal at the base level. Non-significant coefficients were still included in the model because they were significant in other modes. The number of household cars and the interest to use TNC have quite a high significance, households with more cars are less likely to use carsharing services.

For HBO, the relationship between all the age groups and area types and the propensity to use TNC services are also equal at the base level because they had non-significant coefficients. The availability of a higher number of household cars had a similar relationship to HBW where households owning more cars are less likely to choose TNC services. Higher household sizes also had a significant effect on choosing TNC with bigger household sizes having higher interest in the service.

Additionally, when the attributes of gender, employment, studying, household children, household workers and living period in Munich were tested and their insignificance was obvious as is also shown in the full model results, they did not allow for inferences about how they influence TNC services.

It is critical to understand that misinterpretations and unexpected outcomes from such a model can be due to many factors, one of which is the nature of the hypothetical scenarios presented in the stated choice experiment. The scenarios presented might have been relevant to some respondents while being irrelevant to others, meaning that some respondents might have ignored to evaluate the different scenarios independently from each other. Some attributes might not have received the attention as they should to simplify the choice task, and if time and cost are of high significance, it could be that other attributes are not well represented (Baxter & Brumfitt, 2008). The consideration of the different time attributes might have also been ignored by some where choices might have been made based on travel time only rather than the total travel time. This is commonly referred to as attribute exclusion. Examining the comments received by some respondents shed the light on the fact that misunderstandings to the questions questioned was common. Few examples are presented below:

1. *"I would like to add that there are a couple different factors which also would affect the decision of taking a care share vs. Using transport ... for example, if I would personally be driving the car share or be a passenger ... sometimes I need to read/do something in the time of transport which would prevent me from driving ... other times I want to drive for the pleasure of driving .... which also brings up the question of if the route is within the city or on the autobahn?"*
2. *"I am self employed and work in Augsburg 2 days a week, so my answers are a bit weird. I use my car for one day and the train for the other (due to arrival destinations). In and around Munich I bike, walk, or ubahn. I live downtown and so travel by car within the city is not convenient due to traffic/parking/indirect-streets."*
3. *"I would like to use a Private car, but politcs and salary won't let this transportation mode become usefull to everybody."*
4. *"When I'm in a big hurry and the destination is reached much faster by car sharing than public transport and it's not too far away, then I switch to car sharing."*

The comments reflect the difficulty for some respondents to match the scenarios to their actual daily commutes and include other factors that are not related to the choice selection. In the survey the question before each scenario starts with "Imagine the following modes of transportation are available from your…" which means that the scenarios are relative to their usual commute in the cases of HBW or HBO which means that consideration should be taken for the traffic situations during the choice selection.

Referencing to the hypothesis mentioned earlier in section 4 and the analysis in this section, Hypothesis 1, 3, 4, 5, 6 and 7 can be retained while Hypothesis 2 can be rejected since time was not a significant coefficient in the model.

7.2.7. Value of Time

As mentioned earlier, one of the goals from the development of the multinomial logit model is to calculate the VOT of different income groups using TNC. The coefficient of cost was calculated separately for each income group and the time coefficient was calculated separately for each mode. VOT was calculated using both coefficients and the following formula (Antoniou & Matsoukis & Roussi, 2007):

$$Value\ of\ time\ (VOT) = \frac{\beta time}{\beta cost} * 60\ (\frac{€}{\mathrm{hr}})$$

Table 11 presents the results for the estimated VOT across income groups for HBW and HBO trips.

INCOME GROUP	HBW	HBO
<1500€	4.44	12.66
1500€ - 5600€	6.11	27.71
>5600€	8.63	13.02

Table 11: Income groups VOT for TNC by trip purpose

Generally, HBW trips should have higher VOT in comparison to HBO other, since time is more of a critical factor and people would be willing to pay higher to decrease their trip time. This however was not the case in my model because the only attributes changing across my scenarios was for the TNC mode and the higher share of TNC in HBO compared to HBW trips reflects the willingness to use and pay more for TNC when trips performed are other than work. The higher willingness to use TNCs for other trips supports the findings of (Murphy & Felgon, 2016; TTS, 2016)

Various factors can influence the VOT, one of which is higher income groups leads to higher VOT as reported by (Wardman & Chintakayala, 2012) in their study of values of travel time in Europe. This is reflected in the VOT calculated using my model for HBW. For HBO VOT shows no clear trend across income groups and the higher income group of ">5600€" seems to have a lower VOT compared to "1500€ - 5600€" which can be explained by the variations in income group segments reported in section 7.1.1. The VOT for carsharing services can vary across different regions as reported by other studies presented in Table 12.

Author	Study Area	Methodology	VOT ($/hr)
(Small, Winston and Yan, 2005)	Los Angeles, United States	Revealed and Stated preference surveys	21.46
(Hensher, Greene and Li, 2011)	Brisbane, Australia	Stated preference surveys	17.71
(Dixit et al., 2014)	Sydney, Australia	Revealed preference surveys	12.15
(Devarasetty, Burris and Shaw, 2012)	Houston, United States	Stated preference surveys	22.00

Table 12: Value of travel time savings from other studies

The VOT for various modes, purposes and income groups used in the base Munich model is presented in Table 13. For HBW, the VOT for TNC is slightly lower than Auto driver which is quite reasonable since the task of driving is removed, TNCs are perceived as less tedious than driving. For HBO, the VOT for the income groups is much higher than any other mode for HBO trips. In other words, users of other modes are likely to switch to TNC. The higher willingness to use TNCs in comparison to transit supports the findings of (Mahmoudifard & Shabanpour & Kermanshah, 2017) which reports reasons such as affordability, convenience, availability, reliability and fast service influenced the switch of users from other modes to TNCs.

Income Group	Auto Driver		Auto Passenger		Transit	
	HBW	HBO	HBW	HBO	HBW	HBO
<1500€	4.63	4.44	7.01	4.30	8.94	5.06
1500€ - 5600€	8.94	6.11	13.56	8.31	17.30	9.78
>5600€	12.15	8.63	18.43	11.30	23.50	13.29

Table 13: Base model VOT for various modes by trip purpose

7.3. Modal Split

This section presents the modal split on the base scenario without TNCs and the other scenarios with TNCs, by trip purpose. Data from the MiD 2011 was used for the calibration of the mode splits. The modal split for the scenarios with TNC was calculated using the incremental logit approach explained earlier. The results are presented in Table 14.

Mode	HBW		HBE		HBS		HBO	
	Without TNC	With TNC	Without TNC	With TNC	Without TNC	With TNC	Without TNC	With TNC
Auto Driver	65.37	58.63	9.10	8.59	46.63	38.54	35.36	30.43
Auto Passenger	8.34	8.10	22.52	20.90	23.44	21.3	23.39	21.6
Bicycle	11.28	10.96	22.02	22.07	13.85	13.70	13.02	13.15
Bus	3.32	2.93	10.95	9.75	2.13	1.75	1.39	1.27
Train	3.92	3.29	3.78	3.57	1.04	1.00	1.16	1.05
Tram or Metro	5.41	3.8	1.58	1.49	1.55	1.31	1.98	1.61
Walk	2.36	2.31	30.04	30.08	11.36	11.19	23.68	23.49
TNC	-	9.98	-	3.55	-	11.19	-	7.35

Table 14: Summary of base and revised modal splits by trip purpose

Figure 18 provides a visual of the modal split changes. For HBW, more than half of the trips are performed by auto, while 15% are made by non-motorized modes. For HBS and HBO, around 40% of the trips were performed by auto. Walking was mostly used in HBE trips (30%) compared to any other purpose. With the introduction of TNCs, their shares were higher in HBS and HBO, compared to HBW and HBE, as expected. In all trip purposes the share of TNCs on auto mode is 19%.

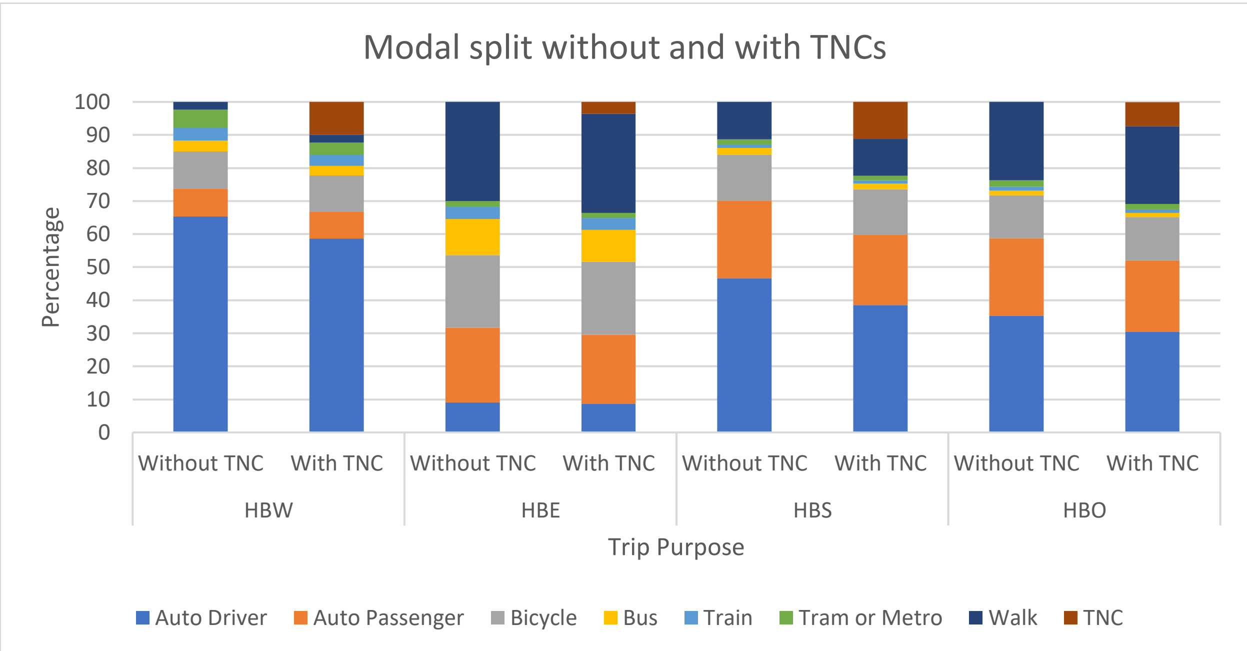


Figure 18: Modal splits without and with TNC

7.4. Simulation

The network for the entire study is downloaded from Open Street Map, visualized in Figure 19. It contains 499,435 links and 212,772 nodes. The total number of agents were scaled to 2% and 25 iterations were performed to complete the simulation within reasonable time.

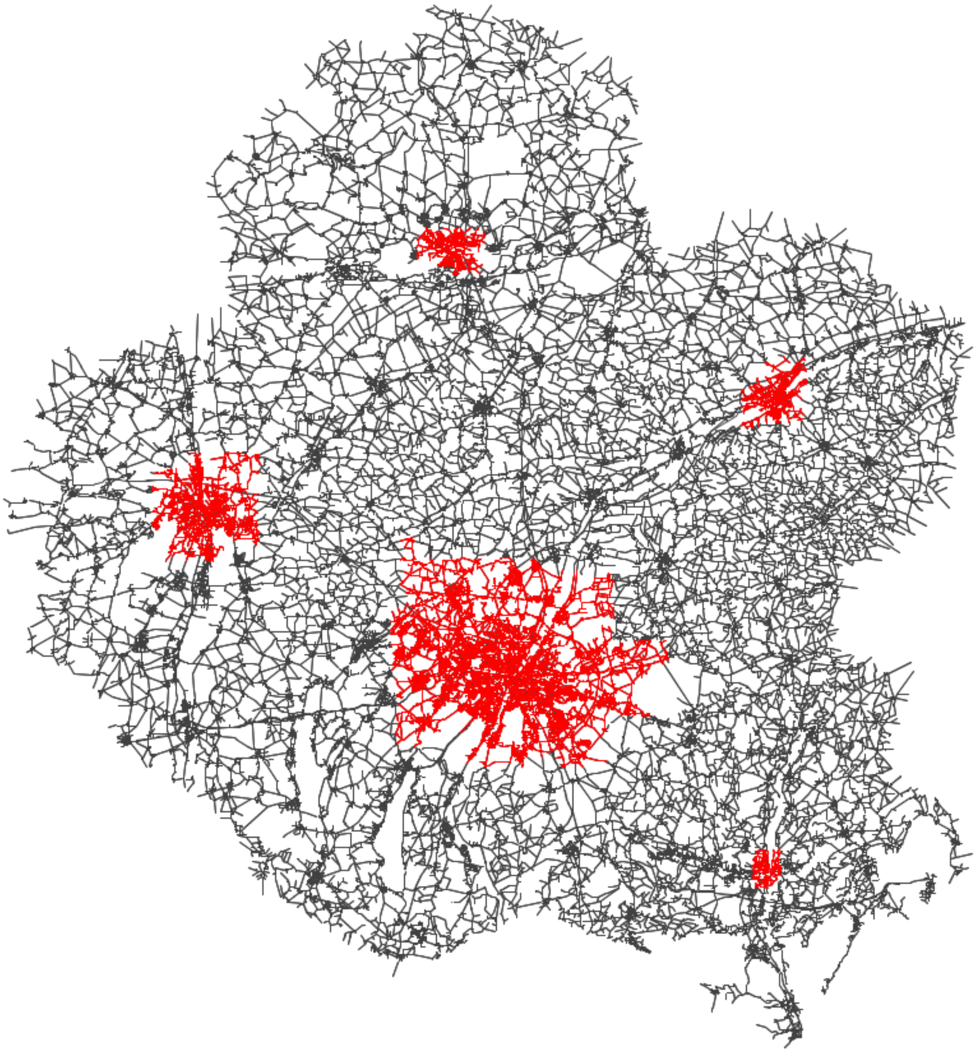


Figure 19: Study Area nodes and links with red-marked core cities

To generate the TNC trips and vehicles in the simulated scenarios, MATSim executes the following:

- If the trip origin and destination is within the inside area (core cities), TNC mode shares are considered. All other trips outside the area consider base mode shares that don't include TNC.
- TNC vehicles in each scenario are distributed randomly in each of the five core cities networks in proportion to their respective population. Distribution occurs on links that allow the car mode.

7.4.1. Case study

The MATSim simulation is run for the full study area presented in section 6.1 and is based in the modal splits in section 7.3 with consideration of the inside and outside areas as described in section 7.4. A total of three scenarios are simulated as presented in Table 15 to analyze the impacts of different TNC fleet sizes with 2 seats per vehicle. Penetration rate represents the share of trips performed by TNC within the full study area.

<table>
<tr><th>Scenario</th><th>TNCs</th><th>Penetration rate</th><th>PCV trips</th><th>TNC trips</th></tr>
<tr><td>0-base</td><td>0</td><td>0</td><td>70,386</td><td>0</td></tr>
<tr><td>1</td><td>2,500</td><td rowspan="2">6.36%</td><td rowspan="2">59,319</td><td rowspan="2">11,067</td></tr>
<tr><td>2</td><td>10,000</td></tr>
</table>

Table 15: Simulated scenarios (scaled at 2%)

In the scenario analyses, I will focus on core cities and links with higher capacity (3000-8000 veh/hr) since they have higher volumes compared to smaller capacity links.

7.4.2. Scenario 0

Base scenarios using 0 TNC vehicles, with base modal split.

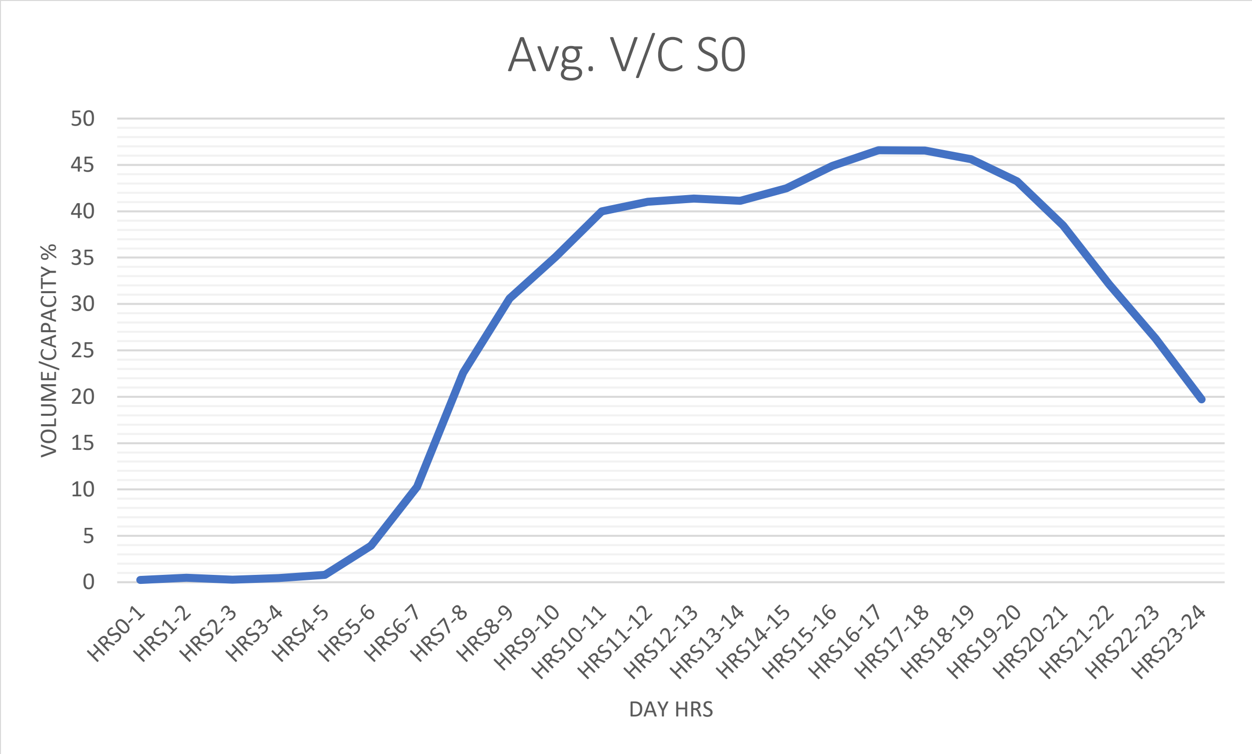


Figure 20: Volume to Capacity percentage on high capacity links (3000-8000) for Scenario 0

The volume to capacity in Figure 20 shows a peak of 46.56% during Hrs. 17-18, on links with capacities 3000-8000 veh/hr in the core cities.

7.4.3. Scenario 1

Scenario 1 simulated using 2500 TNC vehicles in the core cities, with TNC modal split.

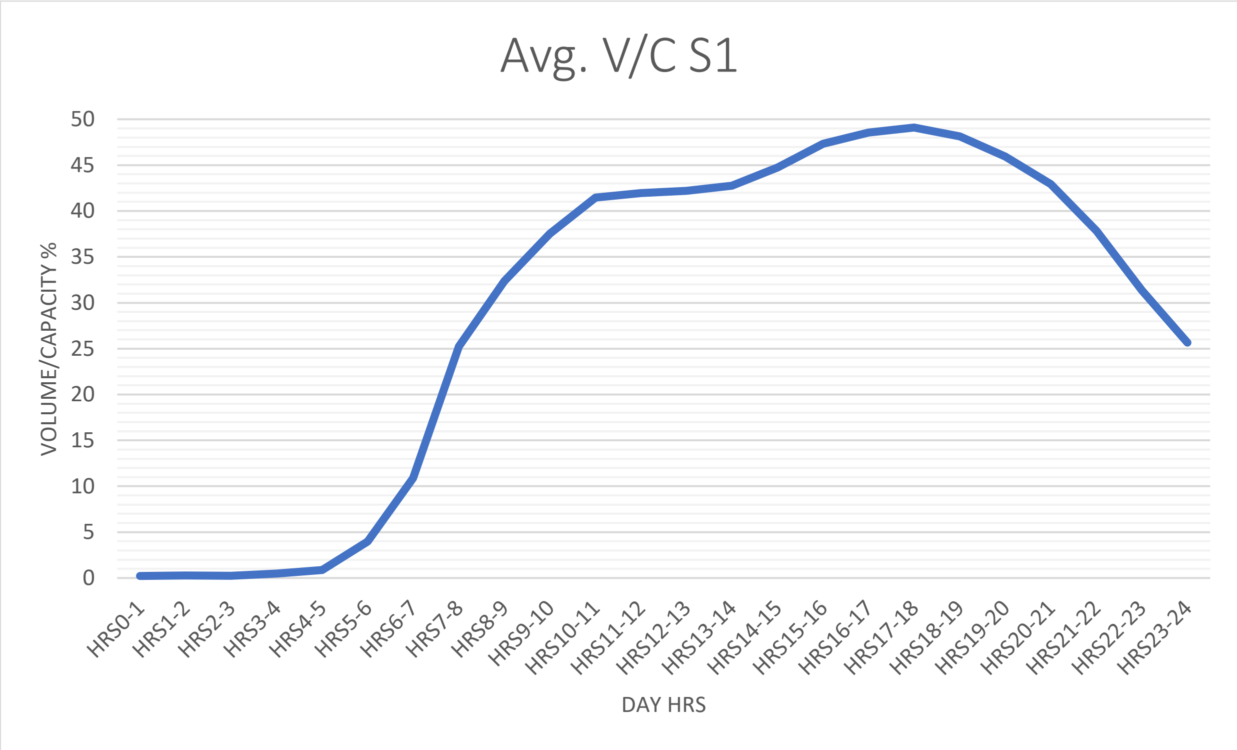


Figure 21: Volume to Capacity percentage on high capacity links (3000-8000) for Scenario 1

The volume to capacity in Figure 21 shows a peak of 49.00% during Hrs. 17-18, on links with capacities 3000-8000 veh/hr in the core cities.

The average trip duration and average waiting times performed by TNCs is presented in Table 16.

Scenario 1	Average TNC trip duration (in-vehicle) [min]	53
	Average passenger waiting time [min]	15

Table 16: Level of service for Scenario 1

Figure 22 reveals the number of TNC vehicles used at different activities during the day. Vehicles are busy handling requests for up to 50% of the time. The highest use of TNC vehicles (occupied drive) occurs during peak time with around 90% of the fleet busy driving passengers.

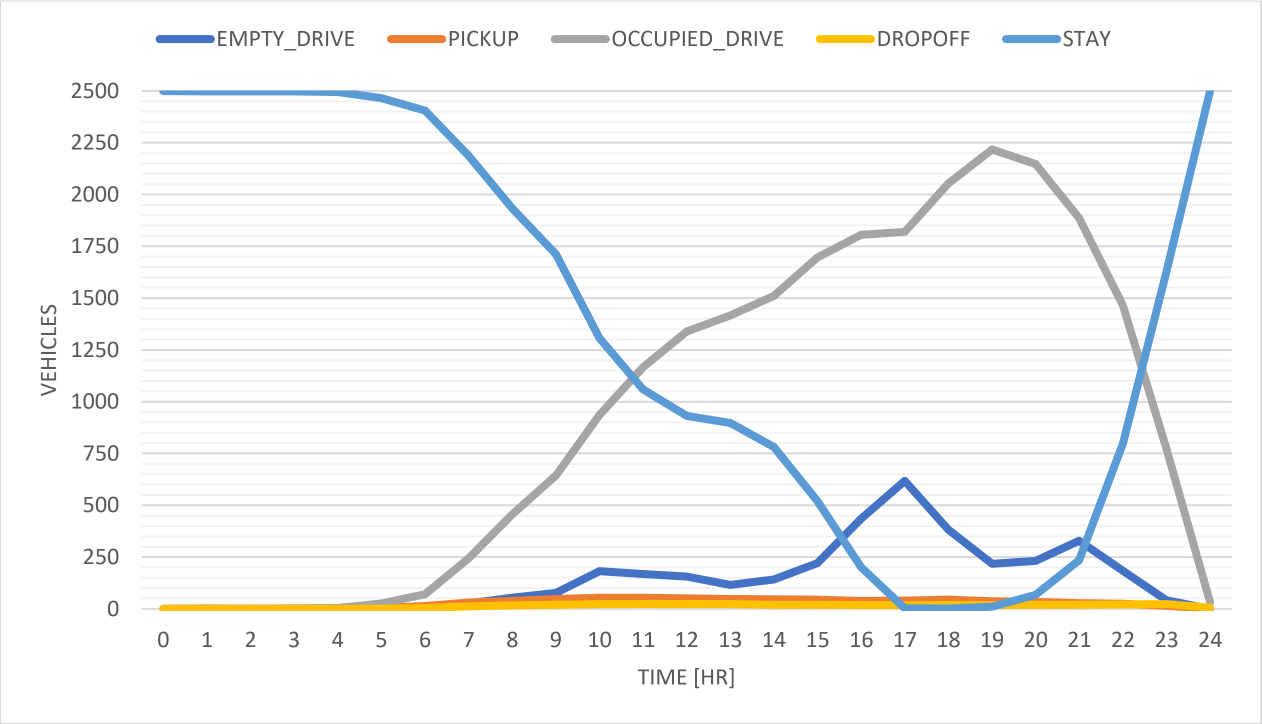


Figure 22: TNC vehicles activity status for Scenario 1

7.4.4. Scenario 2

Scenario 2 simulated using 10,000 TNC vehicles in the core cities, with TNC modal split.

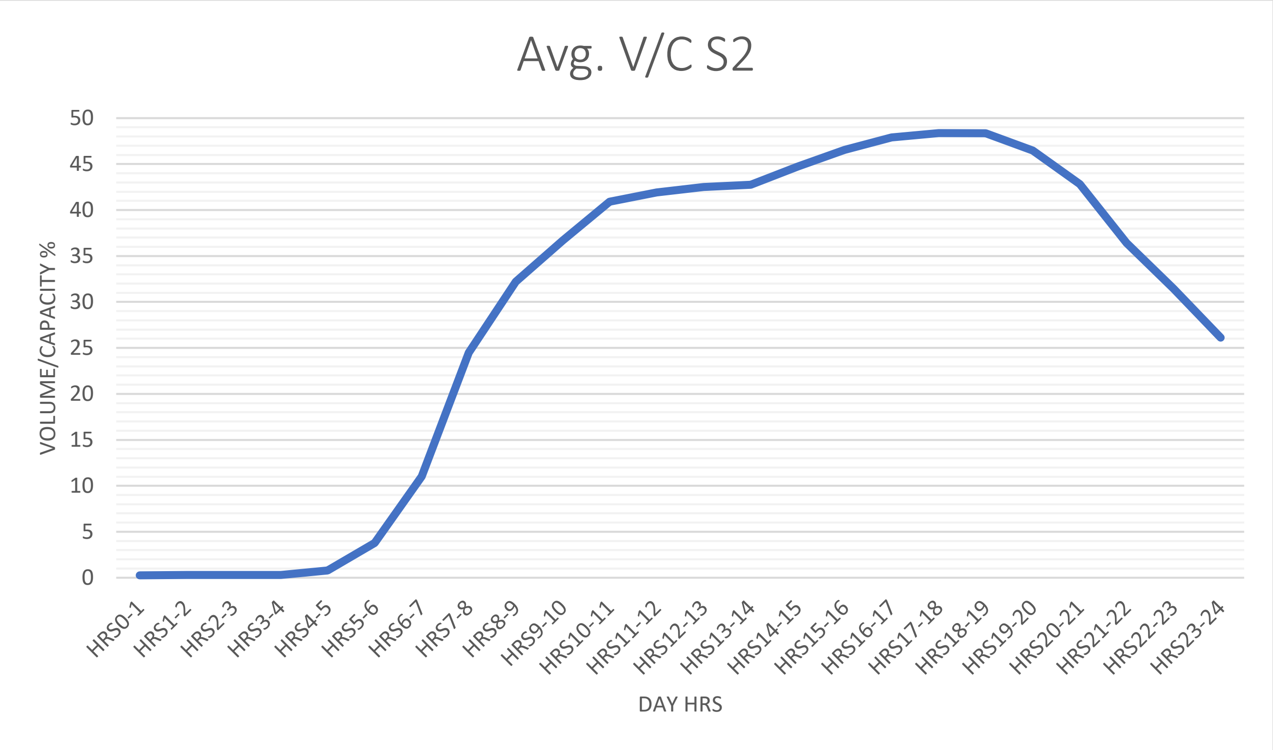


Figure 23: Volume to Capacity percentage on high capacity links (3000-8000) for Scenario 2

The volume to capacity in Figure 23 shows a peak of 48.37% during Hrs. 17-18, on links with capacities 3000-8000 veh/hr in the core cities.

The average trip duration and average waiting times performed by TNCs is presented in Table 17.

Scenario 2	Average TNC trip duration (in-vehicle) [min]	53
	Average passenger waiting time [min]	4.7

Table 17: Level of service for Scenario 2

Figure 24 reveals the number of TNC vehicles used at different activities during the day. Vehicles are busy handling requests for up to 15% of the time. The highest use of TNC vehicles (occupied drive) occurs during peak time with around 20% of the fleet busy driving passengers.

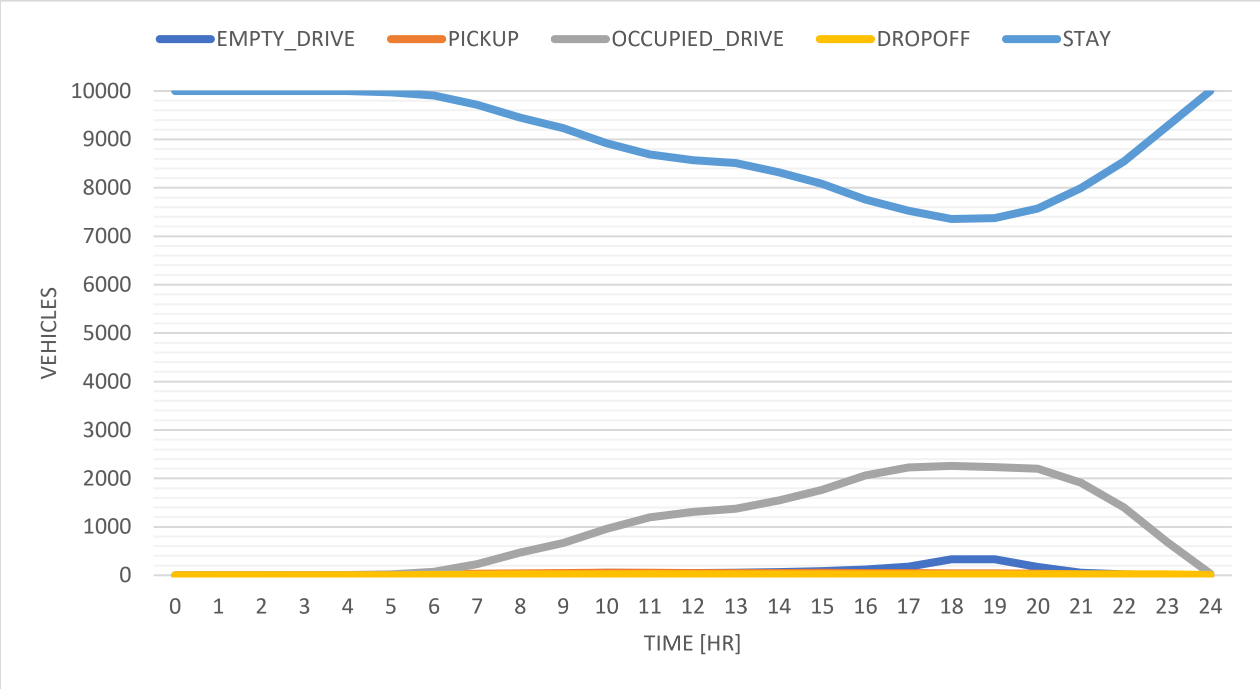


Figure 24: TNC vehicles activity status for scenario 2

7.4.5. Interpretation of results

The introduction of TNC vehicles in the Munich Metropolitan area, slightly influenced the volume to capacity ratios as shown in Figure 25. Compared to the base scenario, the V/C changes during peak time across scenario 1 and scenario 2 was +2.44% and +1.81% respectively.

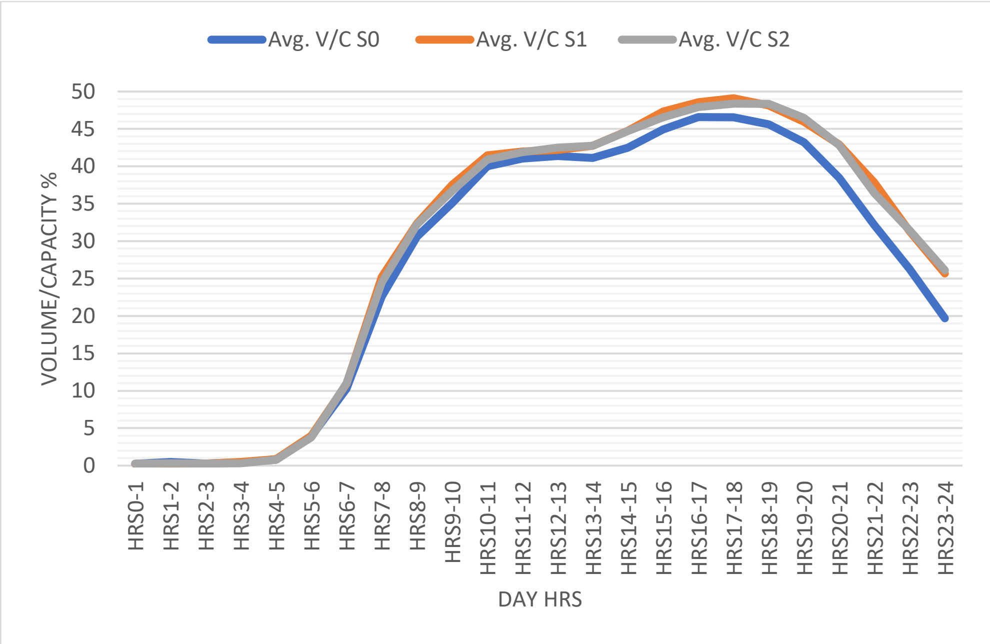


Figure 25: Volume to Capacity percentages on high capacity links (3000-8000) by scenario

To understand the percentage of links at various volume/capacity % during peak times, a cumulative distribution function was used as presented in Figure 26. As expected, scenario 0 is least congested at different V/C percentages followed by scenario 1 and scenario 2.

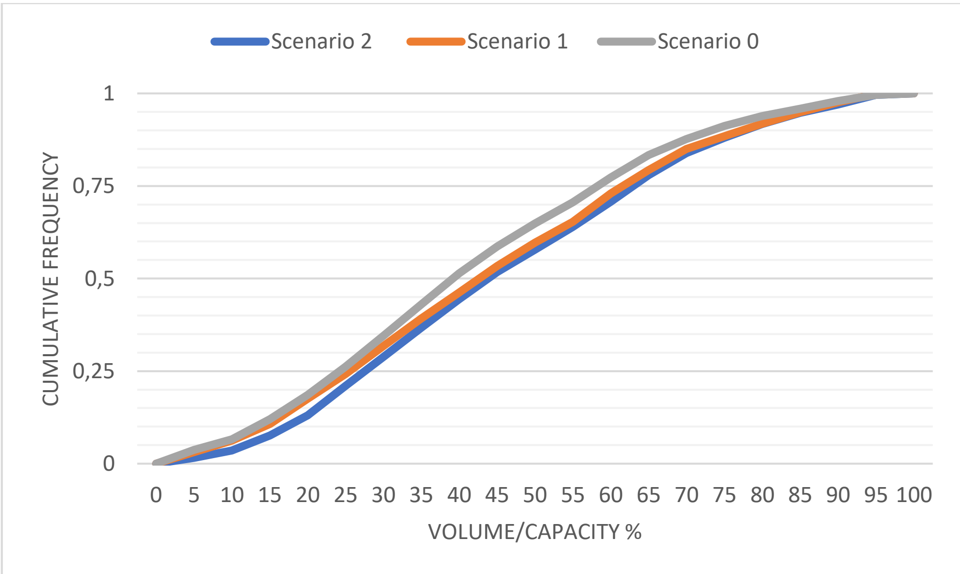


Figure 26: Volume to capacity (percentage) cumulative distribution during peak time (Hrs. 17-18) by scenario

An improved level of service can be observed across scenarios in Figure 27. While the average trip duration remains the same at 53 minutes, the average waiting time was reduced by around 65%, with the addition of 7,500 TNC vehicles from scenario 1 to scenario 2.

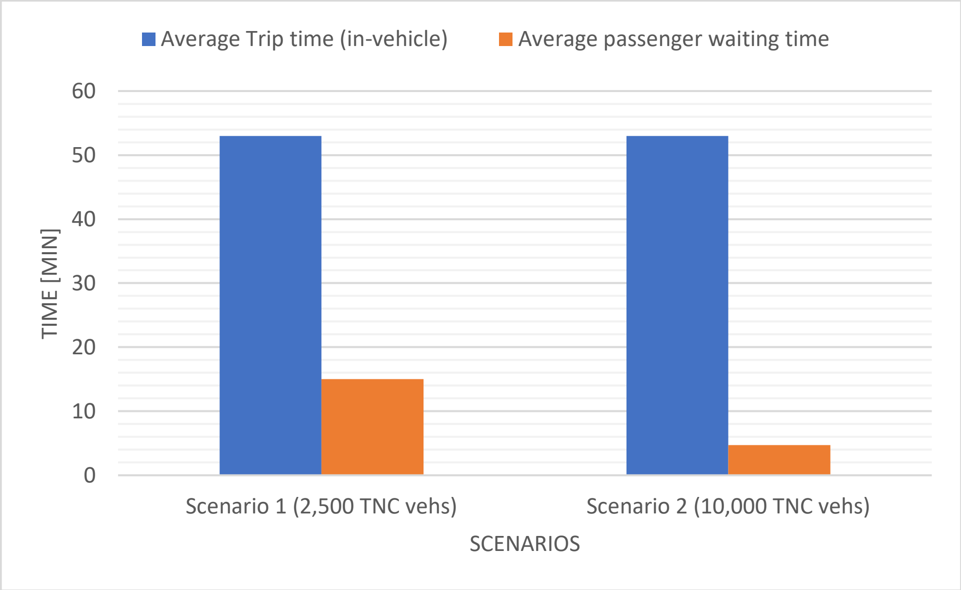


Figure 27: Average TNC Trip and waiting time by scenario

To understand the percentage of passengers served within a particular waiting time, the cumulative distribution function was used as presented in Figure 28. Around 70% of passengers are served within 10 minutes in scenario 1, while around 85% of passengers are served within 5 minutes in scenario 2.

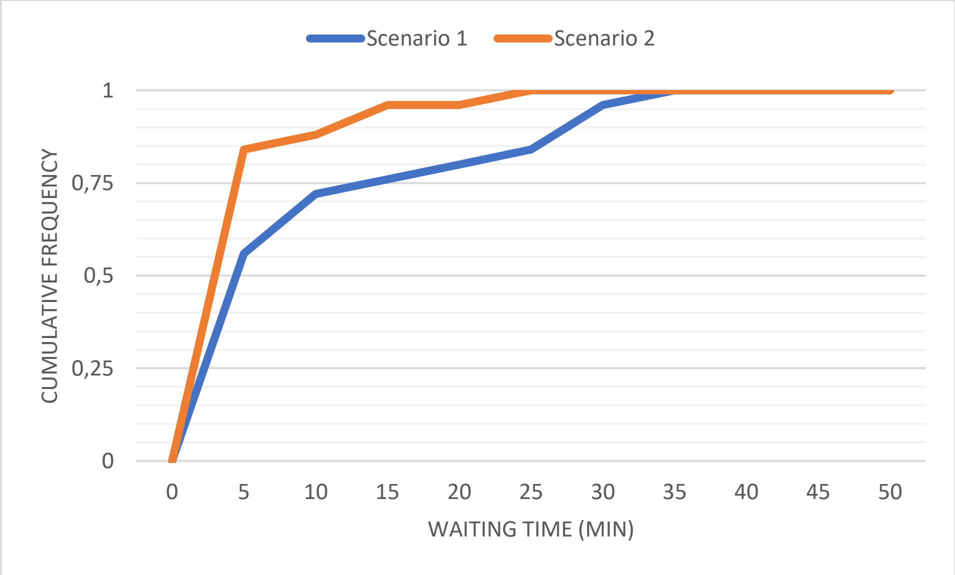


Figure 28: Average passenger waiting time cumulative distribution by scenario

8. Conclusions

The rapid growth and expansion of TNCs with widespread claims about their benefits to other transportation modes, despite the lack of open data and limited research available on the topic, stresses the importance of innovative research methodologies to gather well representative data. Using Munich Metropolitan Region in Germany as a case study, this project predicts the impact of TNCs on urban mobility based on the user's willingness to pay for such services.

In working towards the main objective, an online survey was designed and made available for the study for two weeks, from mid-March 2019. Survey flyers were also distributed in the city center of Munich and 500 valid responses were collected and weighted to well represent the population in the study area. A MNL model was developed to interpret the survey statistics which were used to estimate the VOT to use TNCs. The results based on the study area suggest that market penetration for TNC services may be higher among users with the following characteristics:

- Trips for purposes other than work or education, such as: shopping and social activities.
- Living in households with few or zero number of cars.
- Living in large household sizes.

These findings agree with the findings reported in (TCRP 195, 2018). Despite the potential bias in responses, the results provided a preliminary understanding of the willingness to use TNC services and the preferences of other similar transportation modes. The understanding of the subjective perception of respondents through the survey helped make the estimated mode shares with the incremental logit calculation and the transportation modelling in MATSim less arbitrary when TNCs are analyzed. The simulation of two different scenarios reveals an insignificant change for congestions in core cities, where TNCs were provided, since TNCs work best in core urban areas. While the level of service was improved with a higher fleet size, a smaller fleet size was more efficient in satisfying demand when comparing the number of stay vehicles, which may also affect the supplier's willingness to offer the service.

8.1. Limitations and Recommendations

The section presents the current limitations and recommendations concerning the methodology of the research and several assumptions that have been made to simplify the model.

In the designing of the survey, the choice scenarios were based on an 8 km trip which is assumed to be uncomfortable for performing with other modes that were not included such as bicycle and walking. The use of a one trip example and disregard of the respondents usual travelling distance and time influences the choice of the respondent because the designed survey trip might be preferred with a certain mode while in another trip example, a different mode might be preferred. To mitigate such a limitation, the scope of the experiment can be lengthened by including more scenarios with different distances and times. A "pivot design" can also be helpful, where the survey is tailored for each respondent and the attributes are rotated around based on their most recent real-world commute as a starting point for the hypothetical scenarios. Another survey responses limitation is the hypothetical nature of the scenarios where respondents have a different understanding of the displayed questions. Although, attempts to define TNCs were made and questions were presented as imaginative scenarios, comments from few respondents reflected misunderstandings. Further attempts can be made to ensure a common understanding of the questionnaire scenarios.

Despite the high correlation output from IPF in weighing the surveyed sample to the population across the socio-demographic attributes using IPF, high weights for certain under represented individuals were adopted which can distort other results. To mitigate this, an even wider and diverse sample should be used.

The MNL model and analysis of the statistical data is a complex process. Calculation of willingness to use or VOT of TNC was only based on the MNL coefficient estimations of time and cost only, assuming that respondents consider other factors such as comfort, safety or reliability. Nevertheless, further advanced models can be developed since MNL is a first step (Hensher et al., 2015).

The approach for the calculation of the revised modal splits using an incremental logit model considered only the influence of TNCs on all transportation modes available. Further attempts to calculate the revised modal split using different approaches can be performed.

The results reflecting the impact of TNCs simulated using MATSim assumes that the demand for such a service is only coming from other transportation mode users. Meaning that induced demand was not taken into consideration which can influence the number of trips when a reduction in time or cost happens through the new mode (Kitamura, Fujii and Pas, 1997). The impacts of TNCs in this project were studied through measures of modal split, quality of traffic flow and level of service. To present a wider spectrum of results, VMT and vehicle deadheading miles can be analyzed. Due to the restriction of the hardware capacities and time, simulation was performed for three scenarios with changes to TNC fleet size only, at a 2% sample and 25 iterations. Additional scenarios with varying fleet size, vehicle capacity and higher number of iterations at a larger sample size can be developed for more robust results.

8.2. Future work

Further studies can be performed to simulate changes in the supply or demand side. From the supply side, changes in prices or surge pricing of TNCs during different times can be tested. Pickup and drop-off of passengers can be changed from door-to-door to zone-to-zone or certain stops. From the demand side, the modelling of choices between single occupancy TNC vehicle and multiple-occupancy (pooled ride) can also be explored.

9. References

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., & Rus, D. (2017). *On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment* (Vol. 114).

Antoniou, C., Matsoukis, E., & Roussi, P. (2007). *A Methodology for the Estimation of Value-of-Time Using State-of-the-Art Econometric Models* (Vol. 10).

Axhausen, K. W., & Polak, J. W. (1991). Choice of parking: Stated preference approach. *Transportation, 18*(1), 59-81. Retrieved from https://doi.org/10.1007/BF00150559. doi:10.1007/BF00150559

Baxter, S. K., & Brumfitt, S. M. (2008). Professional differences in interprofessional working. *J Interprof Care, 22*(3), 239-251. doi:10.1080/13561820802054655

Ben-Akiva, M. E., & Lerman, S. R. (1985). Discrete choice analysis: theory and application to travel demand. The MIT Press, Cambridge, Massachusetts.

Birkin, M. (1987). Iterative Proportional Fitting (IPF): Theory, Method and Examples Computer Manual 26, School of Geography, University of Leeds.

Bischoff, J., Maciejewski, M., & Nagel, K. (2017, 16-19 Oct. 2017). *City-wide shared taxis: A simulation study in Berlin.* Paper presented at the 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC).

Bishop, Y., Fienberg, S., & Holland, P. (1975). Discrete Multivariate Analysis: Theory and Practice MIT Press; Cambridge, Massachusetts.

Brodeur, A. & Nield K. (2016). "Has uber made it easier to get a ride in the rain?" IZA Discussion Paper No. 9986. Retrieved from: https://ssrn.com/abstract=2797557

California Public Utilities Commision (2013) *Decision adopting rules and regulations to protect public safety while allowing new entrants to the transportation industry.* Retrieved from: http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M077/K112/77112285.PDF

CBIINSIGHTS (2019). *How Uber Makes - And Loses - Money.* Retrieved from: https://www.cbinsights.com/research/report/how-uber-makes-money/

ChoiceMetrics (2018). User Manual & Reference Guide: The Cutting Edge in Experimental Design. Retrieved from: http://www.choice-metrics.com/NgeneManual120.pdf

Clewlow, R. & Mishra G. (2017). *Disruptive transportation: the adoption, utilization, and impacts of ride-hailing in the United States.* University of California Davis.

Cramer, J., & Krueger, A. B. (2016). Disruptive Change in the Taxi Business: The Case of Uber. *American Economic Review, 106*(5), 177-182. Retrieved from http://www.aeaweb.org/articles?id=10.1257/aer.p20161002. doi:10.1257/aer.p20161002

Devarasetty, P. C., Burris, M., & Douglass Shaw, W. (2012). The value of travel time and reliability-evidence from a stated preference survey and actual usage. *Transportation Research Part A: Policy and Practice, 46*(8), 1227-1240. Retrieved from http://www.sciencedirect.com/science/article/pii/S0965856412000778. doi:https://doi.org/10.1016/j.tra.2012.05.002

Dixit, V., Trieu, J., Jian, S., & Li, X. (2014). *Vale of travel time savings for carshare users in sydney.* Paper presented at the AITPM 2014 National Conference.

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method (4th ed.). Wiley Publishing 2014.

Furnham, A. (1986). Response bias, social desirability and dissimulation. *Personality and Individual Differences, 7*(3), 385-400. Retrieved from http://www.sciencedirect.com/science/article/pii/0191886986900140. doi:https://doi.org/10.1016/0191-8869(86)90014-0

Gannes, L. (2012). *A status symbol moves down market: the context for Uber's lower-priced launch*. All Things D, p. 1, Retreived from: http://allthingsd.com/20120702/a-status-symbol-moves-down-market-whats-behind-the-uberx-launch/

Greene, W., Hensher, D., & Li, Z. (2011). *Embedding risk attitude and decision weights in non-linear logit to accommodate time variability in the value of expected travel time savings* (Vol. 45).

Guasch, A., Figueras i Jové, J., Fonseca i Casas, P., Montañola Sales, C., & Casanovas, J. (2014). *Simulation analysis of a dynamic ridesharing model* (Vol. 2015).
Hall, J. V., & Krueger, A. (2016). *An Analysis of the Labor Market for Uber's Driver-Partners in the United States*. Retrieved from https://EconPapers.repec.org/RePEc:nbr:nberwo:22843
Hall, J. V., & Krueger, A. B. (2017). An Analysis of the Labor Market for Uber's Driver-Partners in the United States. *ILR Review, 71*(3), 705-732. Retrieved from https://doi.org/10.1177/0019793917717222. doi:10.1177/0019793917717222
Harvey, R., and Y. Deshghani (1995). *Incremental Methods for Transit Ridership Forecasting and Traffic Impact Analysis*. Presented at 4th European EMME/2 Users Meeting, Brussels, Belgium.
Henao, A., & Marshall, W. E. (2018). The impact of ride-hailing on vehicle miles traveled. *Transportation*. Retrieved from https://doi.org/10.1007/s11116-018-9923-2. doi:10.1007/s11116-018-9923-2
Hensher, D. A., & Greene, W. H. (2003). The Mixed Logit model: The state of practice. *Transportation, 30*(2), 133-176. Retrieved from https://doi.org/10.1023/A:1022558715350. doi:10.1023/A:1022558715350
Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). Applied choice analysis. Applied Choice Analysis. https://doi.org/10.1007/9781316136232
Hussain, I., Knapen, L., Galland, S., Yasar, A.-U.-H., Bellemans, T., Janssens, D., & Wets, G. (2015). Agent-based Simulation Model for Long-term Carpooling: Effect of Activity Planning Constraints. *Procedia Computer Science, 52*, 412-419. Retrieved from http://www.sciencedirect.com/science/article/pii/S1877050915008066. doi:https://doi.org/10.1016/j.procs.2015.05.006
INRIX Global Traffic Scorecard (2018). Retrieved from: https://www.dmagazine.com/wp-content/uploads/2018/02/INRIX_2017_Traffic_Scorecard_Final_2.pdf
Iseki, H., B. D. Taylor, and M. Miller (2006). *The Effects of Out-of-Vehicle Time on Travel Behavior: Implications for Transit Transfers*. Division of Research and Innovation, California Department of Transportation, Sacramento.
Jawkins, A. (2018). *Uber's Self-Driving Cars Are Back on Public Roads, but Under Human Control*. The Verge. Retrieved from: https://www.theverge.com/2018/7/24/17607898/uber-self-driving-car-publicroads-driver-monitoring
Jiajian, X., Aydt, H., Lees, M., & Knoll, A. (2013, 6-9 Oct. 2013). *A partition based match making algorithm for taxi sharing.* Paper presented at the 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013).
Jiang, W., Lian, J., Shen, M., & Zhang, L. (2017, 16-19 Oct. 2017). *A multi-period analysis of taxi drivers' behaviors based on GPS trajectories.* Paper presented at the 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC).
Kauffman, F. (2018). *Who Was First? Uber or Lyft?.* Quora. Retreived from: https://www.quora.com/Who-was-firstUber-or-Lyft
Kay, W. A., Horni, A., & Nagel, K. (2016). *The Multi-Agent Transport Simulation MATSim*. PB - Ubiquity Press.
Kitamura, R., Fujii, S., & Pas, E. I. (1997). Time-use data, analysis and modeling: toward the next generation of transportation planning methodologies. *Transport Policy, 4*(4), 225-235. Retrieved from http://www.sciencedirect.com/science/article/pii/S0967070X97000188. doi:https://doi.org/10.1016/S0967-070X(97)00018-8
Koppelman, F. (1983). *Predicting Transit Ridership in Response to Transit Service Changes* (Vol. 109).
Landeshauptstadt Munchen (2010). Radverkehr in Munchen. Retrieved from: http://www.radlhauptstadt.muenchen.de/fileadmin/Redaktion/PDF/Radl_Brosch_2010.pdf
Lawler, R. (2014). *Lyft-Off: Zimride's Long Road To Overnight Success*. TechCrunch. Retrieved from: https://techcrunch.com/2014/08/29/6000-words-about-a-pinkmustache/
Lee, C. (2017). *Dynamics of Ride Sharing Competition*. ISEAS Economics Working Paper No. 2017-05

Li, Z., Hensher, D. A., & Rose, J. M. (2010). Willingness to pay for travel time reliability in passenger transport: A review and some new empirical evidence. *Transportation Research Part E: Logistics and Transportation Review, 46*(3), 384-403. Retrieved from http://www.sciencedirect.com/science/article/pii/S1366554509001550. doi:https://doi.org/10.1016/j.tre.2009.12.005

Li, Z., Hong, Y., & Zhang, Z. (2017). *An Empirical Analysis of On-demand Ride-sharing and Traffic Congestion*.

Lovelace, R., & Dumont, M. (2018). Spatial Microsimulation with R.

Lin, P. (2017). *Here is How Grab Can Help You Rent a Car in Singapore Without Paying a Single Cent. Money Smart*. Retrieved from: https://blog.moneysmart.sg/transportation/heres-grab-can-help-rent-car-singaporewithout-paying-single-cent/ 2017

Maciejewski, M., Salanova, J. M., Bischoff, J., & Estrada, M. (2016). Large-scale microscopic simulation of taxi services. Berlin and Barcelona case studies. *Journal of Ambient Intelligence and Humanized Computing, 7*(3), 385-393. Retrieved from https://doi.org/10.1007/s12652-016-0366-3. doi:10.1007/s12652-016-0366-3

Mahmoudifard, S., Kermanshah, A., Shabanpour, R., & Mohammadian, A. (2017). *Assessing Public Opinions on Uber as a Ridesharing Transportation System: Explanatory Analysis and Results of a Survey in Chicago Area*.

McAlone, N. (2015). *Here's how Uber got its start and grew to become the most valuable startup in the world*. Business Insider. Retrieved from: http://www.businessinsider.com/history-of-uber-and-its-rise-to-become-themost-valuable-startup-in-the-world-2015-9

McCarthy, P. S. (2001). *Transportation Economics Theory and Practice: A Case Study Approach.* Blackwell Publishing, Oxford, United Kingdom.

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods, 17*(3), 437-455. doi:10.1037/a0028085

Moeckel, R., & Nagel, K. (2016). Maintaining Mobility in Substantial Urban Growth Futures. *Transportation Research Procedia, 19*, 70-80. Retrieved from http://www.sciencedirect.com/science/article/pii/S2352146516308559. doi:https://doi.org/10.1016/j.trpro.2016.12.069

Moovit Public Transit Index, (n.d.). Retrieved from: https://moovitapp.com/insights/en/Moovit_Insights_Public_Transit_Index-countries

Munizaga, M. A., & Ortúzar, J. d. D. (1999). Nested Logit Modelling: Some Hard Facts, 27th European Transport Conference, P324, 25-36.

Murphy, C., Felgon, S., (2016). *Shared Mobility and the Transformation of Public Transit*. American Public Transportation Association. 39 p.

Muchneeded (2018). Retrieved from: https://muchneeded.com/uber-statistics

NCHRP Report 606 (2008). *Forecasting Statewide Freight Toolkit. Transportation Research Board of the National Academies*, Washington, D.C.

Nederhof, A. J. (1985). Methods of coping with social desirability bias: A review. *European Journal of Social Psychology, 15*(3), 263-280. doi:10.1002/ejsp.2420150303

Nielsen Company, 2014. *Millennials ‑ Breaking the Myths*. Nielsen Company.

Norman, P. (1999). *Putting Iterative Proportional Fitting on the researcher's desk* (Vol. 99).

Orne, M. T. (1962). On the social psychology of the psychological experiment: With particular reference to demand characteristics and their implications. *American Psychologist, 17*(11), 776-783. doi:10.1037/h0043424

Ortúzar, JDD (2000). *Modelling route and multimodal choices with revealed and stated preference data.*, in JDD Ortúzar (ed.), Stated Preference Modelling Techniques, 4th edn, PTRC Education and Research Services Ltd., Londres.

Ortúzar, J. d. D., & Willumsen, L. G. (2011). Modellin Transport (4th ed.), Chichester, West.

Paulhus, D. (2002). *Social desirable responding: The evolution of a construct*.

Paulhus, D. L. (1991). Measurement and control of response bias. In *Measures of personality and social psychological attitudes.* (pp. 17-59). San Diego, CA, US: Academic Press.

R Software Library source: https://rpubs.com/anon-user/3393
Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport Policy, 45*, 168-178. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-84945895393&doi=10.1016%2fj.tranpol.2015.10.004&partnerID=40&md5=9b4a63f170b8306154fbc807aa084e02. doi:10.1016/j.tranpol.2015.10.004
Sarris, M., Daziano, R., Croissant, Y., (2015) *Multinomial Logit Models with Random Parameters*. Retrieved from https://msarrias.weebly.com/description.html
Small, K. A., Winston, C., & Yan, J. (2005). Uncovering the Distribution of Motorists' Preferences for Travel Time and Reliability. *Econometrica, 73*(4), 1367-1382. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-0262.2005.00619.x. doi:10.1111/j.1468-0262.2005.00619.x
Sobel, K.L. (1980). *Travel demand forecasting with the nested multinomial logit model*. Transportation Research Record, No. 775
TCRP Research Report 195 (2018). Retrieved from: http://www.trb.org/Publications/Blurbs/177112.aspx
Thelen, K. (2018). Regulating Uber: The Politics of the Platform Economy in Europe and the United States. *Perspectives on Politics, 16*(4), 938-953. Retrieved from https://www.cambridge.org/core/article/regulating-uber-the-politics-of-the-platform-economy-in-europe-and-the-united-states/DFE30511CEB3281E40CBFDFFA56110E0. doi:10.1017/S1537592718001081
Transportation Tomorrow Survey, (2016). TTS Data Guide. Retrieved from: http://dmg.utoronto.ca/pdf/tts/2016/2016TTS_DataGuide.pdf
Twaddle, H. A.(2011). Stated preference survey desgin and pre-test for valuing influencing factors for bicycle use (MSc thesis, Technical University of Munich). Retrieved from http://mediatum.ub.tum.de/doc/1130707/1130707.pdf
Uber Newsroom. (2014). *Announcing UberPool*. Retrieved from: https://newsroom.uber.com/announcing-uberpool/
USEPA, https://www.fueleconomy.gov/feg/driveHabits.jsp Accessed March, 2019.
Vrtic, M., Schuessler, N., Erath, A., & Axhausen, K. W. (2010). The impacts of road pricing on route and mode choice behaviour. *Journal of Choice Modelling, 3*(1), 109-126. Retrieved from http://www.sciencedirect.com/science/article/pii/S1755534513700319. doi:https://doi.org/10.1016/S1755-5345(13)70031-9
Wardman, M., Chintakayala, P., & Jong, G. (2016). *Values of travel time in Europe: Review and meta-analysis* (Vol. 94).
Whiney, A. (2016). *I Took Via to Work Every Day for a Month. Here's What I Learned*. Retrieved from: https://www.brickunderground.com/live/commute-via 2016.
Yıldızgöz, K., & Murat Çelik, H. (2019). Critical Moment for Taxi Sector: What Should Be Done by Traditional Taxi Sector After the TNC Disruption?: Proceedings of 4th Conference on Sustainable Urban Mobility (CSUM2018), 24 - 25 May, Skiathos Island, Greece. In (pp. 453-460).

10. Appendix

10.1. Full Version of questionnaire (English)

Dear respondent,

Thank you for your participation in my survey.

I am a Masters Transportation Systems student at the Technical University of Munich. My project survey is about important transportation issues, including how, when and why people use different ways of getting around. It should take 5 minutes to complete. With so many transportation choices available, your response will help fill in the picture about the choices people make in travelling around the city. While there are many transportation options available and their use depends on different circumstances, it might be difficult to answer with the “typical” option but as you fill out this survey, think of the option used most often.

For any concerns or suggestions, please do not hesitate to contact me via email: maged.shoman@tum.de

There are 24 questions in this survey.

General Questions

*What is your gender?

Choose one of the following answers

- Male
- Female
- Other
- I prefer not to answer.

*How old are you?

Choose one of the following answers

- <18 years
- 18-24 years
- 25-29 years
- 30-39 years
- 40-49 years
- 50-64 years
- >65 years
- I prefer not to answer.

*Which area type best describes your home location?

Choose one of the following answers

- Urban
- Suburban
- Rural

*How long have you been living in Munich so far?

Choose one of the following answers

- 1-6 months
- 7-12 months
- 1-5 years
- >5 years
- I prefer not to answer.

*Which of the following occupations do you fit in?

Choose one of the following answers

- full-employed
- half-employed
- student (university)
- unemployed
- retired
- I prefer not to answer.
- other

*How many people live in your household?

Choose one of the following answers

- 1
- 2
- 3
- 4 or more

*How many workers live in your household?

Choose one of the following answers

- 0
- 1
- 2
- 3
- 4 or more

*How many children (<18 years) live in your household?

Choose one of the following answers

- 0
- 1
- 2
- 3 or more

*How many cars are available in your household?

Choose one of the following answers

- 0
- 1
- 2
- 3 or more

What is the distance to your nearest transit stop (km)?

Do you have a driver's license?

Yes | No | No answer

*What is your household income per month?

Choose one of the following answers

- <1500€
- 1500€ - 5600€
- >5600€

Transport Related Questions (HBW)

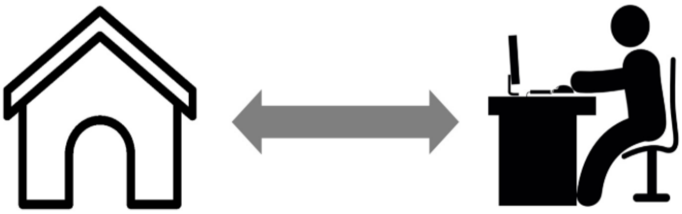
In the following questions, consider the following mode:

Car/ride sharing 	Car/ride sharing is the sharing of car journeys so that more than one person can use the same car or more than one person can travel in the same car, such as Uber, DriveNow or BlaBlaCar.

Which mode do you typically use for the following trip purposes?

	Home → Work	Home → Education	Home → Shop	Home → Other
Private Car	○	○	○	○
Car/ride share	○	○	○	○
Bicycle	○	○	○	○
Bus	○	○	○	○
Train	○	○	○	○
Tram/Metro	○	○	○	○
Walk	○	○	○	○
No answer	●	●	●	●

home to work/education are trips that start at home, with a purpose of work/education at the place of emplyoment/institution.



*Scenario 1: Imagine the following modes of transportation are available from your **home to work/education.** The trip duration and cost using each one are as presented below. Please mark below which of them would you prefer?

	Car/ride sharing	Public Transport	Private Car
Walking time to the vehicle	4 min	3 min	2 min
Waiting time	2 min	5 min	0 min
Travel time in-vehicle (without the parking search time)	25 min	32 min	25 min
Parking search time	-	-	6 min
Walking time to the destination	4 min	3 min	2 min
Travel cost	12 €	3 €	*6 €
Parking cost	0 €	-	2 €

All inclusive cost (fixed & maintenance costs of the car)

Choose one of the following answers

This question is mandatory

Car/ride Sharing | Public Transport | Private Car

*Scenario 2: Imagine the following modes of transportation are available from your **home to work/education.** The trip duration and cost using each one are as presented below. Please mark below which of them would you prefer? (Changes from other scenarios are in **bold**)

	Car/ride sharing	Public Transport	Private Car
Walking time to the vehicle	4 min	3 min	2 min
Waiting time	***5 min***	5 min	0 min
Travel time in-vehicle (without the parking search time)	**29 min**	32 min	25 min
Parking search time	-	-	6 min
Walking time to the destination	4 min	3 min	2 min
Travel cost	**6 €**	3 €	*6 €
Parking cost	0 €	-	2 €

All inclusive cost (fixed & maintenance costs of the car)

Choose one of the following answers

This question is mandatory

Car/ride Sharing | Public Transport | Private Car

*Scenario 3: Imagine the following modes of transportation are available from your **home to work/education.** The trip duration and cost using each one are as presented below. Please mark below which of them would you prefer? (Changes from other scenarios are in **bold**)

	Car/ride sharing	Public Transport	Private Car
Walking time to the vehicle	4 min	3 min	2 min
Waiting time	**2 min**	5 min	0 min
Travel time in-vehicle (without the parking search time)	**29 min**	32 min	25 min
Parking search time	-	-	6 min
Walking time to the destination	4 min	3 min	2 min
Travel cost	**6 €**	3 €	*6 €
Parking cost	0 €	-	2 €

All inclusive cost (fixed & maintenance costs of the car)

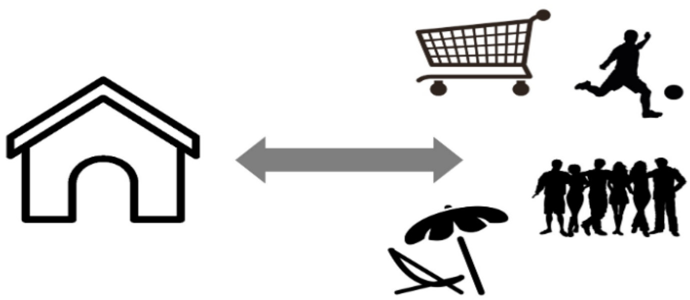
Choose one of the following answers

This question is mandatory

Car/ride Sharing | Public Transport | Private Car

Transport Related Questions (HBO)

home to other destinations (excluding work/education) are trips that start at home, with purposes such as shopping, sports, meeting friends, leisure...etc, excluding work/education.



*Scenario 1: Imagine the following modes of transportation are available from your **home to other destinations (excluding work/education).** The trip duration and cost using each one are as presented below. Please mark below which of them would you prefer?

	Car/ride sharing	Public Transport	Private Car
Walking time to the vehicle	4 min	3 min	2 min
Waiting time	2 min	5 min	0 min
Travel time in-vehicle (without the parking search time)	25 min	32 min	25 min
Parking search time	-	-	6 min
Walking time to the destination	4 min	3 min	2 min
Travel cost	12 €	3 €	*6 €
Parking cost	0 €	-	2 €

All inclusive cost (fixed & maintenance costs of the car)

Choose one of the following answers

Car/ride Sharing | Public Transport | Private Car

*Scenario 2: Imagine the following modes of transportation are available from your **home to other destinations (excluding work/education).** The trip duration and cost using each one are as presented below. Please mark below which of them would you prefer? (Changes from other scenarios are in **bold**)

	Car/ride sharing	Public Transport	Private Car
Walking time to the vehicle	4 min	3 min	2 min
Waiting time	2 min	5 min	0 min
Travel time in-vehicle (without the parking search time)	**29 min**	32 min	25 min
Parking search time	-	-	6 min
Walking time to the destination	4 min	3 min	2 min
Travel cost	**6 €**	3 €	*6 €
Parking cost	0 €	-	2 €

All inclusive cost (fixed & maintenance costs of the car)

Choose one of the following answers

Car/ride Sharing | Public Transport | Private Car

*Scenario 3: Imagine the following modes of transportation are available from your **home to other destinations (excluding work/education).** The trip duration and cost using each one are as presented below. Please mark below which of them would you prefer? (Changes from other scenarios are in **bold**)

	Car/ride sharing	Public Transport	Private Car
Walking time to the vehicle	4 min	3 min	2 min
Waiting time	**5 min**	5 min	0 min
Travel time in-vehicle (without the parking search time)	**29 min**	32 min	25 min
Parking search time	-	-	6 min
Walking time to the destination	4 min	3 min	2 min
Travel cost	**6 €**	3 €	*6 €
Parking cost	0 €	-	2 €

All inclusive cost (fixed & maintenance costs of the car)

Choose one of the following answers

Car/ride Sharing | Public Transport | Private Car

Transport Related Questions.

How often do you travel with the following modes?

	Car/ride Sharing	Public Transport	Private Car	Bicycle	Walk
Daily or almost daily	○	○	○	○	○
1-3 times per week	○	○	○	○	○
1-3 times per month	○	○	○	○	○
few times a year	○	○	○	○	○
less than once a year or never	○	○	○	○	○
No answer	●	●	●	●	●

If you like to share any comments or thoughts about this survey or car/ride sharing in munich, please feel free.

10.2. Full results of weighed survey by category and number of respondents

Survey Language	
en	382.8
de	117.2

Gender	
Male	243
Female	257

Age	
18-24	24.2
25-29	40.7
30-39	96.5
40-49	108
>50	230.5

employment	
yes	437.1
no	47
students	15.9

hhsize	
1	168.3
2	171
3	76
4 or more	84.4

Area Type	
Rural	23.1
suburban	142.5
urban	334.4

living period in munich	
>5 years	329.1
1-5 years	130.6
1-6 months	15.6
7-12 months	14.2
I prefer not to answer.	10.5

Workers in HH	
0	45.9
1	218.8
2	219.3
3	4.7
4 or more	11.3

Children in HH	
0	366.5
1	72.2
2	55.3
3 or more	6

Cars in HH	
0	171.4
1	234.9
2	69.1
3 or more	24.6

Distance to transit (km)	
<0.1	85.5
0.2-0.5	220.5
0.5-1	143.7
1.0-2.0	25.4
2.0-5.0	**13.6**
>5	11.4

Drivers License	
yes	416.5
no	60.5

Household Income	
>5600€	170.45
1500€ - 5600€	309.7
<1500€	19.8

Typically used mode				
	HBW	HBE	HBS	HBO
Bicycle	69.6	13.2	64.4	49
Bus	10.1	3.7	7.6	8.3
Car/ride share	1.4	0.74	2.4	17.9
Private Car	116.6	31.2	153	162.3
Train	78.8	11.3	6.9	40.8
Tram/Metro	169.3	83.4	35.1	57.2
Walk	21.3	19.7	176.6	79.5

HBW/E scenarios			
	Car/ride sharing	Private car	Public Transport
SCN 1	5.74	86.4	360.8
SCN 2	15.3	118.2	319.5
SCN 3	16.2	90.9	345.8

HBO scenarios			
	Car/ride sharing	Private car	Public Transport
SCN 1	12.2	214.5	273.3
SCN 2	39.5	196.9	263.6
SCN 3	30	205.9	264.1

Frequency of mode used					
	1-3 times per month	1-3 times per week	Daily/almost daily	few times a year	never/less than once
Car/ride share	32.1	10.4	0.19	101.22	235.3
Public Transport	112.1	86.5	248.7	41.1	5.1
Private car	62	163	99.4	37.2	76.4
Bicycle	45.6	169.6	71.6	88.9	51.7
Walk	29.4	130.4	237.8	16.5	13.6

10.3. MNL Full Model

Full HBW

```
Call:
gmnl(formula = choice ~ cost:IncomeClasses | ttime + AgeClasses +
    distance_transit + hhsize + hhcars + Area + MucYears + hhwrkrs +
    hhchild, data = data_table, weights = data_table$weights,
    method = "nr")
Frequencies of categories:
    auto      tnc  transit
0.176710 0.059446 0.763844
The estimation took: 0h:0m:25s
Coefficients:
                             Estimate  Std. Error  z-value  Pr(>|z|)
tnc:(intercept)           -1.5791e+01  4.9732e+02  -0.0318 0.9746693
transit:(intercept)       -5.3379e-03  4.7084e+04   0.0000 0.9999999
cost:IncomeClasses€1500   -3.2011e-01  1.8619e-01  -1.7193 0.0855621 .
cost:IncomeClasses€3000   -2.2418e-01  1.5252e-01  -1.4699 0.1415991
cost:IncomeClasses€6000   -1.5898e-01  1.5446e-01  -1.0293 0.3033543
tnc:ttime                 -1.5516e-02  1.3652e-01  -0.1137 0.9095140
transit:ttime              5.2108e-03  1.0950e+03   0.0000 0.9999962
tnc:AgeClasses18-24        1.3959e+01  4.9730e+02   0.0281 0.9776057
transit:AgeClasses18-24   -1.7953e+00  5.2243e-01  -3.4365 0.0005894 ***
tnc:AgeClasses25-29        1.5146e+01  4.9729e+02   0.0305 0.9757032
transit:AgeClasses25-29   -1.2908e+00  4.2899e-01  -3.0089 0.0026216 **
tnc:AgeClasses29-39        1.5136e+01  4.9729e+02   0.0304 0.9757196
transit:AgeClasses29-39   -1.2335e+00  2.9114e-01  -4.2370 2.266e-05 ***
tnc:AgeClasses40-49        1.4391e+01  4.9729e+02   0.0289 0.9769135
transit:AgeClasses40-49   -1.0379e+00  2.6160e-01  -3.9675 7.263e-05 ***
tnc:distance_transit       1.3340e-01  6.6721e-02   1.9994 0.0455623 *
transit:distance_transit  -2.6045e-01  6.4027e-02  -4.0678 4.746e-05 ***
tnc:hhsize                 4.5056e-01  5.2209e-01   0.8630 0.3881387
transit:hhsize             1.3150e+00  2.1984e-01   5.9818 2.207e-09 ***
tnc:hhcars                -1.3562e+00  3.7542e-01  -3.6125 0.0003032 ***
transit:hhcars            -1.7856e+00  1.6596e-01 -10.7594 < 2.2e-16 ***
tnc:Areasuburban           8.9006e-01  1.4599e+00   0.6097 0.5420892
transit:Areasuburban       6.3572e-01  5.0015e-01   1.2711 0.2037103
tnc:Areaurban              9.7529e-01  1.4218e+00   0.6860 0.4927324
transit:Areaurban          5.5733e-01  4.8311e-01   1.1536 0.2486507
tnc:MucYears1-12 mnth      2.8471e+00  2.6045e+00   1.0931 0.2743365
transit:MucYears1-12 mnth  1.6164e+00  2.0650e+00   0.7828 0.4337599
tnc:MucYears1-5 yrs       -1.0069e-02  4.6025e-01  -0.0219 0.9825466
transit:MucYears1-5 yrs    5.0051e-01  2.5685e-01   1.9487 0.0513345 .
tnc:MucYears1-6 mnth       1.2453e+00  1.8035e+00   0.6905 0.4898899
transit:MucYears1-6 mnth   7.0913e-01  1.1367e+00   0.6238 0.5327313
tnc:MucYearsno answer      3.1724e+00  3.5926e+00   0.8830 0.3772192
transit:MucYearsno answer  3.2897e+00  3.2005e+00   1.0279 0.3039990
tnc:hhwrkrs               -5.2728e-01  4.7916e-01  -1.1004 0.2711439
transit:hhwrkrs           -2.5254e-01  1.7335e-01  -1.4569 0.1451483
tnc:hhchild                1.7102e-01  6.6986e-01   0.2553 0.7984852
transit:hhchild            1.3389e-02  2.9867e-01   0.0448 0.9642441
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Optimization of log-likelihood by Newton-Raphson maximisation
Log Likelihood: -524.31
Number of observations: 1228
Number of iterations: 18
Exit of MLE: successive function values within tolerance limit>
```

Full HBO

```
Call:

gmnl(formula = choice ~ cost:IncomeClasses | ttime + AgeClasses + 
    distance_transit + hhsize + hhwrkrs + Area + MucYears + hhchild, 
    data = data_table, weights = data_table$weights, method = "nr")
Frequencies of categories:
   auto     tnc transit 
0.28074 0.08198 0.63728 
The estimation took: 0h:0m:20s 
Coefficients:
                             Estimate  Std. Error z-value  Pr(>|z|)    
tnc:(intercept)           -1.2069e+01  2.7000e+02 -0.0447 0.9643449    
transit:(intercept)       -4.6743e-02  1.9073e+04  0.0000 0.9999980    
cost:IncomeClasses€1500   -6.9513e-01  1.5154e-01 -4.5871 4.496e-06 ***
cost:IncomeClasses€3000   -3.3897e-01  1.0637e-01 -3.1866 0.0014394 ** 
cost:IncomeClasses€6000   -2.9156e-01  1.0664e-01 -2.7340 0.0062574 ** 
tnc:ttime                 -1.5297e-01  9.9313e-02 -1.5403 0.1234910    
transit:ttime             -2.3998e-02  4.4357e+02 -0.0001 0.9999568    
tnc:AgeClasses18-24        1.5015e+01  2.6997e+02  0.0556 0.9556469    
transit:AgeClasses18-24   -1.5025e-01  3.9726e-01 -0.3782 0.7052741    
tnc:AgeClasses25-29        1.6557e+01  2.6997e+02  0.0613 0.9510978    
transit:AgeClasses25-29    9.7450e-01  3.2431e-01  3.0049 0.0026569 ** 
tnc:AgeClasses29-39        1.6039e+01  2.6997e+02  0.0594 0.9526253    
transit:AgeClasses29-39    2.4545e-01  2.0365e-01  1.2053 0.2280988    
tnc:AgeClasses40-49        1.5710e+01  2.6997e+02  0.0582 0.9535958    
transit:AgeClasses40-49   -1.3346e-01  1.8492e-01 -0.7217 0.4704708    
tnc:distance_transit      -4.4029e-02  6.6349e-02 -0.6636 0.5069483    
transit:distance_transit  -2.3225e-01  5.9393e-02 -3.9104 9.213e-05 ***
tnc:hhsize                 5.8722e-01  2.9869e-01  1.9660 0.0493010 *  
transit:hhsize             7.6804e-01  1.3150e-01  5.8407 5.198e-09 ***
tnc:hhwrkrs               -2.9542e-01  2.9887e-01 -0.9884 0.3229337    
transit:hhwrkrs           -5.1706e-01  1.3553e-01 -3.8152 0.0001361 ***
tnc:Areasuburban          -1.7133e-01  1.1067e+00 -0.1548 0.8769645    
transit:Areasuburban      -1.1069e+00  4.0523e-01 -2.7316 0.0063026 ** 
tnc:Areaurban              4.3085e-01  1.0753e+00  0.4007 0.6886515    
transit:Areaurban         -1.4372e+00  3.9365e-01 -3.6510 0.0002613 ***
tnc:MucYears1-12 mnth     -1.2034e+00  3.3737e+03 -0.0004 0.9997154    
transit:MucYears1-12 mnth  8.8057e+00  1.7991e+03  0.0049 0.9960947    
tnc:MucYears1-5 yrs       -3.7769e-01  3.2713e-01 -1.1545 0.2482806    
transit:MucYears1-5 yrs    7.1256e-01  1.8297e-01  3.8943 9.846e-05 ***
tnc:MucYears1-6 mnth      -3.3987e+00  3.1536e+00 -1.0777 0.2811655    
transit:MucYears1-6 mnth  -2.7861e+00  5.4388e-01 -5.1226 3.013e-07 ***
tnc:MucYearsno answer     -2.7621e-01  1.9373e+00 -0.1426 0.8866269    
transit:MucYearsno answer  1.4490e+00  9.7172e-01  1.4911 0.1359226    
tnc:hhchild               -2.0684e-01  3.5449e-01 -0.5835 0.5595613    
transit:hhchild            6.0857e-02  1.6472e-01  0.3695 0.7117838    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Optimization of log-likelihood by Newton-Raphson maximisation
Log Likelihood: -913.05
Number of observations: 1293
Number of iterations: 17
Exit of MLE: successive function values within tolerance limit>
```

Declaration concerning the Master's Thesis

I hereby confirm that the presented thesis work has been done independently and using only the sources and resources as are listed. This thesis has not previously been submitted elsewhere for purposes of assessment.

Munich, May 27th, 2019

Maged Shoman