

Available online at www.sciencedirect.com



Transportation Research Procedia 00 (2021) 000-000



# 24th EURO Working Group on Transportation Meeting, EWGT 2021, 8-10 September 2021, Aveiro, Portugal

# Assessing Equity in Carsharing Systems: the case of Munich, Germany

Giulio Giorgione<sup>a,\*</sup>, Francesco Viti<sup>a</sup>

<sup>a</sup>University of Luxembourg, 2 Avenue de l'Université, Esch-sur-Alzette L-4365, Luxembourg

# Abstract

This paper shows an application of a multi-agent transport simulation to evaluate equity effects of the introduction of a carsharing system. Using vehicles, members, and planning data of Oply, a carsharing service that operated in Munich until March 2020, we analyze the evolution of the distribution of costs and benefits among the inhabitants of this city. By explicitly introducing the income as an active part of the utility calculation we evaluate how offering a new mode of transport impacts the score of the agents. Two scenarios are employed to assess equity in economic terms and accessibility terms. Two different outcomes are expected: firstly, as a high pricing service, carsharing will favor high-income agents, thus skewing benefits towards them; secondly, we show that the granularity of this agent-based simulator makes it a handy tool when conducting policy evaluations on the introduction of a carsharing system.

© 2021 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/) Peer-review under responsibility of the scientific committee of the 24th EURO Working Group on Transportation Meeting. *Keywords:* Carsharing; MATSim; agent-based modelling; Equity

#### 1. Introduction

During the last decades new transportation modes and emerging mobility services have become a stable presence in everyday life. The blossom of new service models created a change in the way private companies and public institutions faced mobility issues leading to a paradigm shift in the transportation planning and management. Privateled services such as carsharing fostered competition among companies while governmental institutions faced new challenges in regulating emerging markets and frame them in the context of multimodality and sustainable mobility. Carsharing is a service composed by individuals who have access to a lease car through a membership program.

\* Corresponding author. Tel.: +352 4666445049; fax:+352 46664435049. *E-mail address:* giulio.giorgione@uni.lu

2352-1465  $\ensuremath{\mathbb{C}}$  2021 The Authors. Published by ELSEVIER B.V.

This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/) Peer-review under responsibility of the scientific committee of the 24th EURO Working Group on Transportation Meeting

Vehicles are rented for a short time by paying a usage fee and are booked on demand (Shaheen et al. 1999). Carsharing operations are essentially a private service, that is why some studies found their main focus on fleet management efficiency while increasing company profit (Di Febbraro et al. 2012; Pfrommer et al. 2014). A potential benefit in the reallocation of vehicles can also be exploited through incentives that offer affordable prices to the user who, by making their trips, will help the carpooling company to balance its fleet (Lippoldt et al., 2019). Given the increasing number of services, competition among operators make carsharing pricing one of the most important topics regarding business sustainability. There is a link between carsharing prices and journey-purpose profiles of the carsharing users, this influences who is using carsharing, when and where (Ciari et al. 2015). Of course, pricing policies don't affect different users in the same way. In fact, to evaluate these types of impacts, an analysis of equity is carried out. Equity in this paper follows the definition by Litman (2020) as "the distribution of impacts (benefits and costs), and the degree to which this distribution is considered fair and appropriate" (Litman, 2020). Equity can be divided into two main categories: horizontal equity, which concerns the distribution of impacts among individuals who can be considered equal; vertical equity, which concerns the distribution of these impacts among unequal individuals (i.e., different economic resources, accessibility, mobility needs and skills). In this paper we will specifically deal with vertical equity with regard to income, also defined as social justice or social inclusion. For instance, when dynamic price is offered, carsharing users with an average and average-to-high value of time (VOT) tend to take resources away from users with a lower spending power (Giorgione et al. 2020). It is not trivial to foresee carsharing impacts, both on the population and on businesses, given the complex mobility patterns emerging from carsharing users, and the different parameters and decisional variables involved in the planning and operations. Testing new strategies, especially brandnew strategies, could be a difficult and resource-intensive task. For example, to set up pricing experiments in a realworld setting could require substantial disruption of carsharing operations. At the same time, the implementation of the wrong business model (i.e., a model that it is not suited to the nearby population) could lead to significant losses in a carsharing service. Considering that we are looking for emerging trends for a complex system driven by many variables and intermixing behavioral processes the use of a simulator is a valuable asset to get insights and can produce advanced screening of operational strategies. In this case, the simulation of innovative transport modes with agentbased models has been proven useful because of their microscopic nature (Ciari et al. 2010). That is, regarding the carsharing, the peculiarity of the services offered can be estimated in a realistic way and can capture car availability at a given location at a given time. In this work we evaluate the impact of a carsharing service on a group of agents differentiated by their income. Employing an agent-based simulator, MATSim, and using the score (i.e., the utility generated by executing the desired activity plan) as main key performance indicator (KPI). We assess the eventual distribution of costs and benefits among the population. Essentially, this work aims at answering two questions:

- Will the carsharing mode exacerbate the differences among diverse income groups?
- Is this intensification local (i.e., around carsharing stations) or is spread over the city?

# 2. Method

Nomenclature		
N	Number of activities	
S	Score/Utility	
q	performed activity	
$\beta_{dur}$	Marginal utility of activity duration	
t <sub>dur</sub>	Performed activity duration	
t <sub>0</sub>	Duration when utility starts to be positive	
αι	Scale factor for the Income	
Iu	Income of user u	

When in need to determine the economic impact of the introduction of a new mode of transport on a given population, it is important to have an economic-sensitive variable ascribed to said population. In this work we are going to differentiate agents for their economic (i.e., income) and spatial (i.e., spatial location) attributes. Income is obtained from the German micro census Statistische Ämter des Bundes un der Länder (2011) and, together with other

demographic data, it is used as input within the land-use model SILO (Moeckel 2011). Finally, we employ this model to generate a synthetic population for MATSim (Rolf Moeckel, 2017), updated to the year of our choice (2020) with income and spatial location assigned to every agent. This population is used to run simulations within MATSim. MATSim is an activity-based, extendable, multi-agent simulation framework implemented in Java (Horni et al. 2016). The carsharing data and the carsharing population is extracted from the Munich dataset of Oply, a B2C carsharing company operating with a round-trip mixed system. Oply offered a two-way service using small areas instead of punctual stations. Using an Iterative Linking Algorithm (ILA) (Giorgione et al., 2021) we link the agent's attributes assigned during the synthetic population generation to the closest Oply member. To do this we proceeded to apply the ILA based on the Euclidean distance within an agent created in the previous step from the micro census and Oply's members. The ILA allocates one agent (drawn from the whole population set) properties to the closest member and, once done so, it deletes the agent leaving only the member with all the desired attributes. By doing so we obtain a pool of around 15000 Two different simulations are run: one without and one with the carsharing service available to all the carsharing members. In order to assess the impact on the agents we evaluate the scoring as described by Horni et al. (2016).

$$S_{plan} = \sum_{q=0}^{N-1} S_{act,q} + \sum_{q=0}^{N-1} S_{trav,mode(q)}$$

$$\tag{1}$$

This is the score to evaluate the agent's plan (i.e., the daily activity chain), with *N* the number of activities and *q* the trip that is induced by the activity. The first term represents the positive component of the utility (in MATSim this is called scoring) related to executing the set of activities, the second one represents the disutility of travelling with a given sequence of modes. The second component of this equation is specific to each mode of transport supported in this case by MATSim (i.e., walk, bike, car, public transport and carsharing). The scores of different income groups are assessed and compared. This means that we need to introduce the income in MATSim in a way that it can impact the score. What could make one choose for one mode of transport or another is the value of time saved by doing that choice. Of course, this choice is dependent on the trip purpose and its utility determinants (time, duration, location). For this reason, the Income is introduced in equation 2, in the part of the scoring evaluating the utility of doing a specific activity (S<sub>act,q</sub>). In this work we consider  $\alpha_I = 1$ .

$$S_{dur} = \left(\beta_{dur,q} * t_{typ,q}\right) * \left(\alpha_I * I_u\right) * \ln\left(t_{dur,q}/t_{0,q}\right)$$
(2)

This implementation therefore imposes a difference not on the cost of travel time, which remains the same for the different groups, but on the impact that the completion of the work activity generates on the score. Following the introduction of the income, we pass to the simulation setup describing the case study used to assess the KPI explained in the previous section.

# 3. Case Study

In Fig.1 we show the network, the distribution of the carsharing members together with their hourly income and the distribution of the stations. While free-floating services tend to intercept customers willing to walk around 300 or 500 meters to reach a vehicles (Guirao et al., 2018), round-trip members tend to walk longer distances to reach the station of departure. Around 80% of the City CarShare users walk at most half a mile (800 meters) to reach a carsharing station (Cervero et al., 2007). Therefore, to consider a realistic area of influence of every station, a round buffer zone with a radius of 800 meters with the station as center is created. This is done to check if the phenomena induced by the introduction of the carsharing are local or distributed on the whole city.

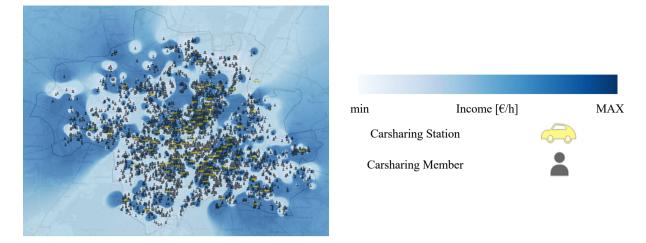


Fig. 1. Munich Network.

The Carsharing offer consists of 79 stations in which are distributed 186 cars. The location of the stations and the allocation of the cars follows the actual Oply distribution. Only the two-way service is offered.

Regarding the population we used the actual members pool of Oply. 14747 Agents are introduced and characterized by their position, hourly income (see Fig.1) and daily activities. In Fig.2a we show the frequency of the Income in the population together with the number of bookings per income group.

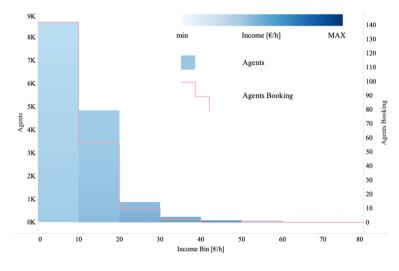


Fig. 2 Hourly Income Frequency

We identify two different scenarios, one in which the carsharing mode is not active and one in which it is. This allows to analyze the emerging impact of introducing the car sharing as additional option to the mode alternatives offered to the car sharing members.

Table 1. Scenarios Identification

Scenario Name	<b>Total Population</b>	<b>Carsharing Mode</b>	Color Code
No Carsharing	14747	× Not Active	
Carsharing	14747	✓ Active	

(3)

These two scenarios are simulated in MATSim using a fixed price offer of  $6\epsilon/h$ , which reflects the pricing policy applied by the company. The price is paid by the hour and no fractionable is considered except for the grace period. The grace period is defined as a time of five minutes in which, any booking closed within this time is not subject to the full hour payment (e.g., a booking that lasts 64 minutes will cost to the user  $6\epsilon$  while a booking that lasts 66 minutes will have a total cost of  $12\epsilon$ ). The main parameter used in evaluating the scoring (i.e., the carsharing constant) amounts to 19.30. This specific value allows the Carsharing scenario to reach a usage of the carsharing similar to an average day for Oply operations.

# 4. Results

Once the scenarios are set up, we run two different simulations on a PC with an Intel(R) Core (TM) i7-8700 CPU @ 3.20GHz, 3192 Mhz, 6 Core(s), 12 Logical Processor(s) and 64 Gigabytes of ram. The elapsed time for the simulation is 24 hours. Data is then processed using MATLAB and Python and edited in Tableau and QGIS for the graphical visualization.

As pointed out in the methodology section, the main KPI we are going to assess is the score (or otherwise defined, the utility). Focusing exclusively on the agents that booked the carsharing service in the Carsharing scenario, we calculate their scoring in both simulations and see how the score has changed, hence, obtaining the delta score ( $\Delta$ S) as shown in the following equation for an agent *u*.

$$\Delta S^{u} = S^{u}_{Carsharing} - S^{u}_{No} Carsharing$$

In order to find an answer to the first question "Will the carsharing mode exacerbate the differences among diverse income groups?", we define different income groups in order to formerly identify the score reached by agents with different purchase power.

Table 2. Income Groups				
Group Name	Hourly Income [€/h]	Annual Income [€/year]		
0	0 - 10	0 - 19200		
10	10 - 20	19201 - 38400		
20	20 - 30	38401 - 57600		
30	Above 30	Above 57601		

First of all, we take a look at the cumulative scoring retrieved for the different income groups in Fig.3.

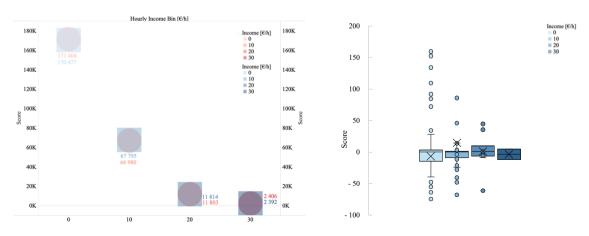


Fig. 3 (a) Cumulative Score per Income Bin; (b) Extract of a daily activity chain.

Fig. 3a shows that, once the carsharing service is offered, the utility of the agents that use the service declines if their income is low. The difference is lightly pronounced. We assess a loss of 0.5% on the cumulative score for incomes lower than 10 e/h, a small increment of 1.2 % for incomes between 10 and 20 e/h and, for all the other income groups, a rather unchanged outcome.

To understand the distribution of the score we show Fig. 3b, here we represent the difference between the scores obtained in the two scenarios by income group. First of all, it is possible to notice how the number of outliers decreases the higher the income gets; this is due to the higher number of agents in that Income group (see Fig. 1a). When comparing the four means we see how the central income groups  $(10 - 20 \ [\text{€/h}] \ \text{and} \ 20 - 30 \ [\text{€/h}])$  are the one that, on average, benefit from the carsharing. The first and the last income groups see a negative difference, more pronounced for the first group ( $\overline{\Delta S_0} = -7$ ) and less for the last one ( $\overline{\Delta S_{30}} = -4$ ). Either way, the last group reveals a smaller variance compared to the first one, this means that the score of this income group tends to stay the same between the two simulations and it is not much affected by the price of the specific transportation mode.

Together with an aggregate analysis, we believe that even a disaggregate approach could lead to important insights. In Fig. 4 we show the scatter of the scoring for every agent and their hourly income.

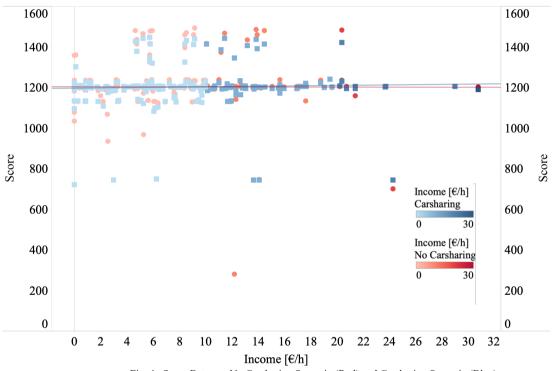


Fig. 4. Score Between No Carsharing Scenario (Red) and Carsharing Scenario (Blue).

Represented as blue squares, as defined in Table 1, there are the agents that booked the carsharing in the Carsharing scenario, while, as red circles, there are the same agents that couldn't use this mode in the No Carsharing scenario because it was not present. The most important insight can be offered by the trend line. The interception of the red circles generates a horizontal line, this means that, overall, the different points balance each other returning a trend line that doesn't particularly favor lower or higher income groups. The moment the carsharing mode is available, the trend line generated by the interpolation of the new points, returns an ascending line. This effect is mainly given by the by the increment in score seen, for the central income groups, in Fig.3b.

Once we assessed that the score changes as the carsharing service is introduced, in Fig. 5 we show whether the intensification of the change in the score happens around the carsharing stations or it is more distributed along the city. In this figure we show the income level (in blue), the agents that used the carsharing mode, whether their score is negative or positive when compared to the first scenario, we represent their income as the size of the miniature and the carsharing stations by a yellow car.

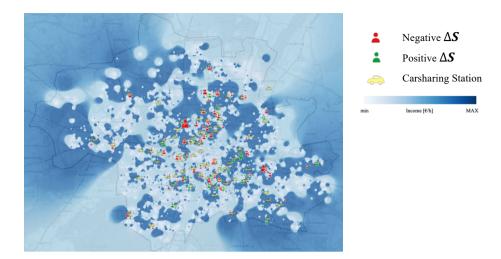


Fig. 5. Booking Map

Given the nature of the service, only agents close to the stations would be supposed to use the carsharing mode. To check that, we show that the area of influence of a carsharing service tends to fade quickly once we get further from the station. As it can be seen from the map, only agents living or that happens to be around a carsharing station at the moment of the booking use the carsharing service. Defining the spatial equity as the distribution of the benefits (and, by logic, even of the disbenefits) on a specific area, we see that their distribution is not equally spread on the whole area but only around the stations. There are no agents from any specific income group booking cars and living (or happen to be) far from the station at the moment they need a carsharing car. This means that all the assessments made so far are localized in an area of influence that is close to the carsharing stations.

Furthermore, in Fig. 6, we show the modal share in No Carsharing of the agents who will chose the carsharing in Carsharing scenario (Fig. 6a), and the modal share of all the agents in No Carsharing (Fig. 6b).



Fig. 6 Modal Share of (a) carsharing users (in Carsharing Scenario) in the No Carsharing; (b) all users in No Carsharing

This shows how agents choosing the carsharing used to have a car usage higher when compared to the average of the whole population. This follows the findings of Cisterna et al., (2021) that sees the round-trip carsharing as a substitute of the car mode, seldomly of public transportation and not a competitor of soft modes.

### 5. Discussions and Conclusions

The idea behind this work is that it is possible to use an agent-based simulator to evaluate the impact of the introduction of a carsharing service on the population of a given area. Once introduced the income as an active part of the utility calculation of the agents score, we assess the output of the simulation. This method employs data fetched from Oply, a Luxembourgish carsharing service operating in Germany. The results of this paper suggest that the introduction of a carsharing service brings an impact on the population. This impact is not evenly distributed neither in spatial nor in economic terms. The nature of the carsharing service, usually a service that is responsible for a tiny part of the modal share of a city, creates the condition for which only the agents leaving close-by a station are impacted.

One of the shortcomings of this paper is that it doesn't link the distance from the station with a specific loss or improvement of the utility, but it restricts the analysis only to whether the service will impact or not the agents.

Furthermore, we showed how higher income groups benefit from the introduction of this service while lower income groups don't receive the same contribution in terms of utility. This conclusion finds support in the literature, for instance Mitra, (2021) shows through a survey that "While lower-income households are less likely to utilize carsharing when compared to higher-income households" but, he adds that "carsharing can enhance mobility for lower-income populations, primarily when interacting with a public transportation coverage variable.". to test the carsharing together with public transportation was not the goal of this paper but we will consider the second sentence as a good application of the software for future works.

What we demonstrate with this work is that, with an agent-based model like MATSim it is possible to simulate the introduction of a new mobility service. We show that the impact seen on the population follows what is expected in a real-world scenario and is dependent on the income of every agent.

Considering that in this paper we show that carsharing usage is sensible to people's income and that it is possible to show this behavior through an agent-based simulator, future works should address the quantification of the relationship carsharing and income more in-depth. A validation phase could be added in order to conclude what the assessments made until now (survey on carsharing members and the simulation approach described in this paper) stated. A next step could include a validation step. Even though the results of this paper come from a population based on national surveys and micro census and on a scenario calibrated on real carsharing operational data, a validation phase could be needed in order to step over the trends and reach the actual usability of this forecasts in day-to-day carsharing operations.

### Acknowledgements

The present project STREAMS (ref. 11608347) is supported by the National Research Fund, Luxembourg.

# References

- Cervero, R., Golub, A., Nee, B., 2007. City CarShare: Longer-Term Travel Demand and Car Ownership Impacts. Transportation Research Record: Journal of the Transportation Research Board 1992, 70–80. https://doi.org/10.3141/1992-09
- Ciari, F., Balac, M., Balmer, M., 2015. Modelling the effect of different pricing schemes on free-floating carsharing travel demand: a test case for Zurich, Switzerland. Transportation 42, 413–433. https://doi.org/10.1007/s11116-015-9608-z
- Ciari, F., Schuessler, N., Axhausen, K.W., 2010. Estimation of car-sharing demand using an activity-based microsimulation approach.
- Cisterna, C., Giorgione, G., Viti, F., 2021. Impact of Congestion Pricing Policies in Round-Trip and Free-Floating Carsharing Systems, in: Advances in Mobility-as-a-Service Systems, Advances in Intelligent Systems and Computing. Springer International Publishing, Cham, pp. 116–126. https://doi.org/10.1007/978-3-030-61075-3\_12
- Di Febbraro, A., Sacco, N., Saeednia, M., 2012. One-Way Carsharing: Solving the Relocation Problem. Transportation Research Record: Journal of the Transportation Research Board 2319, 113–120. https://doi.org/10.3141/2319-13
- Giorgione, G., Ciari, F., Viti, F., 2020. Dynamic Pricing on Round-Trip Carsharing Services: Travel Behavior and Equity Impact Analysis through an Agent-Based Simulation. Sustainability 12, 6727. https://doi.org/10.3390/su12176727
- Giorgione, G., Kliazovich, D., Bolzani, L., Ciari, F., Viti, F., 2021. Systematic Analysis and Modelling of Profit Maximization on Carsharing. Guirao, B., Ampudia, M., Molina, R., García-Valdecasas, J., 2018. Student behaviour towards Free-Floating Carsharing: First evidences of the
- experience in Madrid. Transportation Research Procedia 33, 243–250. https://doi.org/10.1016/j.trpro.2018.10.099
- Horni, A., Nagel, K., Axhausen, K.W., 2016. The multi-agent transport simulation MATSim. London: Ubiquity Press.
- Lippoldt, K., Niels, T., Bogenberger, K., 2019. Analyzing the Potential of User-Based Relocations on a Free-Floating Carsharing System in Cologne. Transportation Research Procedia 37, 147–154. https://doi.org/10.1016/j.trpro.2018.12.177
- Litman, T., 2020. Evaluating Transportation Equity 70.
- Mitra, S.K., 2021. Impact of carsharing on the mobility of lower-income populations in California. Travel Behaviour and Society 24, 81–94. https://doi.org/10.1016/j.tbs.2021.02.005
- Moeckel, R., 2011. Simulating household budgets for housing and transport.
- Pfrommer, J., Warrington, J., Schildbach, G., Morari, M., 2014. Dynamic vehicle redistribution and online price incentives in shared mobility systems. IEEE Trans. Intell. Transport. Syst. 15, 1567–1578. https://doi.org/10.1109/TITS.2014.2303986
- Rolf Moeckel, 2017. SILO Land Use Model [WWW Document]. URL https://wiki.tum.de/display/silo/SILO+Land+Use+Model (accessed 7.21.21).
- Shaheen, S., Sperling, D., Wagner, C., 1999. A Short History of Carsharing in the 90's 5, 24.
- Statistische Ämter des Bundes un der Länder, 2011.