Accessibility, socioeconomic and climate impacts of zone-based shared, electric, autonomous vehicles (SAEVs): simulating the case of Vienna[⋆]

Stefanie Peer[a,∗], Johannes Müller[c], Asjad Naqvi[a,b], Markus Straub[c]

[a] *Vienna University of Economics and Business (WU), Vienna, Austria*

[b] *International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria*

[c] *Austrian Institute of Technology (AIT), Vienna, Austria*

Abstract

Shared, autonomous electric vehicles (SAEVs) are expected to enter the market in the coming decades. Using MATSim, we simulate a use case where a fleet of SAEVs becomes part of the transport system of Vienna (Austria). More specifically, SAEVs are introduced in multiple suburban zones at the outskirts of Vienna, which are characterized by relatively low population density, but have access to at least one rail-based public transport stop. For all combinations of high and low SAEV fleet size and high, low and zero fares, we find that a relatively small share of car trips by residents of these zones (7–14%) are replaced by SAEVs, generating CO2 emissions reductions of 5–11%. In contrast, 23–35% of trips undertaken with active modes (walking, cycling) are replaced by SAEVs, and 10–20% of public transport trips. The potential of SAEVs to lead to lower usage and ownership rates of private cars in suburban areas hence seems to be limited. The potential becomes somewhat larger when the usage and ownership of private cars become more expensive, leading to 17–20% of car trips being replaced by SAEVs and generating CO2 emissions reductions of up to 32%. While switching to SAEVs from active modes and public transport tends to imply travel time savings, the opposite is true for trips originally undertaken by cars. A key policy implication of our findings is thus that even a large fleet size of SAEVs and zero fares are insufficient to generate substantial switches from from private cars to SAEVs in suburban areas. More substantial switches only be achieved with complementary policies that discourage private car usage.

Keywords: Vienna MATSim model, traffic simulation, shared autonomous vehicles, area-based demand-responsive transport (DRT), emissions, socioeconomic impacts, first-mile last-mile micro-transit

[⋆]We gratefully acknowledge support from Austrian Climate Research Programme (ACRP) Grant number KR17AC0K13731. All errors are our own.

[∗]Corresponding author: stefanie.peer@wu.ac.at

1. Introduction

Shared, Electric, Autonomous Vehicles (SAEVs) are expected to be gradually released to the market in the upcoming decades (Adler et al., 2019). SAEVs are likely to substantially lower the generalized cost of travel and hence constitute an attractive transport mode for travelers (Meyer et al., 2017). Moreover, due to the SAEVs being electric and the possibility to share cars and rides, they are also expected to be beneficial from an environmental point of view. Nevertheless, recent studies shed doubt on the notion that SAEVs are always welfare-enhancing, as they may lead to a strong increase in vehicle kilometers traveled, which in turn may go hand in hand with an increase in congestion (Taiebat et al., 2019), only limited greenhouse gas emission reductions, and – if active modes are replaced by SAEVs – negative public health effects (Nunes & Hernandez, 2020).

This paper investigates transport-related, environmental and socioeconomic impacts of SAEVs if their operational area is constrained to specific zones in the outskirts of urban regions. In these zones, the lower population density typically renders the provision of area-wide conventional (scheduled, high-capacity) public transport inefficient, but they still contain at least one subway or railway station with good service. SAEVs are assumed to be part of, or a complement to the public transport system, and operate as demand-responsive vehicles with an occupancy of maximum four persons without fixed routes. Our use case hence corresponds closely to the setup presented in Stark et al. (2019), where a feeder system of shared, automated vehicles cover the first and the last miles. According to Stark et al. (2019) the advantages of this model include affordability (due to inclusion in the PT fare system), promotion of multi-modal trips (feeding into mass public transport), potential reduction of traffic, and enhanced accessibility in poorly connected areas.

Besides simulating various fare levels and fleet sizes, we investigate the role of imposing higher taxes on private car ownership and usage. This is done to obtain an indication to which extent the potential of SAEVs to replace private car trips can be enhanced, and what the implications are in terms of travel times and CO2 emissions.

We utilize a large-scale multi-agent MATSim model (Axhausen et al., 2016) recently developed and calibrated for the city of Vienna (Müller et al., 2022). For accurately capturing multi-modal trips, a routing algorithm, that goes beyond the standard MATSim model is implemented. We track the impacts of the simulated scenarios on standard mobility measures like travel time and distance as well as on CO2 emissions. Emissions are captured at the trip, car, and the road link level. Moreover, socioeconomic information, which also informs the assumed time preference structure, is used to identify who benefits from the introduction of SAEVs. Besides the mobility impacts, environmental and distributional impacts are highly relevant from a policy perspective and have not been sufficiently discussed so far in relation to SAEVs.

We define the SAEV fleet size relative to the number of points of interest like work places, schools, leisure areas etc. contained in the operational areas of the SAEVs. We use two SAEV fleet sizes; small (12 SAEVs/1000 facilities) and large (25 SAEVs/1000 facilities), and three price categories; a fare of 0 cents per minute, a low price of 10 cents per minute, and a high price of 30 cents per minute. Our results show that the willingness to switch to SAEVs is fairly limited for trips that use private cars in the baseline scenario (without SAEVs). Instead, most of the switches take place for trips in which environmentally-, space-, and health-friendly modes (walking, biking, and public transport) have been used in the baseline scenario (see Kaddoura et al. 2020b for a similar finding). Unsurprisingly, overall SAEVs are chosen more frequently (also by car owners) in the low-price scenarios and with the larger fleet sizes.

In the second part of the experiments, we impose the assumption that the ownership and/or usage of private cars becomes more expensive. As expected, these scenario leads to a larger increase in SAEV usage resulting in higher emission savings. But this outcome comes at the cost of substantially higher travel times, time costs, and as a result reductions in utility levels. A relatively large share of urban and employed agents manage to keep their travel time close to the baseline but do not necessarily switch to SAEVs as the main mode, but also rely on biking or PT.

The key policy implication of our experiments is that the introduction of SAEVs as part of the public transport in suburban areas is unlikely to convince a large number car users to switch to SAEVs and give up their private car. This is because even for a large fleet size, we find that daily travel time increases by on average about an hour for those individuals who use their car in the baseline scenario (no SAEVs) but are forced to give it up once SAEVs are introduced. If this use case of SAEVs as part of the public transport system should become competitive, accompanying pull measures (e.g., expansion of the conventional public transport system) and push measures (e.g., restrictions on cars in the inner city, road tolls) seem necessary.

Methodologically, this paper is most closely related to other agent-based simulation studies of employing SAEVs as demand-responsive transport service outside large urban agglomerations (Viergutz & Schmidt, 2019; Leich & Bischoff, 2019; Kaddoura et al., 2020b; Cyganski et al., 2018), or as first- and last-mile service inside urban agglomerations (Shen et al., 2018). Unlike several of the related papers (e.g. Leich & Bischoff, 2019; Shen et al., 2018), we do not ignore mode shifts, and also allow agents who have not used public transport in the baseline to use SAEVs. Even more so, we are specifically interested in the extent to which agents who own and use a car in the baseline switch to SAEVs, as this switch is the most desirable from an environmental point of view. In general, unlike this paper, none of these related studies emphasizes the environmental and distributional effects of introducing SAEVs. Our paper adds to the limited literature on environmental effects of SAEVs (e.g. Shaheen & Bouzaghrane, 2019), and the distributional (socioeconomic) impacts of SAEVs, which have so far has been mostly derived from stated preference studies (e.g. Spurlock et al., 2019).

The remaining paper is structured as follows. Section 3 introduces the MATSim model for the city of Vienna, the set up of the SAEVs, and definition of the zones in which SAEVs are allowed to operate, and the computation of CO2 emissions. Section 4 discusses the results of the policy experiments, and Section 5 concludes and provides recommendations for future research.

2. Literature

Most papers that study the introduction of SAEVs conclude that it leads to a significant increase in vehicle kilometers traveled (see for instance the review by Pernestål & Kristoffersson (2019) of 26 simulation studies), in particular if SAEVs are left unregulated. The primary reason is induced demand due to the availability of SAEVs as efficient, comfortable, inexpensive, and safe travel mode (e.g. Meyer et al., 2017; Loeb & Kockelman, 2019; Becker et al., 2020; Wadud et al., 2016; Fagnant, 2015; Taiebat et al., 2019), which additionally offers the advantage that travel time can be used productively (e.g. Molin et al., 2020). SAEVs are also likely to attract new user groups who are currently limited to the role of car passengers (mostly, elderly, disabled, and young people). Moreover, idle rides may take place, in order for SAEVs to avoid parking charges (Millard-Ball, 2019; Zhang & Wang, 2020)[1], for relocation of vehicles according to expected demand patterns (Bischoff & Maciejewski, 2020; Guan et al., 2020), and charging (Weiss et al., 2017; Lin et al., 2019). An increase in vehicle kilometers traveled can increase road congestion significantly, slowing down and rendering also other modes that share a common infrastructure with SAEVs more unreliable. To which extent a possible increase in travel times may be dampened by ride-sharing (e.g. Moreno et al., 2018; Tirachini, 2019; Zhang et al., 2015) as well as more efficient use of road space by automated vehicles (e.g. Ambühl et al., 2016), is still fairly speculative. Existing ride-hailing platforms like Uber and Lyft may, however, provide a first indication: they have led to an increase in congestion during peak periods (Tirachini & Gomez-Lobo, 2020; Fielbaum, 2019).

The main environmental benefits of SAEVs, compared to cars with combustion engine, are due to electrification, which leads to a reduction in local air pollution (Rafael et al., 2020)[2], noise, and greenhouse gases (the latter being dependent on the share of renewables in the electricity generation). Other factors that play a role in determining the environmental footprint of SAEVs are less certain and often context-dependent (see the review article by Shaheen & Bouzaghrane (2019)). One important aspect concerns the mode choice behavior of travelers when SAEVs are introduced: the switch from a car with combustion engine to an SAEV has clear environmental benefits; in contrast, a switch from public transport, walking and cycling to SAEVs tends to have negative environmental consequences, while also being detrimental for efficient use of public space and public health (e.g. Kaddoura et al., 2020b; Liu et al., 2017; Nunes & Hernandez, 2020). The effects of automation *per se* on energy use (and in turn on greenhouse gas emissions) are still uncertain, with some

[1]The main currently available steering instruments with respect to road transport will become widely obsolete with the introduction of SAEVs: parking charges will induce automated vehicles to keep cruising or park elsewhere, and taxes on fuel do not apply to electric vehicles (Adler et al., 2019).

[2]The reduction in local pollution due to electrification can be substantial. But it should not be neglected that up to 50% of external air pollution from vehicle use are from sources other than fuel combustion, such as PM2.5 and PM10 particulate matter that comes from tires and brakes (Grigoratos & Martini, 2015).

analyses projecting a reduced and others an increased impact (Wadud et al., 2016; Larson & Zhao, 2020; Taiebat et al., 2019; Kopelias et al., 2020). Induced demand for travel due to being able to use in-vehicle time more productively (Malokin et al., 2019) as well as the direct energy consumption related to the automation (for sensors etc.) (Gawron et al., 2018) are important determinants of the overall effect.

Various policy options exist to ensure that the introduction of SAEVs is not welfare-diminishing. For city centers where private fleet providers are likely to enter the market (if granted access), road tolls that are designed such that they lead to an internalization of external costs (including cost associated with time losses imposed on others, local and greenhouse gas emissions, and noise) have been advocated (Kaddoura et al., 2020a), and will become easier to implement for automated vehicles (Adler et al., 2019). In less densely populated areas, subsidies are likely to be required to render SAEVs an attractive alternative to using a private vehicle (Nunes & Hernandez, 2020). This implies a relevant use case where SAEVs are part of, or complement to the public transport system. While most papers consider SAEVs to be in private fleet ownership, there are some studies that have investigated the potential use of SAEVs in public transport.[3] For instance, Kassens-Noor et al. (2020) and Chee et al. (2020) study how automated vehicles are perceived by potential users, and what drives their intention to use them in the context of the USA (Michigan) and Europe (Stockholm), respectively. Unsurprisingly, comfort and service frequency are identified as crucial factors, while a perceived lack of safety acts as a barrier. Stark et al. (2019) discusses different use cases of automated vehicles (AVs) in relation to public transport, based on a stakeholder process conducted in Germany. They identify three main use cases: (a) traditional bus model with automated buses, (b) feeder system to cover first and last mile, (c) individualized on-demand mobility.

While most studies on SAEVs focus on urban areas (Lin et al., 2019; Pernestål & Kristoffersson, 2019; Guan et al., 2020), those studies that model SAEVs (or shared autonomous vehicles (SAVs))[4] as being part of the public transport system have focused on the complementary role of SAEVs in rural and sub-urban areas as well as small and mid-sized towns where mass public transport cannot be provided efficiently, and where, due to a lack of profitability, private fleet operators would not provide their services. Moreover, the alternative to allow SAEVs to operate in inner, densely populated city centers may largely be detrimental to welfare, as SAEVs add to congestion. Among the papers that study SAEVs outside urban areas are Viergutz & Schmidt (2019) who simulate the operation of a demand-responsive system of SAVs in the rural town of Colditz (Germany), Leich & Bischoff (2019) who focus on implementing AV-based public transport in suburban areas of Berlin, and Cyganski et al. (2018) and Wang et al. (2018) who study the use of SAVs in the mid-sized towns of Brunswick (Germany) and Sioux Falls (US), respectively.

[3] In some instances (such as in Berlin, Bern and Vienna) autonomous buses have already been added to the public transport system. So far, however, they mostly operate at low speeds and under direct human supervision.

[4] Most related studies do not discuss the environmental implications and hence do not differentiate whether shared autonomous vehicles run on fuel or electricity.

Different designs of using SAEVs (or SAVs) as part of the public transport system have been studied. Kaddoura et al. (2020b) simulate on-demand SAVs that are added to existing modes of transportation. They compare a setting where the service area contains the inner-city area of Berlin and one where it contains the entire city. They find that for small service areas and low prices, undesirable mode switches away from cycling and walking towards the newly introduced modes are common. Larger areas make desirable switches away from cars more attractive. Again for the case of Berlin, Leich & Bischoff (2019) simulate the replacement of conventional bus lines in suburban areas of Berlin by on-demand SAVs. They find an increase in operating costs and only a slight decrease in travel time. Using a similar setup, Shen et al. (2018) and Ongel et al. (2019) find more promising results for Singapore: they find that replacing low-demand bus routes by on-demand SAVs leads to improvements in service quality and cost efficiency (Shen et al., 2018), and that using automated vehicles for scheduled and on-demand vehicles leads to substantial cost savings (Ongel et al., 2019).

Multiple studies compare a fully flexible, demand-responsive fleet of SAVs with a less flexible system. Viergutz & Schmidt (2019) come to the conclusion that in rural areas too much flexibility may be too costly or suffer from poor service quality (such as long wait times). Similarly, Chen & Nie (2017) find that running e-hailing vehicles along a fixed-route transit line and with a stable headway outperforms a more flexible, on-demand, zone-based system.

3. Model setup

3.1. Overview

Our model is based on the MATSim software, which simulates the traffic flow of the city of Vienna and its surroundings in a radius of approximately 30 kilometers from the city center. The simulated area covers approximately 4,100 square kilometers and contains a population of around 2.3 million including the 1.7 million inhabitants that reside in Vienna (Eurostat, 2011). The road network data (comprising 156,000 links) are taken from OpenStreetMaps (OSM). Data on potential activity locations (facilities) – categorized into home, work, education, shopping, leisure, and errands – are based on land use categories and points of interest, both derived from OSM, as well as open data on population density (Eurostat, 2019) and employment density (Wirtschaftskammer Österreichs, 2019). Figure 3.1 shows a map of the simulated zone and the location patterns of the facilities.

3.2. Population and plan generation

MATSim requires an initial set of daily schedules or "plans" for agents. These were created by cleaning, geo-constraining, and resampling data from the Austrian national mobility survey "Österreich unterwegs 2013/ 2014" (Tomschy et al., 2016) for the simulated region. A representative population sample of 12.5% enters our simulations (a simulation of the full population) would not be feasible for computational reasons). See Müller et al. (2022) for a more detailed elaboration.

Figure 3.1: MATSim simulation area

Note: Facilities are marked as colored dots. Background map: ©OpenStreetMap.

As the mobility survey contains activity location information only at the municipal code, an algorithm needs to be applied to assign realistic geo-coordinates for the agents' home locations and the destinations visited on the simulated day. This optimization algorithm relies on the reported travel times and trip distances from the survey data. From this, we obtain geo-coded locations for each agent's sequence of activities (for details see Müller et al. 2022).

The baseline scenario (without SAEVs) is calibrated to the travel diaries given in the Österreich Unterwegs 2013-2014 survey. More details on the calibration can be found in Müller et al. (2022).

3.3. Mode choice, routing, and calibration

Overall, we account for five transportation modes - walking, bike, car, public transport (PT), and SAEVs. Two modes, cars and SAEVs, are simulated on the MATSim road network. The travel times and routes of the other modes (walk, bike, and PT) are are not simulated on the network, but generated by existing timetables and other information, such as topography and average walking and cycling speeds. The SAEVs are enabled using the Demand-Responsive Transport (*DRT*) module of MATSim (Maciejewski & Nagel, 2013). This module allows ride-sharing trips and automatic re-location of vehicles according to the demand patterns of the agents.[5]

Before running a simulation, plausible inter-modal plans for the entire day are calculated for each agent and stored. The availability of transport modes and the location of personal vehicles is thereby taken into account. For instance, personal vehicles must be brought back home at the end of the day and can only be used at a location when the agent used it last. The plans of the agents are fed into an inter-modal routing algorithm to generate the transport mode and route for each trip. The inter-modal routing algorithm is not part of MATSim, but instead we make use of the inter-modal routing algorithm, Ariadne (Prandtstetter et al., 2013). It goes beyond the standard MATSim routines, which currently are not capable of generating inter-modal routes. Inter-modal trips, however, are an essential feature of our simulation, since it allows agents to use SAEVs in combination with public transport. If the routing algorithm yields a car or SAEV choice, the corresponding information including location and time, is added to the MATSim simulation. The coherent integration of routing and mode choice outside of MATSim significantly increases the performance and reduces computational time, as also explored elsewhere in the literature (Hörl et al., 2019).

3.4. Utility functions

MATSim works with a scoring function to evaluate the success of an agent's travel diary at the end of the day. The basic logic behind this utility function is to consider the time spent on activities other than travel positively, and penalize travel time (with the penalties differing across modes). In order to capture preference heterogeneity, we split the synthetic population into ten sub-population groups and assign them different dis-utility scores for each mode (see Müller et al. (2022) for a more detailed explanation). This heterogeneity follows the different socio-economic characteristics and therefore reflects the different preference structures of different social groups. The values are estimated based on stated and revealed preference collected from a representative diary-based survey of Austrian workers (Hössinger et al., 2020; Jokubauskaite et al., 2019; Schmid et al., 2019), where an essential finding was that public transport travel times are valued lower (hence, they cause less dis-utility) than car travel times.[6] For SAEVs, we assume that in-vehicle time is valued at 75% of the corresponding value attached to time spent driving a car, hence reflecting that travel time in SAEVs can be used more productively as travelers are released from the driving task and can focus on other activities (Fosgerau, 2019; Ho et al., 2015).

3.5. Zoning

The scenarios discussed in this paper consider SAEVs with restricted operational areas. The main underlying idea is a policy that limits the use of such a service to areas at the outskirts

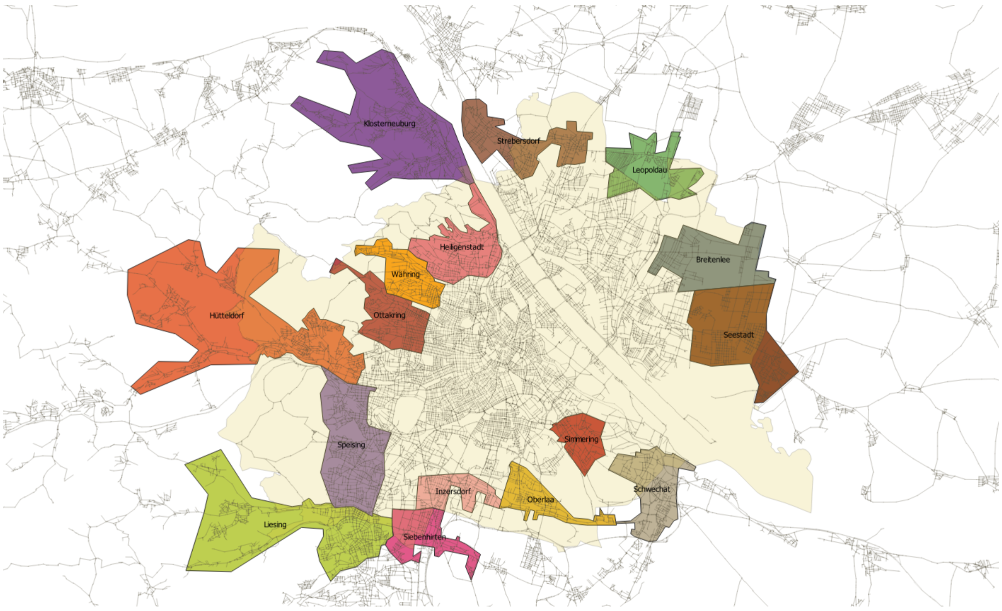
[5] Bischoff & Maciejewski (2020) show that for a fleet of autonomous vehicles, re-balancing of vehicles can decrease waiting times by around 30% without increasing the overall distance travelled.

[6] A potential explanation brought forward by the authors of the cited studies is that smartphones and other mobile devices have rendered public transport travel times more enjoyable and productive compared to car travel times.

of the city. These areas usually do not have a dense public transport network which is why car ownership rates and car trips are higher than in the city center. SAEVs can help to solve the first/last mile problem by improving connectivity to prioritized (usually rail-based) public transport. For the simulations, we define 16 zones in the outskirts of Vienna consisting of low-density residential areas with low-frequency public transport (busses), but also access to at least one subway or railway station with good service (more than one connection every 20 minutes during rush hour). While the Viennese public transport system is generally of very high quality, it thins out significantly as the distance from the city center increases.

The exact selection of the zones can be seen in Figure 3.2. Each areas contains between 2,000 to 11,000 facilities in the paper, and the SAEV fleet size in the corresponding area is proportional to that number.[7] Each SAEV is assigned to one zone and is only allowed to

Figure 3.2: Simulation zones with separate SAEV fleets in the outskirts of Vienna



pick and drop off passengers within that zone. In order to ensure that the SAEVs are used strictly as a last mile service, and not for routes from one zone to another, each zone has its own zone-specific SAEV fleet.

3.6. CO2 Emissions

In our simulation model, private cars are the only transport mode that causes CO2 emissions (we ignore emissions accruing for energy generation and vehicle production processes). The emissions for each car that is present in the simulation are calculated after the last iteration using the Emissions Module (*ev*) for MATSim developed by Hülsmann et al. (2011) and

[7] In the MATSim framework, zones are implemented as a *shape area-based* operational scheme (Maciejewski & Nagel, 2013).

further extended by Kickhöfer et al. (2013). A detailed description of the calculation of the emissions can be found in Kickhöfer (2014) and Axhausen et al. (2016). Since MATSim simulates the traffic at the car level, emissions can be estimated very accurately and assigned to locations in the road network as well as to the trips of specific agents.

In general, MATSim distinguishes between warm emissions and cold emissions. While warm emissions are emitted during the whole trip and are independent of the engine's temperature, cold emissions occur in addition during the warm-up phase of the engine. For the computation of the warm emissions, MATSim uses driving speed, stop duration, and vehicle characteristics; for the computation of the cold emissions it uses driving speed, distance traveled, parking time and vehicle characteristics (André & Rapone, 2009; Weilenmann et al., 2009). Other factors such as air conditioning and different road gradients are ignored. For the vehicle characteristics, we refer to average values from the Handbook Emission Factors for Road Transport version 4.1 (HBEFA 4.1 Notter et al. 2019).

Finally, note that we do not model the charging behavior of electric vehicles (the SAEVs), as MATSim's extension for electric vehicles (Waraich et al., 2013) is unfortunately not compatible with the use of multiple SAEV fleets (which we require due to the definition of the SAEV zones).

4. Simulations

4.1. Overview

A baseline simulation without SAEVs is used as a benchmark to compare changes across key variables. It reflects the status-quo in the larger Vienna region in terms of its population (and characteristics thereof), existing infrastructure and vehicle ownership characteristics, and hence does not account for demographic or technological changes (e.g. more people switching to privately owned electric vehicles) that might occur over time. In addition to the baseline simulation without SAEVs, we conduct the following nine experiments:

- 12 SAEVs per 1000 facilities at 00 cents per minute
- 12 SAEVs per 1000 facilities at 10 cents per minute
- 12 SAEVs per 1000 facilities at 30 cents per minute
- 25 SAEVs per 1000 facilities at 00 cents per minute
- 25 SAEVs per 1000 facilities at 10 cents per minute
- 25 SAEVs per 1000 facilities at 30 cents per minute
- 25 SAEVs per 1000 facilities at 00 cents per minute and 100% increase in fuel costs
- 25 SAEVs per 1000 facilities at 00 cents per minute and 25% increase in the costs of owning a car
- 25 SAEVs per 1000 facilities at 00 cents per minute with a 100% increase in fuel costs and a 25% increase in the costs of owning a car

Hence, in all experiments the supply of SAEVs is fixed to either 12 or 25 vehicles per 1000 facilities located inside the zones. In total, these sum up to 1,118 and 2,338 SAEVs respectively, representing medium to large fleet size scenarios. For comparison, there are 4800 taxis in the city of Vienna (Kluge et al., 2020), which would correspond to 600 in our simulation (as only 12.5% of the population is simulated). Moreover, for the comparison it needs to be considered that the existing taxis are present throughout the entire city of Vienna, whereas those in our simulations are limited to the pre-defined zones.

In the simulations, SAEVs are introduced at three price levels; 0 cents, 10 cents, and 30 cents per minute. The lower fares, especially the 0 cent price, reflect a strongly subsidized fare, as common with most public transport systems (including the Viennese one). The highest price corresponds closely to what studies predict to be the fare level charged by private SAEV fleet operators (Bösch et al., 2018; Compostella et al., 2020).

The last three experiments are all based on the larger fleet size (25 SAEVs per 1000 facilities) and 0 costs, and aim to test, to which extent SAEV take-up increases if the usage and/or ownership of private cars becomes more expensive. Higher usage costs are represented by fuel costs doubling from 9.1 ct/km to 18.2 ct/km. Higher ownership costs are reflected by a 25% increase in the costs associated with owning a car (incl. insurance, depreciation etc.) from 13.5 Euro/day to 16.9 Euro/day. Car ownership costs are only charged if a person uses the car on the day of simulation.

For comparisons across the different scenarios, we can make use of the fact that within the MATSim framework, the same trip, defined by an origin and destination node, exists across all simulations and can thus be assigned a unique identifier. This allows us to track and compare changes in key statistics like travel times, distances, modal split, and emissions across the simulations. Data is also recorded on the road network, which provides an additional set of variables to measure speeds, congestion levels, and emissions.

4.2. Impact of SAEVs

For all agents who reside in the SAEV zones and all scenarios, Table 4.1 shows descriptive statistics for the following four key indicators: travel time, the monetary valuation thereof, distance traveled, and CO2 emissions.

Table 4.1: Descriptive statistics for all agents in zones

								Increase in cars costs		
	Baseline	12 SAEVs			25 SAEVs			25 SAEVs 0 cents		
		0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	100% gas+25% cost
Average travel time (hh:mm)	01:17	01:15	01:14	01:14	01:15	01:14	01:14	01:17	01:17	01:19
	(00:47)	(00:44)	(00:43)	(00:43)	(00:43)	(00:43)	(00:43)	(00:44)	(00:44)	(00:45)
Time costs (Eur)	13.22	12.56	12.51	12.51	12.45	12.42	12.45	12.60	12.67	12.85
	(8.35)	(7.63)	(7.54)	(7.39)	(7.42)	(7.39)	(7.37)	(7.50)	(7.46)	(7.59)
Average distance (km)	25.29	25.82	25.71	25.55	25.92	25.79	25.58	25.92	25.97	25.98
	(20.31)	(20.32)	(20.27)	(20.27)	(20.33)	(20.29)	(20.27)	(20.30)	(20.35)	(20.35)
CO2 emissions (kg)	18.74	16.82	17.20	17.72	16.64	16.89	17.50	14.46	14.63	12.65
	(33.73)	(33.71)	(33.97)	(34.13)	(33.80)	(33.85)	(34.03)	(32.01)	(32.75)	(30.95)

For the first six scenarios, where the costs associated with private cars are unchanged, the introduction of SAEVs leads to relatively small shifts in these indicators. The average daily travel time of the agents residing in the SAEV zones decreases by two to three minutes (2.5–4%), and their average time costs decrease by 25 to 40 cents (2–3%). Average distances increase only very slightly compared to the baseline (at most by 0.63 km in the scenario with the larger fleet size and 0 price). The largest change can be observed for CO2 emissions, which decline by 5-11% when SAEVs are introduced. The reduction in emissions, as expected, is higher for the lower price scenarios and for the larger fleet size scenarios, as more agents switch to SAEVs under these conditions.

The last three columns of Table 4.1 show the results of those scenarios where not only SAEVs are introduced, but at the same time also private car usage and/or ownership become more expensive. Together with assuming a large SAEV fleet size and 0 costs for SAEV usage, these scenarios lead to a larger change in the indicators than the first six scenarios, in which the costs associate with private car usage and ownership remained constant. We find that, unlike for the first 6 scenarios, average travel time increases somewhat (by at maximum 2 minutes) or remains constant as agents increasingly switch to SAEVs. Average time costs go down to a small extent (the largest decline is 62 cents), as the travel time in SAEVs is valued lower due to the possibility to spend the time on work and entertainment activities. The average distance traveled remains almost the same as in the baseline just as in the first six scenarios. The CO2 emissions decline substantially as more private car owners switch to SAEVs than in the first six scenarios, where the costs for using and owning a private car were unchanged. The average decrease is highest (6.09 kg, corresponding to 32%) for the last scenario where both the costs for private car usage and for private car ownership are increased.

To investigate more specifically the impact of the SAEV introduction on car users, Table 4.2 shows the simulation results only for those agents who used a car in the baseline and who reside in one of the SAEV operating areas. We find that for this group of agents, the average travel time goes up by 7 to 10 minutes in the first six scenario, and 16 to 22 minutes when private car usage and/or ownership becomes more expensive (from 77 minutes in the baseline scenario). Compared to the slight average increases for the entire population living in the zones (see Table 4.1), these increases are quite substantial. The average time costs again exhibit a similar pattern, although a bit less pronounced as a switch to SAEVs goes hand in hand with lower time valuations. Average distances are affected only slightly – in all scenarios they go up by around 0.5 to 1 km. Again, the largest change occurs for CO2 emissions, which decrease from 58 kg in the baseline to around 50 kg (-13%) in the first six scenarios, and to 38 kg (-34%) if both car usage and ownership become more expensive.

4.3. Who is switching to SAEVs?

Table 4.3 shows the share of trips that switch to SAEVs from other transport modes. To determine this at the trip level, a main mode for each trip is defined using the following ranking: SAEVs > PT > Car > Bike > Walk. The main mode for a specific trip is then always defined as the mode that ranks highest, irrespective of the travel time or the distance traveled by different modes within a trip. This methodology is consistent with the Österreich

Table 4.2: Descriptive statistics for all agents residing in the zones who use the car in the baseline

								Increase in cars costs		
	Baseline	12 SAEVs			25 SAEVs			25 SAEVs 0 cents		
		0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	100% gas+25% cost
Average travel time (hh:mm)	01:00	01:10	01:08	01:07	01:10	01:09	01:07	01:16	01:16	01:22
	(00:32)	(00:34)	(00:32)	(00:32)	(00:33)	(00:33)	(00:32)	(00:38)	(00:36)	(00:40)
Time costs (Eur)	12.51	13.55	13.41	13.23	13.60	13.44	13.21	14.01	14.20	14.73
	(6.69)	(6.25)	(6.19)	(6.17)	(6.24)	(6.22)	(6.20)	(6.39)	(6.28)	(6.47)
Average distance (km)	36.88	37.47	37.35	37.17	37.56	37.43	37.22	37.54	37.67	37.70
	(23.02)	(22.94)	(22.91)	(22.91)	(22.87)	(22.88)	(22.93)	(22.81)	(22.86)	(22.84)
CO2 emissions (kg)	57.63	49.63	50.70	52.22	49.11	49.97	51.83	43.23	43.74	38.06
	(36.38)	(42.29)	(41.95)	(41.05)	(42.76)	(42.36)	(41.32)	(43.12)	(44.33)	(44.07)

Unterwegs 2013–2014 report (Tomschy et al., 2016), based on which the agent population has been defined.

Table 4.3: Mode switch to SAEVs - all agents

							Increase in cars costs		
	12 SAEVs			25 SAEVs			25 SAEVs 0 cents		
	0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	100% gas+25% cost
Walk + Bike	30.85	28.91	22.77	35.24	31.65	24.19	35.73	35.84	36.06
Car	11.61	10.02	7.04	13.81	11.59	7.58	16.62	16.84	19.84
PT	18.25	14.27	9.55	20.28	15.62	10.29	20.43	20.52	20.62
All modes	18.56	16.06	11.72	21.23	17.84	12.54	22.56	22.71	24.04

Table 4.3 shows the switch to SAEVs from other modes for all agents residing inside the SAEV operating zones. As expected, switches to SAEVs are higher at lower prices and larger fleet sizes. Looking at the different modes from which agents switch towards SAEVs, we find that in particular those trips that have been conducted with active modes (walking and biking) in the baseline scenario are replaced by SAEVs. Depending on the scenario, 23–36% of trips undertaken with active transport modes are replaced by SAEVs. These switches tend to be undesirable from several perspectives: active transport modes have no emissions, are beneficial from a health perspective, and very space-efficient. Similarly, switches away from traditional public transport towards SAEVs are usually not desirable from social welfare point of view (unless they generate large benefits to users). Depending on the scenario, we find that 10–22% of public transport trips are replaced by SAEVs. Lower ridership numbers in public transport might lead to capacity adjustments by the public transport operator, for instance by decreasing the service frequency, which in turn leads to public transport becoming less attractive.

Those mode switches that tend to be most desirable from a societal point of view are those where private car trips are replaced by SAEVs. We find that these switches take place to a fairly limited extent in the first six scenarios (7–14% of car trips are replaced; as expected, the percentage is lowest for the scenario with low fleet size and the high price). This share increases substantially in those scenarios where private car usage and/or ownership becomes more expensive. In these scenarios, 17–20% of private car trips are replaced with SAEV rides.

Table 4.4 provides an overview of the socio-economic characteristics of SAEV users, and how they compare to the average characteristics of the agents residing in the zones (first column).

Table 4.4: Characteristics of SAEV users

	Baseline	12 SAEVs			25 SAEVs			Increase in cars costs 25 SAEVs 0 cents		
		0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	100% gas+25% cost
Males (%)	49.47	46.84	46.05	44.22	46.14	45.56	44.40	46.65	46.62	47.00
Average age	41.81	42.12	41.68	40.97	41.37	40.97	40.67	41.58	41.62	41.79
Urban (%)	81.46	75.33	73.29	69.73	73.29	71.30	68.95	73.31	73.36	73.40
Single (%)	21.28	19.86	19.38	18.53	19.51	19.39	18.81	19.55	19.77	19.76
Has kids (%)	37.30	38.34	39.53	41.65	39.51	40.75	41.95	39.19	39.22	39.06
Educated (%)	32.17	28.68	27.59	25.44	28.16	26.61	25.10	28.79	29.03	29.81
High income (%)	42.24	42.86	43.05	43.48	43.40	43.30	43.21	43.48	43.17	43.46
Has a Car (%)	61.35	53.03	51.30	47.99	51.79	49.98	47.36	53.63	53.81	55.49
Has a PT ticket (%)	48.15	44.70	44.66	42.22	44.26	43.70	41.92	44.24	43.98	44.01

The first Baseline column gives the population statistics. The remaining columns show the share of population that switch to SAEVs for each scenarios.

The table shows that agents who make use of SAEVs are somewhat less likely to be male and single, and more likely to have children than the population average. SAEV users also tend to be slightly less educated but somewhat richer than the average. They are less likely to be resident of an area with a high urbanity level, and less likely to have a car, or a public transport pass.

4.4. SAEV trips

Table 4.5 provides statistics on the SAEV trips. The first row shows the total number of SAEVs in the model (part of the scenario definition) and the next row shows the total distance traveled. At lower prices, the average distance that an SAEV travels increases since demand is higher. The total distance traveled by SAEVs goes up further when private car use/ownership is priced more heavily.

Since SAEVs are shared, and the number of passengers can vary, the *Ride sharing* section in Table 4.5 shows what percentage of the total distance traveled is either empty, single rides, or shared. The share of empty kilometers increases at higher prices and smaller fleets sizes (and hence in those scenarios with less overall demand), ranging from 27 to 34% of the total distance travelled. Single occupancy rides account for 45–52% of the total SAEV distance and their share goes up at higher prices. At lower prices, we can observe more sharing among the agents.

As to be expected, the number of SAEV rides are substantially higher at lower prices and at the larger fleet size. For instance, if the price goes up from 0 cents to 30 cents, the number of SAEV rides goes down by about 33%. Similarly, holding prices constant, doubling the fleet size from 1118 to 2338 vehicles results in an increase of 12% SAEV rides.

Table 4.5: Characteristics SAEV demand

	12 SAEVs			25 SAEVs			Increase in cars costs, 25 SAEVs 0 cents		
	0 cents	10 cents	30 cents	0 cent	10 cents	30 cents	100% gas	25% cost	100% gas+25% cost
SAEVs									
Total SAEVs (count)	1,118	1,118	1,118	2,338	2,338	2,338	2,338	2,338	2,338
Total distance (km)	139,773	126,309	99,434	142,328	124,802	93,128	152,594	152,913	161,950
Avg distance/SAEV (km)	125.02	112.98	88.94	60.90	53.38	39.83	65.27	61.13	68.27
Total empty distance (km)	43,692	40,676	33,915	38,762	34,269	24,936	41,066	41,631	43,316
Ride sharing									
0 passengers (%)	31.26	32.20	34.11	27.23	27.46	26.78	26.91	27.23	26.75
1 passenger (%)	45.24	46.00	47.05	46.34	48.40	51.97	46.19	46.24	45.71
2 passengers (%)	17.51	16.89	14.92	19.55	18.37	16.56	19.61	19.49	20.05
3 passengers (%)	4.37	3.80	2.89	5.10	4.37	3.56	5.32	5.18	5.34
4 passengers (%)	1.62	1.10	1.02	1.78	1.41	1.14	1.97	1.86	2.15
Customers									
SAEV rides (count)	43,943	38,658	29,027	47,790	41,174	30,549	51,070	51,040	54,369
Average wait time (mm:ss)	03:05	02:58	02:49	02:43	02:41	02:31	02:44	02:43	02:44
Average travel time (mm:ss)	09:50	09:31	08:56	09:36	09:17	08:40	09:38	09:35	09:38
Emissions									
Change in CO2 emissions (%)	-9.94	-8.47	-6.43	-10.94	-9.96	-7.33	-20.99	-20.22	-30.34
Change outside zones (%)	-3.78	-3.20	-2.60	-3.75	-3.62	-3.02	-16.05	-13.31	-25.92

The demand for SAEVs is also reflected in the average wait times for hailed SAEV rides. Across the scenarios, the average wait time does not vary much and generally amounts to 2.5 to 3 minutes. In this context it should be noted that for SAEVs, we assume a 1-minute minimum wait time and a maximum wait time of 10 minutes (after which a trip is cancelled). For example, for the first experiment, the average wait time is approximately 3 minutes which goes down as the fleet size goes up. This result is expected as more cars will cater better to the demand. Similarly, at higher prices, the average wait time for SAEVs decline, as a result of lower demand. Finally, wait times for SAEVs do not change much in those scenarios where cars ownership and/or usage become more expensive.

Those scenarios in which the costs of private car usage and/or ownership are increased, are based on the assumption of the larger fleet size and 0 costs. As a consequence, it is not surprising that the demand patterns associated with these scenarios are fairly similar to the scenario with the larger fleet and 0 costs (but no changes in costs related to private cars). This is particularly true in terms of the extent to which SAEVs are idle, and shared. Also the average wait time and travel time are similar to that reference scenario. Differences can be observed with respect to overall distance driven and the number of SAEV trips: both indicators exhibit a 7-14% increase relative to the larger fleet and 0 costs scenario in which private car costs are unaffected. A fairly pronounced difference can also be observed with respect to the CO2 emissions, where the decline relative to the baseline is 10-19 percentage points higher than for the higher fleet and 0 cost scenario without changes in the costs for private car usage and/or ownership.

The bottom part of Table 4.5 provides the change in CO2 emissions for roads inside the zones compared to the baseline scenario. For the first six scenarios, the drop in emissions is between 6 and 11% in the zones, and for the other six scenarios between 14 and 18%. The higher bound occurs for those scenarios where more car trips are replaced by SAEV trips (i.e. those with low prices and the higher fleet size). This result is a direct consequence of our assumption that cars are the only source of direct CO2 emissions. The table further also shows changes in CO2 emissions produced along the road network outside the SAEV zones. These amount to reductions in the range of -3 to -4% for the first six scenarios (no change in the costs for private cars). This spillover effect is mostly due to agents switching from cars to other modes (among them, SAEVs) when traveling to and from destinations outside the SAEV-zones.[8] For the three scenarios in which private car ownership and/or usage is assumed to become more expensive, the decline in CO2 emissions outside the zones are much stronger than in the first six scenarios, namely between 13 and 26%. These declines can however not be exclusively attributed to spillover effects, but is due to car usage and/or ownership becoming generally more expensive.

5. Conclusions and directions for future research

In this paper, we introduce shared, autonomous, electric vehicles (SAEVs) in zones outside of the city center of Vienna (Austria), where population density is relatively low but access to prioritized (rail-based) public transport is available. The simulations are programmed in MATSim. We simulate a small (10 SAEVs/1000 facilities) and a large (30 SAEVs/1000 facilities) fleet of demand-responsive SAEVs with a maximum capacity of four persons, as well as a scenario in which SAEV is free, a low SAEV fare (10 cents/minute) and a high SAEV fare (30 cents/minute). For all combinations of price and fleet size, we find that only a fairly small share of agents switches from cars to SAEVs, and that SAEVs are mainly used by agents that have traveled on zero-emission modes (cycling, walking, public transport) in the baseline scenario (i.e. the status quo without cars). As a result, CO2 emissions savings relative to the baseline (for the agents residing in the SAEV zones) are fairly low: 5-11%. Moreover, a switch away from cycling and walking may also have negative public health impacts (Nunes & Hernandez, 2020).

In the second part of the experiments, we introduce scenarios in which not only SAEVs are introduced (with a fare of 0 EUR/min and the larger fleet size), but also the ownership and/or usage of private cars becomes more expensive. We find that under such conditions, more agents who used cars in the baseline scenario can be convinced to switch to alternative modes including SAEVs. We find that under these conditions, significantly higher CO2 reductions (up to 32%) can be generated, as car users increasingly use SAEVs as well as active modes and public transport.

From a policy perspective, our results thus imply that introducing demand-responsive SAEVs as part of the public transport system at the outskirts of cities will lead to some reductions in CO2 emissions, but may have other negative societal consequences when pedestrians, cyclists and public transport users switch to SAEVs. Emission reductions are only expected to be large if accompanying policies are implemented that render car usage and ownership

[8]We find no evidence that the presence of SAEVs affects travel times outside the zones.

unattractive. However, as our simulations show these emission reductions come at the cost of significantly longer travel times. These costs may be decreased by investing in cycling infrastructure and conventional mass public transport also in the less densely populated areas of Vienna.

Our findings are broadly in line with the relevant literature. Also Kaddoura et al. (2020b) obtained the result that with smaller zones, mainly "undesirable switches" away from walking, cycling and public transport towards SAEVs take place. Similar to Cyganski et al. (2018) we also find that the uptake of SAEVs is fairly moderate, and as Viergutz & Schmidt (2019) we can conclude that SAEVs are likely not be the panacea for public transport provision in areas with fairly low population density. In contrast to these studies, we emphasize also environmental and socioeconomic impacts of SAEVs.

Our simulations are of course not without limitations. For instance, we assume there is no latent demand for additional trips; the plans of the agents are not altered by the introduction of SAEVs. This assumption has been made to ensure tractability and allow for comparisons of specific trips across experiments. But it is inconsistent with other studies that predict a strong increase in vehicle kilometers traveled (Pernestål & Kristoffersson, 2019). Not only is the introduction of an additional, attractive transport mode likely to increase the number of trips, it may also lead to longer trips, not at least because in the longer run people may relocate to more remote (and hence cheaper) locations, inducing further urban sprawl (Duarte & Ratti, 2018; Meyer et al., 2017).

Overall, we look at a situation where SAEVs are only introduced in the designated zones at the outskirts of Vienna, while otherwise assuming that the status-quo remains. This scenario might be somewhat unrealistic in several dimensions, including the assumptions that private car ownership rates remain unchanged, that private cars predominantly operate on fossil fuels, and that the demographic and geographical characteristics of the Greater Vienna Area remain as they are. In fact, by the time SAEVs are introduced, also other changes along these dimensions will have taken place. We have chosen not to make any specific assumptions on these other dimensions (besides fixing them to the status-quo) in order to have a clearly identifiable baseline and not having to make other assumptions.

Another disadvantage of our simulation approach is that it takes the agents' plans as given. It hence ignores that the availability of a new transport mode may also lead to changes in travel demand (due to changes in trip origins and destinations, trip timing, or in the planned activities). The review paper by Pernestål & Kristoffersson (2019) concludes that most studies that account for changes in demand find that SAEVs are likely to lead to more vehicle kilometers traveled (induced demand). While this is certainly an important aspect to consider for simulations in which SAEVs can operate throughout the entire city, it may, however, be less relevant for our simulation scenarios, as our focus is on first- and last-mile trips.

In addition to tackling the above limitations, some of the other aspects of the simulation model might be refined in future research. This includes taking into account the charging of SAEVs, and a dynamic interaction between demand (mode choice) and supply (SAEV fleet size and pricing). Testing different algorithms for ride-sharing and re-balancing of fleets, different fare systems (e.g. fixed price), different SAEV capacities as well as introducing pick-up and drop-off points rather than pick-ups and drop-offs at the door may be interesting extensions for future work.

References

Adler, M. W., Peer, S., & Sinozic, T. (2019). Autonomous, connected, electric shared vehicles (ACES) and public finance: An explorative analysis. *Transportation Research Interdisciplinary Perspectives*, *2*, 100038.

Ambühl, L., Ciari, F., & Menendez, M. (2016). What about space?: A simulation based assessment of AVs impact on road space in urban areas. In *16th Swiss Transport Research Conference (STRC 2016)*. STRC.

André, M., & Rapone, M. (2009). Analysis and modelling of the pollutant emissions from European cars regarding the driving characteristics and test cycles. *Atmospheric Environment*, *43*, 986–995.

Axhausen, K., Horni, A., & Nagel, K. (2016). *The multi-agent transport simulation MATSim*. Ubiquity Press.

Becker, H., Becker, F., Abe, R., Bekhor, S., Belgiawan, P. F., Compostella, J., Frazzoli, E., Fulton, L. M., Bicudo, D. G., Gurumurthy, K. M. et al. (2020). Impact of vehicle automation and electric propulsion on production costs for mobility services worldwide. *Transportation Research Part A: Policy and Practice*, *138*, 105–126.

Bischoff, J., & Maciejewski, M. (2020). Proactive empty vehicle rebalancing for demand responsive transport services. *Procedia Computer Science*, *170*, 739–744.

Bösch, P. M., Becker, F., Becker, H., & Axhausen, K. W. (2018). Cost-based analysis of autonomous mobility services. *Transport Policy*, *64*, 76–91.

Chee, P. N. E., Susilo, Y. O., & Wong, Y. D. (2020). Determinants of intention-to-use first-/last-mile automated bus service. *Transportation Research Part A: Policy and Practice*, *139*, 350–375.

Chen, P. W., & Nie, Y. M. (2017). Connecting e-hailing to mass transit platform: Analysis of relative spatial position. *Transportation Research Part C: Emerging Technologies*, *77*, 444–461.

Compostella, J., Fulton, L. M., De Kleine, R., Kim, H. C., & Wallington, T. J. (2020). Near-(2020) and long-term (2030–2035) costs of automated, electrified, and shared mobility in the United States. *Transport Policy*, *85*, 54–66.

Cyganski, R., Heinrichs, M., von Schmidt, A., & Krajzewicz, D. (2018). Simulation of automated transport offers for the city of Brunswick. *Procedia computer science*, *130*, 872–879.

Duarte, F., & Ratti, C. (2018). The impact of autonomous vehicles on cities: A review. *Journal of Urban Technology*, *25*, 3–18.

Eurostat (2011). Geostat population distribution / demography. https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography.

Eurostat (2019). Eurostat Bevölkerungsraster. https://ec.europa.eu/eurostat/de/web/gisco/geodata/reference-data/population-distribution-demography/geostat. Online; retrieved on 24. July 2020.

Fagnant, D. J. (2015). Dynamic Ride-Sharing and Optimal Fleet Sizing for a System of Shared Autonomous Vehicles. *Proceedings of the 94th Annual Meeting of the Transportation Research Board in Washington DC*, .

Fielbaum, A. (2019). Strategic public transport design using autonomous vehicles and other new technologies. *International Journal of Intelligent Transportation Systems Research*, (pp. 1–9).

Fosgerau, M. (2019). *Automation and the value of time in passenger transport*. OECD.

Gawron, J. H., Keoleian, G. A., De Kleine, R. D., Wallington, T. J., & Kim, H. C. (2018). Life cycle assessment of connected and automated vehicles: sensing and computing subsystem and vehicle level effects. *Environmental science & technology*, *52*, 3249–3256.

Grigoratos, T., & Martini, G. (2015). Brake wear particle emissions: a review. *Environmental Science and Pollution Research*, *22*, 2491–2504.

Guan, J., Zhang, K., Zhang, S., & Chen, Y. (2020). How is public transit in the megacity peripheral relocatees' area in China? Captive transit rider and dynamic modal accessibility gap analytics in a peripheral large-scale residential area in Shanghai, China. *Journal of Transport and Land Use*, *13*, 1–21. URL: https://www.jtlu.org/index.php/jtlu/article/view/1505. doi:10.5198/jtlu.2020.1505.

Ho, C. Q., Mulley, C., Shiftan, Y., & Hensher, D. A. (2015). Value of travel time savings for multiple occupant car: evidence from a group-based modelling approach. In *Australasian Transport Research Forum 2015 Proceedings*.

Hörl, S., Balać, M., & Axhausen, K. (2019). Pairing discrete mode choice models and agent-based transport simulation with MATSim. In *2019 TRB Annual Meeting Online* (pp. 19–2409). Transportation Research Board.

Hössinger, R., Aschauer, F., Jara-Diaz, S., Jokubauskaite, S., Schmid, B., Peer, S., Axhausen, K., & Gerike, R. (2020). A joint time-assignment and expenditure-allocation model: value of leisure and value of time assigned to travel for specific population segments. *Transportation*, *47*, 1439–1475.

Hülsmann, F., Gerike, R., Kickhöfer, B., Nagel, K., & Luz, R. (2011). Towards a multi-agent based modeling approach for air pollutants in urban regions. In *Conference on "Luftqualität und Straßen"* (pp. 144–166). FGSV-Verl. Available Open Access acceptedVersion at https://depositonce.tu-berlin.de/handle/11303/10353.

Jokubauskaite, S., Hössinger, R., Aschauer, F., Gerike, R., Jara-Diaz, S., Peer, S., Schmid, B., Axhausen, K., & Leisch, F. (2019). Advanced continuous-discrete model for joint time-use expenditure and mode choice estimation. *Transportation Research Part B: Methodological*, *129*, 397–421.

Kaddoura, I., Bischoff, J., & Nagel, K. (2020a). Towards welfare optimal operation of innovative mobility concepts: External cost pricing in a world of shared autonomous vehicles. *Transportation Research Part A: Policy and Practice*, *136*, 48–63.

Kaddoura, I., Leich, G., & Nagel, K. (2020b). The impact of pricing and service area design on the modal shift towards demand responsive transit. *Procedia Computer Science*, *170*, 807–812.

Kassens-Noor, E., Kotval-Karamchandani, Z., & Cai, M. (2020). Willingness to ride and perceptions of autonomous public transit. *Transportation Research Part A: Policy and Practice*, *138*, 92 – 104. URL: http://www.sciencedirect.com/science/article/pii/S0965856420305929. doi:https://doi.org/10.1016/j.tra.2020.05.010.

Kickhöfer, B. (2014). *Economic policy appraisal and heterogeneous users*. Ph.D. thesis Technische Universität Berlin.

Kickhöfer, B., Hülsmann, F., Gerike, R., & Nagel, K. (2013). Rising car user costs: comparing aggregated and geo-spatial impacts on travel demand and air pollutant emissions. In *Smart Transport Networks*. Edward Elgar Publishing.

Kluge, J., Kocher, M. G., Müller, W., & Zenz, H. (2020). Empfehlungen für die gestaltung eines tarifs für die neue konzessionsart personenbeförderungsgewerbe mit pkw–taxi im bundesland wien, .

Kopelias, P., Demiridi, E., Vogiatzis, K., Skabardonis, A., & Zafiropoulou, V. (2020). Connected & autonomous vehicles–environmental impacts–a review. *Science of the total environment*, *712*, 135237.

Larson, W., & Zhao, W. (2020). Self-driving cars and the city: Effects on sprawl, energy consumption, and housing affordability. *Regional Science and Urban Economics*, *81*, 103484.

Leich, G., & Bischoff, J. (2019). Should autonomous shared taxis replace buses? A simulation study. *Transportation Research Procedia*, *41*, 450–460.

Lin, Y., Zhang, K., Shen, Z.-J. M., & Miao, L. (2019). Charging Network Planning for Electric Bus Cities: A Case Study of Shenzhen, China. *Sustainability*, *11*, 4713. URL: https://www.mdpi.com/2071-1050/11/17/4713. doi:10.3390/su11174713.

Liu, J., Kockelman, K. M., Boesch, P. M., & Ciari, F. (2017). Tracking a system of shared autonomous vehicles across the austin, texas network using agent-based simulation. *Transportation*, *44*, 1261–1278.

Loeb, B., & Kockelman, K. M. (2019). Fleet performance and cost evaluation of a shared autonomous electric vehicle (SAEV) fleet: A case study for Austin, Texas. *Transportation Research Part A: Policy* *and Practice*, *121*, 374–385.

Maciejewski, M., & Nagel, K. (2013). A microscopic simulation approach for optimization of taxi services. In *3rd International Conference on Models and Technologies for Intelligent Transportation Systems 2013* (pp. 1–10). TUDpress.

Malokin, A., Circella, G., & Mokhtarian, P. L. (2019). How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios. *Transportation Research Part A: Policy and Practice*, *124*, 82–114.

Meyer, J., Becker, H., Bösch, P. M., & Axhausen, K. W. (2017). Autonomous vehicles: The next jump in accessibilities? *Research in transportation economics*, *62*, 80–91.

Millard-Ball, A. (2019). The autonomous vehicle parking problem. *Transport Policy*, *75*, 99–108.

Molin, E., Adjenughwure, K., de Bruyn, M., Cats, O., & Warffemius, P. (2020). Does conducting activities while traveling reduce the value of time? Evidence from a within-subjects choice experiment. *Transportation research part A: policy and practice*, *132*, 18–29.

Moreno, A. T., Michalski, A., Llorca, C., & Moeckel, R. (2018). Shared autonomous vehicles effect on vehicle-km traveled and average trip duration. *Journal of Advanced Transportation*, *2018*.

Müller, J., Straub, M., Richter, G., & Rudloff, C. (2022). Integration of different mobility behaviors and intermodal trips in matsim. *Sustainability*, *14*, 428.

Notter, B., Keller, M., Althaus, H.-J., Cox, B., Knörr, W., Heidt, C., Biemann, K., Räder, D., & Jamet, M. (2019). *HBEFA 4.1*. Technical Report Bundesamt für Umwelt BAFU, Umweltbundesamt.

Nunes, A., & Hernandez, K. D. (2020). Autonomous taxis & public health: High cost or high opportunity cost? *Transportation Research Part A: Policy and Practice*, *138*, 28–36.

Ongel, A., Loewer, E., Roemer, F., Sethuraman, G., Chang, F., & Lienkamp, M. (2019). Economic assessment of autonomous electric microtransit vehicles. *Sustainability*, *11*, 648.

Pernestål, A., & Kristoffersson, I. (2019). Effects of driverless vehicles-comparing simulations to get a broader picture. *European Journal of Transport & Infrastructure Research*, *19*.

Prandtstetter, M., Straub, M., & Puchinger, J. (2013). On the way to a multi-modal energy-efficient route. In *IECON 2013-39th Annual Conference of the IEEE Industrial Electronics Society* (pp. 4779–4784). IEEE.

Rafael, S., Correia, L. P., Lopes, D., Bandeira, J., Coelho, M. C., Andrade, M., Borrego, C., & Miranda, A. I. (2020). Autonomous vehicles opportunities for cities air quality. *Science of the Total Environment*, *712*, 136546.

Schmid, B., Jokubauskaite, S., Aschauer, F., Peer, S., Hössinger, R., Gerike, R., Jara-Diaz, S. R., & Axhausen, K. (2019). A pooled RP/SP mode, route and destination choice model to investigate mode and user-type effects in the value of travel time savings. *Transportation Research Part A: Policy and Practice*, *124*, 262–294.

Shaheen, S., & Bouzaghrane, M. A. (2019). Mobility and energy impacts of shared automated vehicles: a review of recent literature. *Current Sustainable/Renewable Energy Reports*, *6*, 193–200.

Shen, Y., Zhang, H., & Zhao, J. (2018). Integrating shared autonomous vehicle in public transportation system: A supply-side simulation of the first-mile service in Singapore. *Transportation Research Part A: Policy and Practice*, *113*, 125–136.

Spurlock, C. A., Sears, J., Wong-Parodi, G., Walker, V., Jin, L., Taylor, M., Duvall, A., Gopal, A., & Todd, A. (2019). Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area. *Transportation Research Part D: Transport and Environment*, *71*, 283–301.

Stark, K., Gade, K., & Heinrichs, D. (2019). What does the future of automated driving mean for public transportation? *Transportation Research Record*, *2673*, 85–93.

Taiebat, M., Stolper, S., & Xu, M. (2019). Forecasting the impact of connected and automated vehicles on energy use: a microeconomic study of induced travel and energy rebound. *Applied Energy*, *247*, 297–308.

Tirachini, A. (2019). Ride-hailing, travel behaviour and sustainable mobility: an international review. *Transportation*, (pp. 1–37).

Tirachini, A., & Gomez-Lobo, A. (2020). Does ride-hailing increase or decrease vehicle kilometers traveled

(VKT)? A simulation approach for Santiago de Chile. *International journal of sustainable transportation*, *14*, 187–204.

Tomschy, R., Herry, M., Sammer, G., Klementschitz, R., Riegler, S., Follmer, R., Gruschwitz, D., Josef, F., Gensasz, S., Kirnbauer, R., & Spiegel, T. (2016). *Österreich unterwegs 2013–2014: Ergebnisbericht zur österreichweiten Mobilitätserhebung*. Technical Report. URL: https://www.bmk.gv.at/dam/jcr:8f6e2654-356e-4d2c-a75f-624e8c8bb485/Zitationshinweise_oeu_2013-2014.pdf.

Viergutz, K., & Schmidt, C. (2019). Demand responsive-vs. conventional public transportation: A MATSim study about the rural town of Colditz, Germany. *Procedia Computer Science*, *151*, 69–76.

Wadud, Z., MacKenzie, D., & Leiby, P. (2016). Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice*, *86*, 1–18. URL: http://dx.doi.org/10.1016/j.tra.2015.12.001. doi:10.1016/j.tra.2015.12.001.

Wang, B., Medina, S. A. O., & Fourie, P. (2018). Simulation of autonomous transit on demand for fleet size and deployment strategy optimization. *Procedia computer science*, *130*, 797–802.

Waraich, R. A., Galus, M. D., Dobler, C., Balmer, M., Andersson, G., & Axhausen, K. W. (2013). Plug-in hybrid electric vehicles and smart grids: Investigations based on a microsimulation. *Transportation Research Part C: Emerging Technologies*, *28*, 74–86.

Weilenmann, M., Favez, J.-Y., & Alvarez, R. (2009). Cold-start emissions of modern passenger cars at different low ambient temperatures and their evolution over vehicle legislation categories. *Atmospheric environment*, *43*, 2419–2429.

Weiss, J., Hledik, R., Lueken, R., Lee, T., & Gorman, W. (2017). The electrification accelerator: Understanding the implications of autonomous vehicles for electric utilities. *The Electricity Journal*, *30*, 50–57.

Wirtschaftskammer Österreichs (2019). Beschäftigungsstruktur Österreich 2019. http://wko.at/statistik/eu/europa-beschaeftigungsstruktur.pdf.

Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015). The Performance and Benefits of a Shared Autonomous Vehicles Based Dynamic Ridesharing System: An Agent-Based Simulation Approach. *Transportation Research Board*, (p. 15). URL: https://www.researchgate.net/publication/312057400.

Zhang, W., & Wang, K. (2020). Parking futures: Shared automated vehicles and parking demand reduction trajectories in Atlanta. *Land Use Policy*, *91*, 103963. URL: https://linkinghub.elsevier.com/retrieve/pii/S0264837718314443. doi:10.1016/j.landusepol.2019.04.024.