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Research note

Impact of autonomous vehicles on household relocation: An agent-based simulation

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ABSTRACT

The agent-based land use/transport model SILO/MITO/MATSim is adapted to simulate the impact of AVs on household relocation. The revised model accounts for the fact that households who own conventional cars are sensitive to parking availability at their dwelling. As AVs could park themselves anywhere, this sensitivity to parking is reduced for households who own AVs. Distance to work, which serves as a hard constraint for household relocation with conventional cars, becomes less critical for households who use an AV to commute as they may perform other activities while commuting. The induced demand of travel by AV is represented and leads to increased congestion.

Several scenarios were designed to analyze the effects of reduced value of time for AV travel, parking restrictions and increase of congestion. The simulation shows that AVs will compete with transit and reduce transit ridership by three quarters. The average commute distance is expected to double, and the vehicle-kilometers traveled will increase by one third. The impact of AVs on the distribution of population, however, is marginal. The urban sprawl caused by less burdensome commuting is largely compensated by the increased attractiveness of core cities in the absence of parking issues for AVs.

1. Introduction

Autonomous vehicles (AVs) are expected to make travel more comfortable and less burdensome. We assume that there are at least two opposite effects on urban form. On the one hand, the reduced need to find parking for shared AVs could encourage some people to move into urban areas. The fact that they do not have to pay for parking anymore (because the AV can park itself elsewhere) makes central locations where parking is limited more attractive to live. Therefore, it is perceivable that AVs foster reurbanization.

On the other hand, AVs may entice people to move farther away from their work location and other travel destinations. This will enable people to live in larger or less expensive homes, to live in a greener environment or to live within a desired school district. Given that the AV allows the traveler to work or watch a movie, commuting time will be perceived to be less burdensome. Therefore, AVs may increase urban sprawl.

AVs are further expected to increase the capacity of the road network, once the AV penetration rate is high. Autonomous (and connected) vehicles can travel at much shorter distances, and inefficient waves of congestion will be eliminated if the speed of every vehicle can be coordinated. While the effect is expected to be more pronounced on highways, the impact on urban streets will be limited. Traffic signals will still be required to coordinate between AVs and non-motorized travel will remain the largest bottleneck within cities. Furthermore, AVs are expected to induce additional travel. As traveling by AV will be more comfortable and less expensive (at least if the AV is shared) than traveling by a conventional car, it is likely that more people will travel by car. In part, new travel will be generated, and in part, trips will be diverted from non-motorized travel and transit to AVs. In addition, empty trips by shared AVs that drive to the next customer or AVs that search for a parking spot could increase travel demand substantially. The additional travel demand is likely to overcompensate for the increased road capacity.

For research questions where no observed data are available (which is true here because AVs are not available for purchase yet), simulation models are a powerful tool to quantify the impact under various assumptions. While a simulation model cannot foresee the future, such models are capable of representing important interactions between land use and transport, and thereby, can forecast changes under certain assumptions.

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The aim of this paper is to understand the impacts of AVs on household relocation decisions. Specifically, the effect of AVs in commute mode choice is simulated by taking into account parking availability and changes in value of time. Dwelling choices are represented with an agent-based integrated land use/transport model.

2. Literature review

In the last decade, a considerable amount of literature has discussed the potential impacts of AV technology on future mobility and urban development. Several comprehensive reviews of the state of the art provide a good overview of this literature. (Bagloee et al., 2016; Becker & Axhausen, 2017; Faisal et al., 2019; Fraedrich et al., 2019; Hawkins & Nurul Habib, 2019; Martínez-Díaz et al., 2019; Parida et al., 2019; Soteropoulos et al., 2019). The vast majority of studies focused on the impacts of AVs on travel behavior, traffic flows, changes in vehicle miles traveled (VMT) or vehicle ownership and sharing. Less attention has been given to land-use impacts, specifically on relocation decisions. As acknowledged in many of these reviews, a more comfortable commute (Malokin et al., 2019; Singleton, 2019) can make households and firms relocate further from city centers, although the increase on congestion and less restrictive parking needs can make city centers more attractive for AV users.

To the authors' knowledge, there are only five studies that quantified relocation decisions due to AV technology. While three of them indicated that urban sprawl may be triggered (Carrese et al., 2019; Moore et al., 2020; Zhang & Guhathakurta, 2018), another study concluded that there would be more moving patterns than just moving out of the study area (Meng et al., 2019); and a countrywide study led to both dispersion and concentration of population in different cities (Gelauff et al., 2019).

Zhang and Guhathakurta (2018) examined the potential changes in residential location choice in the Atlanta metropolitan area if only shared AVs are used to fulfil all travel demand. They used a simulation model that included a residential location choice model by market segment and an aggregated travel demand model. New commute costs in terms of distance were provided by the travel demand model to simulate new residential locations. In all tested scenarios, commute distances increased after shared AVs were adopted, varying from 11% to 23%. However, the authors did not calculate congestion levels and did not consider privately owned AVs or transit as travel modes.

Carrese et al. (2019) used a stated preference survey to understand residential relocation from the city center of Rome to the suburbs after the introduction of AVs. The willingness to relocate and the acceptable distance of relocation were set and used to assign traffic to the road network. The longer commute distances increased travel times by 12% for suburban residents who work in the city center, although intra-urban congestion was reduced by 10%. The results suggest additional suburbanization. The authors considered neither travel time, nor travel monetary costs, nor housing costs. Furthermore, commute mode choice and residential relocation were not modelled at the same time.

Moore et al. (2020) used a stated preference survey to understand the potential impacts of AVs on individual decisions that may result in urban sprawl in the Dallas-Fort Worth metropolitan area. Specifically, they modelled five behavioral dimensions simultaneously: technology-savviness propensity, interest in productive use of travel time propensity, interest in residential relocation, interest in work relocation and tolerance to an increase of commute travel time. They estimated the increase of commute time distributions due to location choice. Households willing to relocate their home or work accepted an increase of commute travel time with AVs. As a consequence, the authors forecasted urban sprawl. The results suggest that urban sprawl may increase from 30% to 68%, depending on the share of population that relocates their home and workplace or both. The authors indicate that the model results could be used as input for LUTI models, which would add real estate markets, congestion and other characteristics.

Meng et al. (2019) studied the impact of AVs on auto ownership and moving patterns in the city of Singapore. They used SimMobility, an agent-based microsimulation platform. For long-term decisions, housing market, household vehicle ownership and job location choice are considered. Accessibility measures in the form of logsums are used in the models to account for the impact of privately owned AVs. The results indicated that the number of persons moving into the study area increased with AVs compared to the base scenario, suggesting the population would concentrate in the urban core instead of sprawling. Regarding vehicle ownership, the share of households who do not own a vehicle increased from 59% to 74% after AVs became available.

Finally, Gelauff et al. (2019) studied whether cities would grow or decline in the Netherlands after the adoption of AVs. They used the LUCA spatial general equilibrium model, which is a LUTI model that studies the effects of transportation developments on population distribution, land prices and welfare. For the full automation scenario, private AVs were assumed to provide the traveler with more productive time by reducing the value of time in car trips by 20% for trips longer than 5 km. The results indicate that commute distances increased by 25% because of lower generalized costs of transport. The modal split for cars and private AVs was maintained, with an increase of shared AVs that substitute mostly bicycles due to longer trips. The analysis showed that car automation increased urban sprawl, while public transit automation concentrated population in urban areas. This double effect resulted in an increase of relocation to the 4 largest cities (Randstad: Amsterdam, Rotterdam, The Hague, Utrecht) and their suburbs, and a decrease of relocation in central cities outside the Randstad. Road capacity and congestion were not considered in this analysis.

The previous studies showed that the results could either lead to urban sprawl or city densification, depending on the assumptions of the model. On one hand, there are some aspects that have not been fully considered in previous studies but were acknowledged to be important. As indicated by Vyas et al. (2019) and Zakharenko (2016), there is a relaxation of car parking and mode combination constraints with AVs, which could modify the mode choice pattern (and relocation choices) substantially. In that sense, it could be significant to include parking availability at both home and work ends for the household relocation choice model. Furthermore, willingness to pay to own AVs or use shared AVs would depend on income (Bansal & Kockelman, 2016; Gurumurthy & Kockelman, 2020) and residential location (Lavieri et al., 2017). There is likely to be a temporal transition between conventional and autonomous vehicle ownership (Hawkins & Nurul Habib, 2019). Additionally, the impact of AVs on traffic congestion due to empty trips could be significant (Martínez-Díaz et al., 2019; Milakis & Snelder, 2017) and may balance out the increased travel time productivity. From this perspective, it is important to consider an integrated approach where both transportation and land-use effects are modelled together. Using a much more tightly integrated land use/transport models, as suggested by Hawkins and Nurul Habib (2019) and Lavieri et al. (2017), could account for specific aspects of AV technologies. Such models could respond to the "demand for studies that demonstrate how AV can respond to more fundamental challenges and goals", as pointed out by Fraedrich et al. (2019). The research presented here tries to fill this gap.

3. Method

For this research, an agent-based integrated land-use and transport modeling suite is implemented for the Munich metropolitan area in Germany. While a model is not able to foresee the effects of AVs, it is helpful to quantify the impact under given assumptions. Model assumptions are based on the literature or derived through the following sections. The introduction and usage of AVs is modelled by extending the car ownership, household relocation and mode choice models. Parking availability is introduced as another location factor in household relocation. This paper is limited in the potential effects of private AVs, and does not investigate the potential effects of shared AVs.

The modeling suite and the current relocation model are described in Sections 3.1 and 3.2, respectively, and the modifications necessary to simulate the impact of AVs are developed through Sections 3.3 to 3.6. In Section 3.7, the model scenarios are described. Lastly, Section 3.8 defines the study area where the model was applied.

3.1. Model overview

Three agent-based models were extended and applied to analyze the impact of AVs on land use and transportation. The land use model SILO simulates the demographic transitions over time, including household relocation. MITO is a travel demand model that simulates the travel time budget for every household and creates multi-modal trips. This travel demand is assigned to a network using MATSim. Fig. 1 provides an overview of this integrated land use/transport model. All models used here are agent-based and open source (https://github.com/msmobility/silo, https://github.com/msmobility/mito and https://github.com/matsim-org/matsim-libs).

The land use model SILO (Moeckel, 2017) updates the population on a year-by-year basis from the base year 2011 to the future year 2050. Demographic events, such as giving birth, marriage, leave parental household, death, and household relocation are executed in random order to avoid an artificial path dependency. The interaction between events is accounted for in the following year. For example, if a couple living in a small apartment has a child born, the probability to relocate the next year is larger than without the child. Household relocation decisions are simulated based on dwelling attributes, household attributes, zonal attributes and in particular travel time to work of all workers of a household, as explained in the next subsection. New dwellings are built by developers who attempt to mimic the location preferences of households. Demographic transition, household relocation and updates of the real estate market are simulated in an agent-based environment. Housing prices are updated based on vacancy rates in the neighborhood.

The travel demand model MITO (Moeckel et al., 2020) was implemented to simulate travel demand of every person. The model is a trip-based model, but simulates travel behavior for individual agents. Also, this model calculates the travel time budget in minutes for every household. This budget influences destination choice, i.e. people who spent a lot of time commuting are less likely to do much other travel, while people who telecommute might compensate by additional discretionary travel. Mode choice uses a nested logit model, and time-of-day choice schedules trips in 1-min intervals.

MATSim is an agent-based transport simulation framework (Horni et al., 2016) that was used for traffic assignment. MATSim can be used as a Dynamic Traffic Assignment (DTA) model that simulates individual vehicles on the road network. A major benefit of a DTA model like MATSim is that the number of vehicles on a link can never be larger than the link capacity, which is a common shortcoming of static user equilibrium assignment methods. Travel times and distances are fed back to SILO and MITO.

The model runs from 2011 to 2050. While the land use model updates the demography in one-year increments, the transport models run every 10 years due to their longer runtimes.

3.2. Household relocation model

The decisions that synthetic households make when they want to relocate are based on the model described in this subsection. Further details are included in Moeckel (2017). Individual decisions (household by household) are made in two steps: first, a region is selected, and second, a dwelling in the selected region is chosen. Both decisions are based in a random utility choice model, where the utilities of each region and dwelling are calculated as follows. The utility of a region increases if it is well accessible, it has a lower share of foreign households and the average housing price is low, as seen in Eq. (1).

$$U_{region} = \left(\alpha \cdot u_{accessibility} + \beta \cdot u_{share} + (1 - \alpha - \beta) \cdot u_{price}\right) \cdot f_{HBW} \qquad (1)$$

Where:

- U_{region} is the utility of a region
- $u_{accessibility}$ is the utility of the average accessibility of employment at the candidate region. *accessibility* is the potential, gravity-based accessibility to jobs of the dwelling region defined by Hansen (1959)
- u_{share} is the utility of the share of foreign households (defined as having at least one non-German household member) at the candidate region, if the evaluation of the dwelling is made by a non-foreign household. If the evaluation of the dwelling is made by a foreign household, the share of foreign households is replaced by the share of non-foreign households. This factor represents the level of segregation by nationality
- u_{price} is the utility of the average housing price at the candidate region

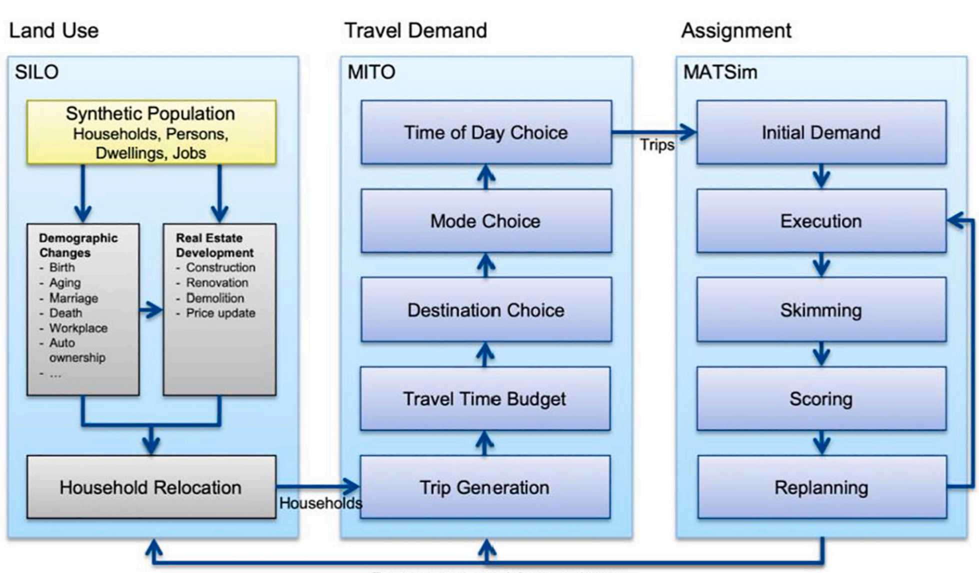

Fig. 1. Flowchart of the integrated land use/transport model SILO-MITO-MATSim.

- f_{HBW} is a factor depending on the time from home to work, if the household chooses the candidate region, calculated according to Eq. (2).
- α, β are parameters, that depend on household sizes and income levels.

$$f_{HBW} = \prod_{j}^{J} exp(\beta \cdot t_{j,mode}) \tag{2}$$

Where:

- $j = 1\ldots J$ are workers in the household
- $t_{j,\ mode}$ is the average travel time of worker j from the candidate housing region to his/her work location. Here, zone-based travel times are used. The mode is selected using the commute mode choice model explained later in Section 3.4
- β is a parameter dependent on the Value of Time (VOT), equal to 0.2

The variables $u_{accessibility}$, u_{share} and u_{price} can take the values between zero and one, by normalizing the corresponding variable. The maximum utility of each variable is equal to one and is given to the best (i.e. most useful) value of each variable (e.g. higher accessibility or lower price).

Once a region is selected, a set of 20 dwellings there is sampled. The dwelling choices are limited to that number since a household would never search the totality of available dwellings in a region, but only a reasonable amount. The utilities of each dwelling are calculated as shown by Eq. (3). Within the utility of a dwelling we combine optional factors, that include area, quality and accessibility (one of them being good can complement the others, so their utility is added to each other) with strong constraints, such as price and distance to work (if one of them is very poor - i.e. a dwelling is not affordable - the utility of the dwelling is very low, and thus they are multiplied by each other).

$$U_{dwelling} = {u_{optional}}^{\delta} \cdot {u_{price}}^{\varepsilon} \cdot {f_{HBW}}^{(1-\delta-\varepsilon)} \tag{3}$$

Where:

- $u_{optional} = \alpha \cdot u_{area} + \beta \cdot u_{accessibility,\ car} + \gamma \cdot u_{accessibility,\ pt} + (1-\alpha-\beta-\gamma) \cdot u_{quality}$ is the utility of the optional factors area, accessibility and quality of the candidate dwelling
- u_{price} is the utility of the dwelling price of the candidate dwelling
- f_{HBW} is a factor depending on the time from home to work, if the household choose the candidate dwelling, calculated according to Eq. (2).
- α, β, γ, δ, ε are parameters, that depend on household sizes and income levels.

A sensitivity analysis of the most relevant factors is included in appendix. The sensitivity analysis includes already the effect of the introduction of AVs, as explained in the next sections.

3.3. Ownership of autonomous vehicles

The base version of the SILO/MITO/MATSim model considers only the ownership of conventional vehicles (CV). Each household is assigned with a certain number of cars (and this number is updated every year) as a function of household composition, annual income or place of residence. The existing CV-ownership models were estimated and calibrated based on the German national household travel survey and the German mobility panel (Okrah et al., 2018) and consists of two multinomial logit models. The first one defines the choices in the base year (no-car, 1 car, 2 car, etc.). The second one represents the changes in ownership as a function of changes in household or person attributes in the simulated year (decrease, maintain or increase the number of cars owned).

In this paper, we add a sub-module which calculates the probability for a household to switch from a CV to an AV. This model keeps the total number of cars in the household and may switch a CV to an AV. We do not model a reduction of the number of cars (as predicted by Zhang et al. (2018)), although such reduction will not have impact in the mode choice decisions, as the ownership of one AV already makes it possible that it is shared by more than one worker (as seen later in Section 3.4). This module considers only privately owned AVs. For every household, the probability of replacing a CV by an AV is given by a binary logit model, where the zero-alternative is “not to replace” (its utility is equal to zero). The utility of replacing a CV by an AV is calculated by Eq. (4).

$$U_{switch\ to\ AV} = 2.5 - 3.5 \cdot r_{AV\ to\ CV} + 0.00035 \cdot i_{annual} \tag{4}$$

Where:

- $U_{switch\ to\ AV}$ is the utility of switching a CV to an AV. The utility of not switching is equal to zero (reference case)
- $r_{AV\ to\ CV}$ is the ratio between the purchase costs of an AV divided by the purchase costs of a CV
- i_{annual} is the annual income of the household

We set the model coefficients heuristically to progressively increase the number of AVs. In this paper, we propose that in AV-scenarios those vehicles are first introduced in 2025 at a very high price (10-times a CV). The costs decrease until the year 2040, when it is equal to the costs of a CV (Fig. 2). The years of introduction are proposed based on the results of several expert workshops reported by Milakis and Snelder (2017).

Purchasing of AVs is represented in a two-step model (auto ownership of CV and a model to replace a CV with an AV) to allow for a modular extension of the land use model SILO. The two model steps run sequentially. In practice, it is likely with high penetration rates of AVs (e.g., after 2040) that households who buy a CV will immediately replace it with an AV.

3.4. Commute mode choice for household relocation

To evaluate household satisfaction with their home location (to decide whether to move or not) and dwelling utilities (to choose where to move to), workers select a preferred commute mode. In SILO, conventional vehicles (CV) and public transport are considered. If walking is faster than transit, walking is considered instead of public transport. This choice is based on (1) travel time by each mode, (2) availability of cars in the household (where each car can be used by only one commuter at a time, and workers cannot commute by car if all cars in the household have been taken) and (3) having a driving license. We cannot use a model estimated directly from any data, since SILO needs to perform mode choice decisions to candidate dwellings during the relocation

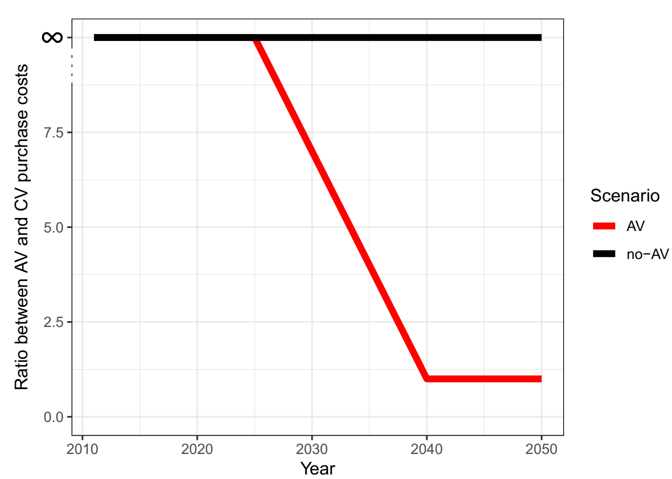

Fig. 2. Assumed ratio of AV and CV purchase costs for the scenarios with and without AV.

choices. We are not aware of any dataset from either revealed or stated preferences surveys that describes it.

The probability of using CV (vs. public transport) is equal to zero when no car or no license is available to the worker. If they have a license and cars, the utility of CV and PT is calculated by Eq. (5), equivalent to each one of the terms of the Eq. (2). After this calculation, the workers within the household, starting from the one with highest probability to use CV, choose to commute by CV or transit, as far as cars are still available. Once every car in the household is taken, the rest of the workers of this household use public transport.

$$U_{mode} = exp(\beta \cdot t_{mode}) \tag{5}$$

Where:

- U_{mode} is the utility by mode (without taking car and license ownership constraints into consideration)
- β is a negative parameter (its value is discussed in Section 3.5)
- t_{mode} is the travel time by mode

For this paper, the mode choice model was modified to account for AVs. If the household does not own an AV, the existing model is used. If the household owns an AV, it is available for all its members because the AV can return home after dropping off one worker. Therefore, the workers' probability to choose between AV and public transport is calculated with the binary logit model described before, but substituting CV by AV. However, the major difference is that, with AVs, there is no intra-household car availability limitation (a single AV can pick up or drop off more than one household member, as predicted by Zhang et al. (2018)), nor driving license restrictions (which are not required to ride in an AV).

3.5. Changes in value of time

When using a fully-automated vehicle, the passengers do not need to pay attention to driving any more. According to Malokin et al. (2019) and Singleton (2019) the possibility of performing other activities while traveling can modify mode choice decisions and may result in a lower value of time compared to driving by car.

In the SILO, households evaluate the satisfaction with their current place of residence and compare it to the utility of other vacant dwellings. In addition to evaluating the quality of the dwelling and the neighborhood, the distance to work for every worker in the household is an important location factor. The travel time to work is converted to a utility with Eq. (5) in Section 3.3. The coefficient β of this equation was calibrated to match the base-year travel time distribution of workers in the study area.

For travel in AVs, the Value of Time (VOT) is reduced as the impedance of travel time is reduced. This also affects the lower burden of commuting that is considered for household relocation. The (negative) utility of travel time is adjusted for AVs as shown in Eq. (6).

$$U_{mode} = exp(-0.20 \cdot t_{mode}) if\ mode\ is\ CV\ or\ public\ transport$$

$$U_{AV} = exp(-0.12 \cdot t_{AV}) if\ mode\ is\ AV. \tag{6}$$

Where:

- U_{mode} is the utility of a mode
- t_{mode} is the travel time by mode

According to Malokin et al. (2019), based on a revealed preference survey for public transport commuters, the value of time for AV travelers would be 40% lower. Similarly, Moore et al. (2020) have estimated that the VOT could decrease between 30% and 68%, depending on whether the survey respondents are willing to change their job and home locations or not. We propose the coefficient -0.12 in Eq. (6), which corresponds to 0.6 times -0.2, assuming that a reduction of 40% in VOT can be associated with a reduction of 40% of the disutility of commute time. Fig. 3 shows the resulting higher travel time utilities for AVs. The appendix shows the differences in regional and dwelling utility when the commute is made by AV, in comparison with CV or public transport. In Section 4.1 we further discuss the parameters that describe the reduction of VOT by means of a sensitivity analysis.

3.6. Parking

AVs have the potential to eliminate the time-consuming parking search. AVs will be able to navigate themselves to an available parking place, which could be out of town, and wait there to be summoned again (as predicted by Zakharenko (2016)). The effect of parking availability (and parking costs) in mode choice has been studied in the past (e.g. by Franco and Khordagui (2017) or Weis et al. (2012)). However, the impacts of parking availability on relocation are not studied widely. While Weinberger (2012) reports an effect of parking availability in the choices to drive, she recognizes that residential choice needs to be considered as well. To account for parking availability in relocation without AVs, we collected parking data in the study area. Afterwards, we modify the dwelling and mode utility calculations.

Parking places are quantified and allocated to zones in the study area. This is calculated differently for on-street and off-street parking. The number of spaces in on-street parking $n_{on-street}(z)$ in zone z is estimated by Eq. (7) based on the length of roads (of certain types).

$$n_{on-street}(z) = \frac{1}{6.5} \cdot p_{on-street} \cdot \sum_{link \in z} l_{link} \cdot x_{type} \tag{7}$$

Where:

- $n_{on-street}(z)$ is the number of on-street parking spaces in zone z
- 6.5 is the average length of a parking space in meters
- $p_{on-street}$ is the percentage of the link length where parking is allowed, taking into consideration intersections and driveways. Based on aerial photos of a subsample of roads we set this parameter to 0.6
- l_{link} is the link length, obtained from the OpenStreetMaps (OSM) road network in meters
- x_{type} is a dummy variable that depends on the link type (obtained from OSM) and takes the value 1 if parking is allowed (e.g. secondary, tertiary or residential roads) and 0 otherwise (e.g. motorway). The analysis of aerial photos of a subsample of roads of each type is used to judge whether they typically allow on-street parking or not

The synthetic population of SILO included a list of synthetic

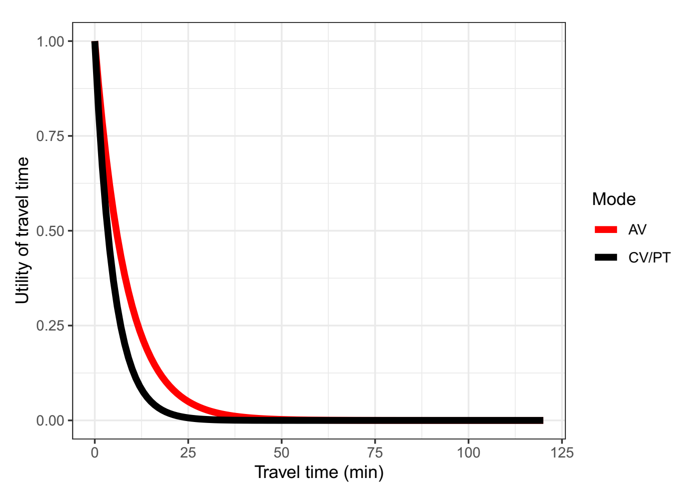

Fig. 3. Changes in travel time utility with AVs.

dwellings, which were enriched by parking spaces to represent off-street parking. Based on the number of parking places listed by real estate ads, the following average number of parking spaces by dwelling type were derived: 1.6 for single-family detached houses, 1.3 for single-family attached houses, 1 for multi-family apartments (with less than 5 units per building) and 0.8 for multi-family apartments (with 5 or more units per building). The total number of private parking spaces $n_{off-street}(z)$ per zone is equal to the sum of the spaces of the dwellings placed at zone z.

The potential total parking demand $n_{demand}(z)$ of each zone was defined by the number of car trips that arrive in that zone according to the travel demand model MITO.

With these three numbers, a combined indicator was calculated by Eq. (8).

$$n_{balance} = n_{demand}(z) - n_{on-street}(z) - n_{off-street}(z) \tag{8}$$

The indicator $n_{balance}$ measures the difference between demand and supply. By using the quartiles of $n_{balance}$ we defined a zonal parking quality indicator $q_{parking}$: Q0, Q1, Q2 and Q3 quality: Q0 indicates it is very difficult to park in the respective zone (supply is below demand) and Q3 indicates good parking availability in the respective zone (supply exceeds demand). Parking cost is not taken into consideration. As there are no parking data available for the study area, the parking indicator $q_{parking}$ is approximated by using this method. It is derived from the difference between the rough estimate of supply and demand and should only be used in relative terms to compare zones within the study area.

For household relocation, the availability of parking was introduced as an additional location factor. The households compare the number of cars they own with the number of parking spaces of the dwelling they evaluate. If the difference is positive (excess of parking spaces in the dwelling), the utility is not affected by parking availability. If the difference is negative (lack of parking spaces), the utility of the dwelling (Eq. (3)) is multiplied by a parking penalty factor that depends on the street parking quality according to Eq. (9). If parking in this zone is easy ($q_{parking}(z) = 3$), the penalty is 1 and irrelevant. As parking becomes more difficult, the penalty factor becomes stronger and lowers the dwelling's quality.

$$p_{parking}(dwelling) = 0.1 + 0.3 \cdot q_{parking}(z) \tag{9}$$

Where:

- $p_{parking}(dwelling)$ is a penalty factor for parking based on the dwelling's zone
- $q_{parking}(z)$ is the parking quality indicator of the dwelling's zone z ($q_{parking} \in \{0,1,2,3\}$)

We assume that the availability of parking will have a reduced relevance for households who own AVs, as AVs can park autonomously away from the dwelling. Therefore, the parking penalty is significantly lower, as defined by Eq. (10). The penalty was not set to 0, as a closer parking location is still preferable to summon the car on short notice. A discussion on various penalties for AVs compared to the penalties for CV is provided in Section 4.1.

$$p_{parking}(dwelling) = 0.55 + 0.15 \cdot q_{parking}(z) \tag{10}$$

When the most likely mode is selected for commuting to work with Eq. (6), the presence of parking at the job location is included as an additional penalty term of the CV utility. Consequently, commute mode choices of CVs is penalized for commuting to locations where parking is difficult. Eq. (11) is an extension of Eq. (6) and used to calculate the utility of each mode

$$U_{CV} = exp(\beta \cdot t_{CV}) \cdot p_{parking}(job) \tag{11}$$

Where:

- U_{CV}, β and t_{CV} are the utility, coefficient and travel time as described in Eq. (3)
- $p_{parking}(job)$ is calculated as described in Eq. (9), but at the zone where the job (destination of commute trip) is located.

There are no penalties due to parking at the job location (therefore $p_{parking}(job) = 1$) if the commute is made by public transport or an AV.

3.7. Scenarios

A complete set of scenarios was defined to understand the intensity and direction of each single impact that AVs might have as described in the literature. A final scenario includes all the effects combined. The following scenarios were tested (also summarized in Table 1):

1. **no-AV**: base scenario where AVs are not available. This scenario serves as the reference for scenarios 2 and 3.
2. **AV scenario**: AVs are introduced in 2025. Agents who own AVs may choose AV as a commute mode and relocate based on such a decision. The modules of AV-ownership and AV-mode choice are switched on (see Sections 3.2 and 3.3) in 2025. In the paper we assume fully-automated vehicles (automation level 5) only.
3. **AV + VOT**: AVs are introduced in 2025 and the users of AVs experience a reduced Value of travel Time (VOT). The modules of AV ownership and mode AV mode choice are switched on, with lower VOT for AV commuters (see Section 3.4).
4. **no-AV + Parking**: base scenario where AVs are not introduced, but parking restrictions are switched on. This scenario serves as the reference for scenario 5.
5. **AV + Parking**: AVs are introduced in 2025 and parking restrictions at home and work affect relocation. Relocation of AV users is less sensitive to parking than for CV users. The modules of AV ownership and AV mode choice with parking restrictions are switched on (see Section 3.5). No change of VOT is applied.
6. **no-AV + Transport congestion**: base scenario where AVs are not introduced, but the transport model runs every 10 years and travel times are updated (see description in Section 3.1). This scenario serves as the reference for scenario 7.
7. **AV + Transport congestion**: AVs are introduced in 2025 and the travel times are updated using a transport model simulation that runs every 10 years. The modules of AV ownership and AV mode choice are switched on, but no changes in VOT or parking restrictions are applied.
8. **no-AV-All**: base scenario where AVs are not introduced, but parking restrictions are applied and the transport model runs every 10 years. This scenario serves as the reference for scenario 9.
9. **AV-All**: AVs are introduced in 2025 and all the previous mentioned modules are switched on.

3.8. Study area

The modeling suite was implemented for the Munich metropolitan area. The region has a population of 4.5 Million and is forecast to continue to grow by 1% annually to 6.5 Million by 2050. The study area was delineated by commute flows. Given the rather high housing prices in Munich, commute distances tend to be fairly long. For this reason, the five cities Augsburg, Ingolstadt, Landshut, Munich and Rosenheim and their respective suburban areas were included (Fig. 4). As employment in Munich is growing faster than housing, commute distances increase over the 40 simulated years even in the base scenario. The region is subdivided into 4924 zones that vary in size by population density, from 200 × 200 m in dense city centers to larger zones in rural areas (Molloy & Moeckel, 2017).

Table 1
Scenario overview.

Scenario/effect	AV ownership	Mode choice with AV	Change in VOT	Parking restriction	Transport model feedback	Reference scenario without AVs
1: no-AV	No	No	No	No	No	–
2: AV	Yes	Yes	No	No	No	1
3: AV + VOT	Yes	Yes	Yes	No	No	1
4: no-AV + Parking	No	No	No	Yes	No	–
5: AV + parking	Yes	Yes	No	Yes	No	4
6: no-AV + Transport congestion	No	No	No	No	Yes	–
7: AV + Transport congestion	Yes	Yes	No	No	Yes	6
8: no-AV-All	No	No	No	Yes	Yes	–
9: AV-All	Yes	Yes	Yes	Yes	Yes	8

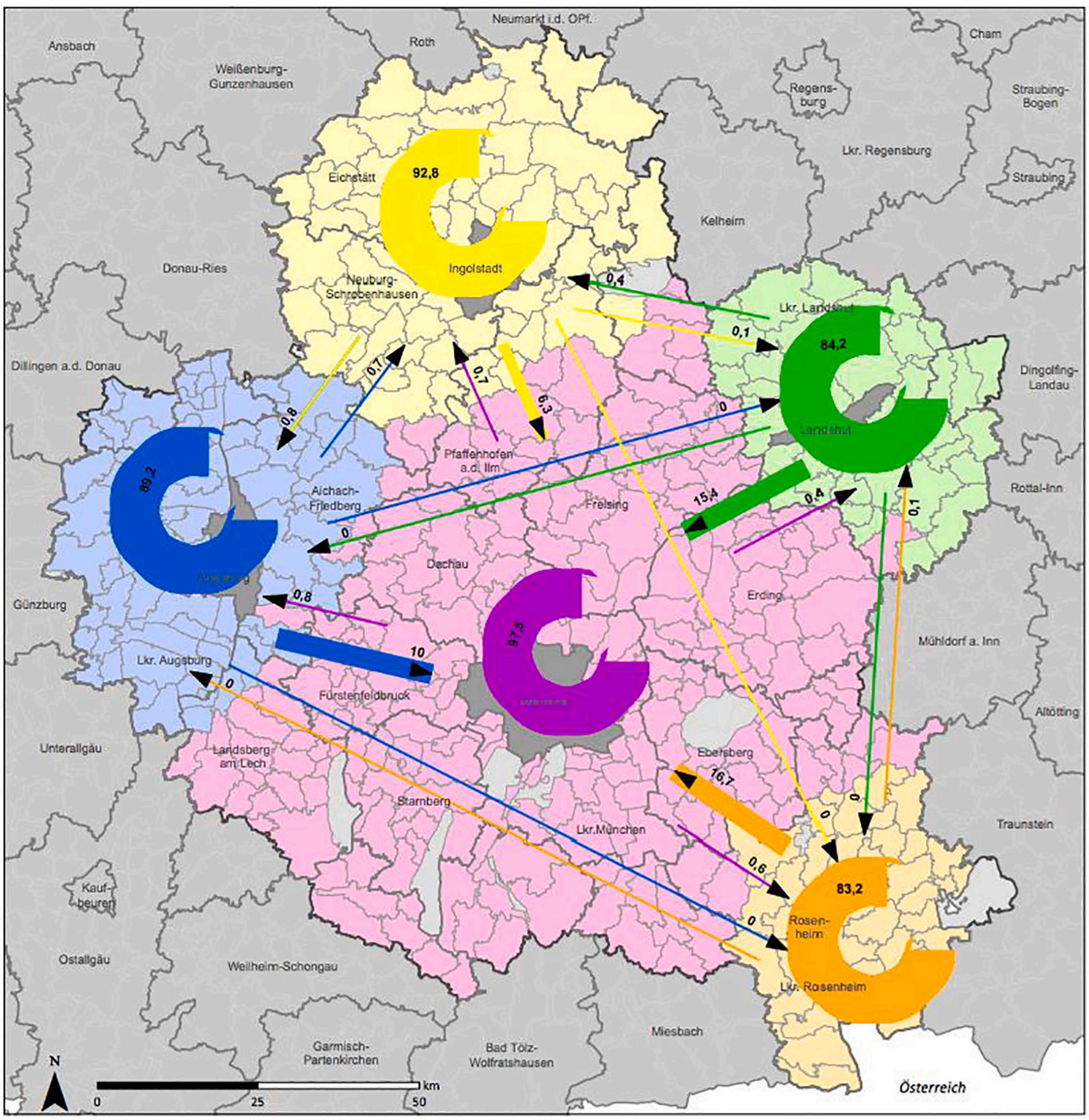

Fig. 4. The study area of the Munich metropolitan area includes Munich, Augsburg, Ingolstadt, Landshut and Rosenheim, and their respective commute shed. The colors represent the dominant commute destination for each municipality, and the arrows show the percent commute flows between the five city regions.

4. Results

4.1. Evaluation of model assumptions

We first evaluate the parameters and hypotheses described in Sections 3.3 to 3.6 by using a simple hypothetical relocation example. Here, we test the sensitivity of the most relevant assumptions described above, regarding the impact of AVs on VOT and on parking at home locations. Fig. 5 summarizes the relocation alternatives of two workers that each belong to a single-worker household. For the first one, the job

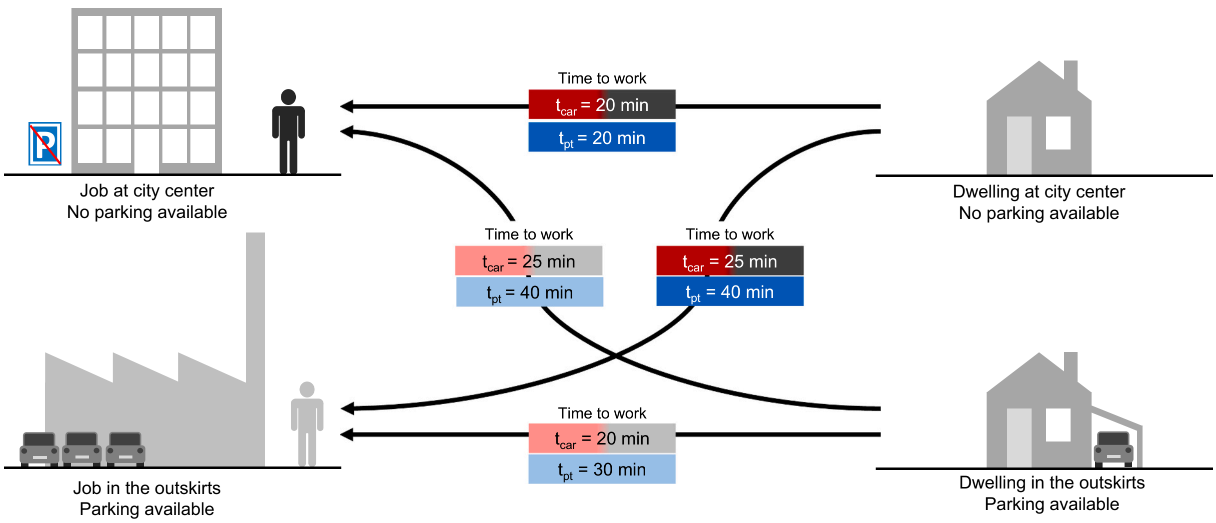

Fig. 5. Relocation alternatives for two different single-worker households: both households evaluate the same two dwellings, but different commute times occur to the city center (based on the dark-labeled travel time data) and to the outskirts or suburbs (based on the light-labeled travel time data).

is located in the city center, and for the other one, the job is located in the outskirts or in an inner suburb. Two dwellings are evaluated for both households, one dwelling in the city center (without parking) and another one in the outskirts (with parking). The rest of the dwelling attributes, including size, price and others, are the same for the two dwellings. The travel times by mode were selected based on an example in the area of Munich (Germany).

In Fig. 6, the choices of a household that owns AVs are represented, at different sets of model parameters that deviate from the ones proposed in Sections 3.3 to 3.6.

By reducing the VOT compared to CV (from using the same beta for AV and CV (left figure) to a reduction by 80% for AV (right) in Fig. 6a), we observe an increase in the probability of commuting by AVs (the modal share shaded in red increases). Furthermore, there is also an increase in the amount of persons willing to relocate outside of the city center (if the job is in the center, light shaded) or in the center (if the job is in the outskirts, dark shaded), showing a clear effect of urban sprawl linked to the decrease of VOT. By looking at the relaxation of parking restriction in Fig. 6b, when the parking penalty is reduced (from a penalty equal to CV to a softer penalty – left to right in the Figure) we also observe that AVs are more attractive. However, the direction of the impact of using AVs is an increase of the probability of relocating in the city centers (dark color), since improvement in parking penalties do not affect much the willingness to relocate at areas with already good parking availability. In light of the sensitivity analysis, and in absence of empirical data to validate our result, we decided to use the parameters as proposed in Sections 3.3 to 3.6.

Such "toy scenario" is useful to understand the sensitivities in the model. However, it does not represent any constraints in available housing, nor does it account for changes in the housing market or levels of congestion on the highway network. To provide more realistic results, the proposed scenarios are tested in the Munich metropolitan study area described in Section 4.2.

4.2. Scenario results

This section summarizes the results of the scenarios that were introduced in Section 3.7. Results are analyzed with regard to AV ownership, mode share, passenger kilometers traveled, average commute time and redistribution of population.

4.2.1. AV Ownership

Given the assumption made in Section 3.3 regarding the evolution of private AV purchase costs, the model anticipates a gradual substitution of CVs by AVs. Fig. 7 shows the AV share with respect to the number of cars by year. After the first introduction of AVs in 2025, households start slowly to change to the new car technology. Ten years later, the pace of substitution is much faster. At the end of the simulated period, almost every vehicle is autonomous.

4.2.2. Modal share

Fig. 8 shows a forecast of the auto/transit share with CVs (left) and the expected impact of AVs on modal shares (right). The major effect is observed in all model setups with AVs and shows a reduction of the public transport share from 25% to a residual 6% (which corresponds mostly to households who have no car and are public transport captive). The absence of limitations to car availability and license ownership motivates the increase in auto travel, which occurs in parallel to the introduction of AVs described by Fig. 7. Alternative scenarios in which VOT is modified or the influence of parking is included do not substantially change the modal share or the ownership of AV, and are omitted in Fig. 8.

4.2.3. Passenger-kilometer traveled

The shift from public transport to AVs results in an increase of the total passenger-kilometer traveled on the road network, as seen in Fig. 9. Although an estimation of passenger-kilometer traveled from this figure is approximate (as empty AV-trips are not considered and pooling within the household does not reduce the amount of passenger-km), the figure indicates that the presence of AVs will substantially increase the distance traveled by car (for instance, Henao & Marshall, 2019 reported that deadheading can exceed 40% for ride sharing services). The share of public transport modes drops, and congestion may increase.

4.2.4. Average commute time

Fig. 10 shows the average commute time in the entire study area for different scenarios. The introduction of private AVs (and the subsequent change in mode choice behavior) does not, by itself, change in the average commute times (Scenario AV). However, if changes in VOT for AV users are considered, we observe an increase of the average commute time that starts after AVs are introduced (red line is above the black line). If the effect of parking is added to the model, the effect is the inverse (red line under the black line): the scenarios without AVs show a higher average commute time, which results in households relocating out of large cities because parking there is difficult. This effect is lower when AVs are introduced. The average commute distance does not

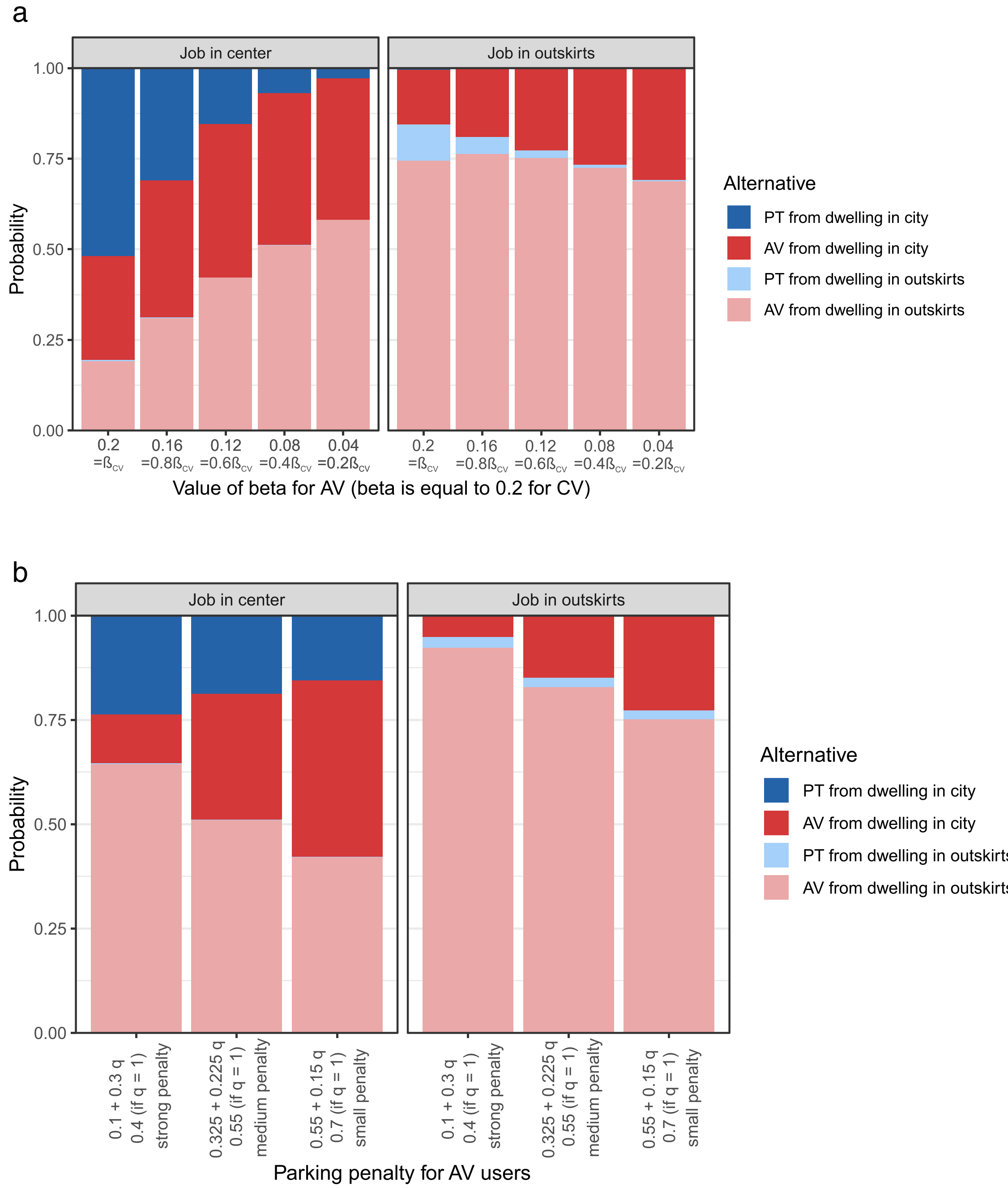

Fig. 6. Probability of selecting a dwelling and commute mode by households who own AVs. The plot on the left refers to the worker in the city center, the plot on the right to the one in the outskirts. The colors represent commute modes. Dark colors represent dwelling choices in the city and light colors in the outskirts.
(a) Sensitivity analysis of VOT, by comparing different values of β (with a reduction of 0.4, the utility of AVs is calculated with β equal to $0.2 \cdot (1–0.4) = 0.12$).
(b) Sensitivity of parking restrictions at home for AVs. The horizontal axis shows three penalty functions, equivalent to the Eq. (10) with different coefficients (the values for neighborhoods with the second-most difficult parking situation [$q = 1$] is shown). The left bars in each plot represent the penalties used CVs, and the right bars represent the lighter penalties chosen for AVs as shown in Eq. (10).

change much due to congestion if the transport model is run every 10 years. The scenario AV-All combines all the effects, which shows a small reduction with AVs but seems to balance out most impacts.

4.2.5. Population redistribution

In this section, we compare the distribution of population across the study area with and without AVs. The results were calculated for the final year 2050, when the use of AVs is available to all income groups and the availability of this mode has shown some impact on household relocation. The places of work and residence are classified into four area types, according to the German Household Travel Survey (Deutschen Zentrums für Luft- und Raumfahrt (DLR), 2017). These categories range from core cities (the densest urban areas) to rural areas (the sparsely populated municipalities in the countryside). The number of jobs remains unchanged in the simulation, as the same growth rate is applied in every scenario. Therefore, we observe in this section the relocations of households between the zones of the study area.

The introduction of AVs (without changes to VOT and implementation of parking restrictions) is shown in the first row of Fig. 11. The scenario shows a slight increase of the population that relocates to core

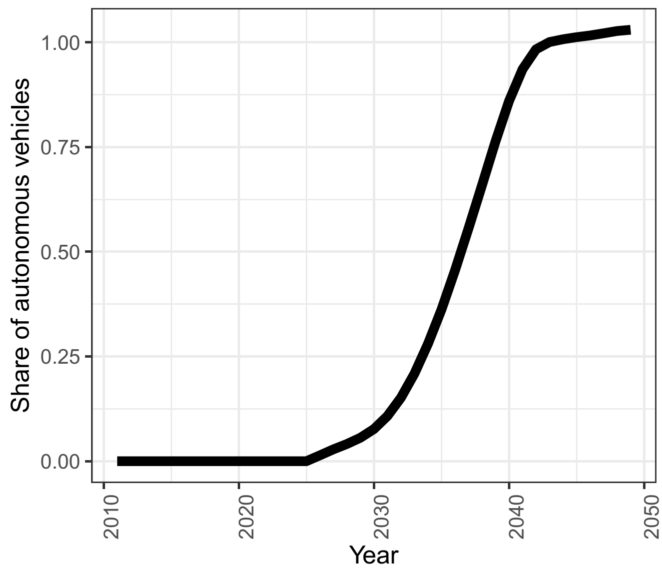

Fig. 7. Share of autonomous vehicles by year.

cities. This may be caused by workers that now can travel by AV, making dwellings in core cities (that generally are better accessible) more attractive. However, the effects of this scenario on relocation are very small.

Under the assumption of a 40% reduction of VOT for AV users (Scenario AV + VOT in the second row of Fig. 11), an increased trend to urban sprawl is observed. For all area types, the workers tend to relocate to other area types, decreasing the number of workers that live and work in the same area types. This impact is consistent with the increase of commute times reported in the section Average Commute Time.

The addition of parking penalties to the mode choice decision and the household relocation decision (Scenario AV + Parking) increases the number of workers who choose core cities (third row in Fig. 11). The effect is moderate, with more than 15,000 core-city workers who choose to live in the core cities. Here, the possibly more attractive dwellings in core cities are no longer penalized by parking difficulties if AVs are used. The effect is consistent with the reductions in commute times reported in the section Average Commute Time.

The interaction of transport and land use motivates the overall growth of travel times, as observed already in the previous section on Average Commute Time. In Fig. 11 (fourth row), however, no specific trend in terms of redistribution of workers by area types can be observed.

If all the effects are combined, the results appear less pronounced (fifth row in Fig. 11). The migration of workers from city cores to the outskirts due to a relaxation of commute time impedance (decrease of VOT) is compensated by the increase of attractiveness of dwellings in core cities in absence of parking restrictions. Therefore, the population in core cities may even increase slightly by decreasing the number of residents in the outskirts.

5. Discussion

The purchase of private AVs was modelled based on the ratio between the cost of an AV and a CV. As expected, high income households were more likely to switch earlier to AVs, compared to lower income groups. We proposed a period of introduction of the AV technology over 15 years, starting in 2025 and ending in 2040. By 2040, the costs of both types of vehicle were already equal. Accordingly, almost every car is replaced by an AV towards the end of the simulation period in 2050, and the presence of CV is marginal. Based on the very low modal share of taxis and ride-sharing services in the study area (less than 1%, according to the German household travel survey (Deutschen Zentrums für Luft- und Raumfahrt (DLR), 2017)), we excluded the impact of shared AVs from the relocation model. Policies that favor shared AVs or restrict the ownership of private vehicles in city centers may result in a very different forecast. The penetration of private AVs that we simulated

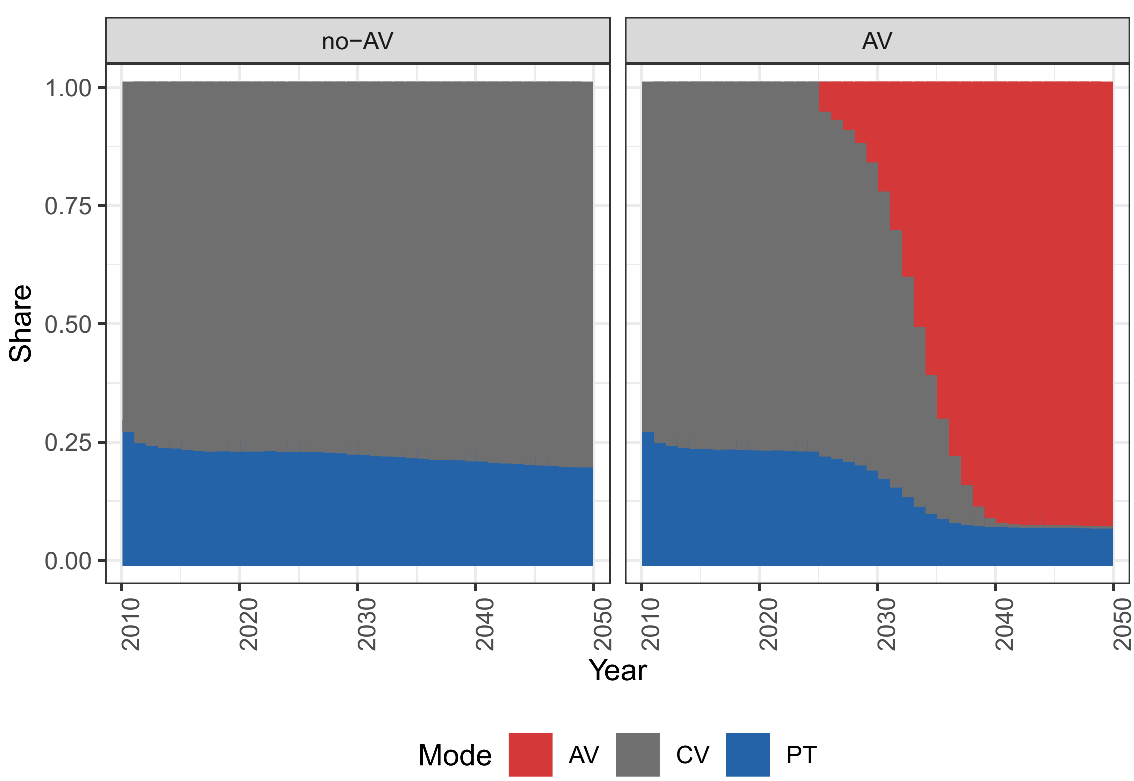

Fig. 8. Modal share for commute trips without (left) and with (right) the introduction of AVs.

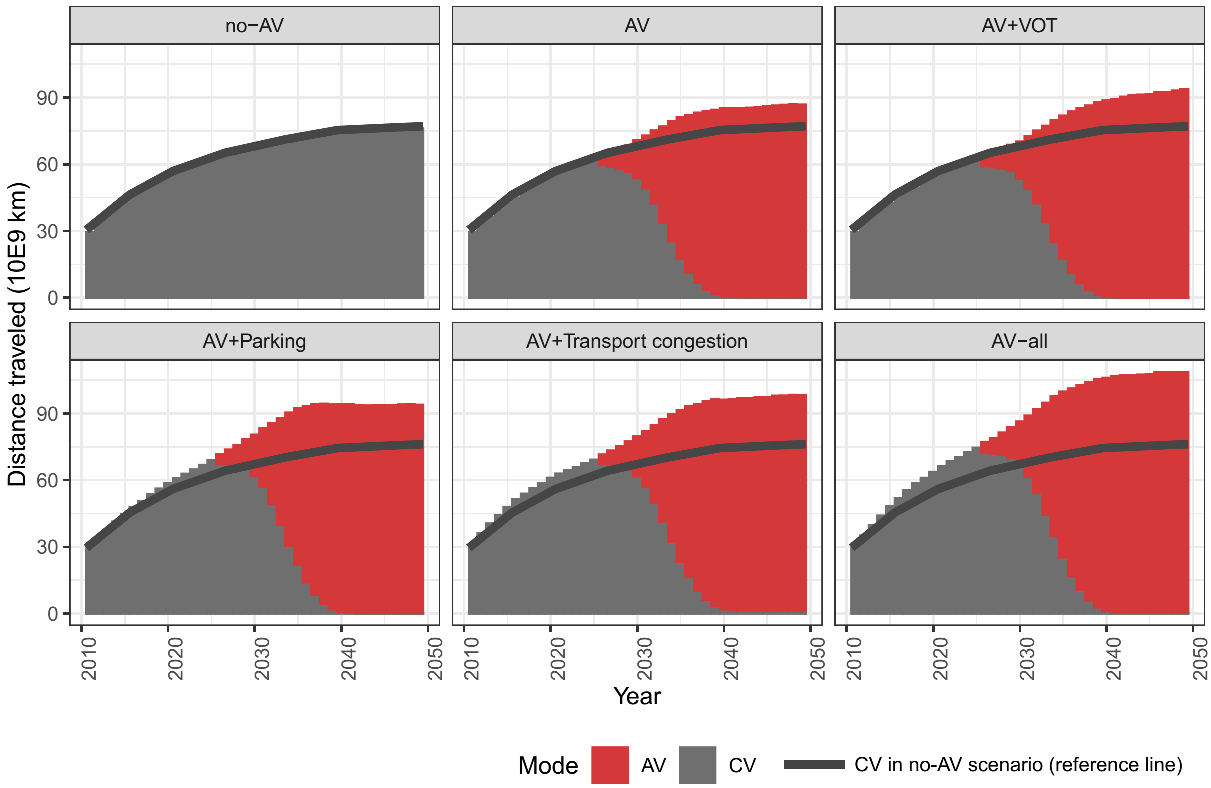

Fig. 9. Passenger-km traveled on commute trips by mode and scenario (empty trips not included).

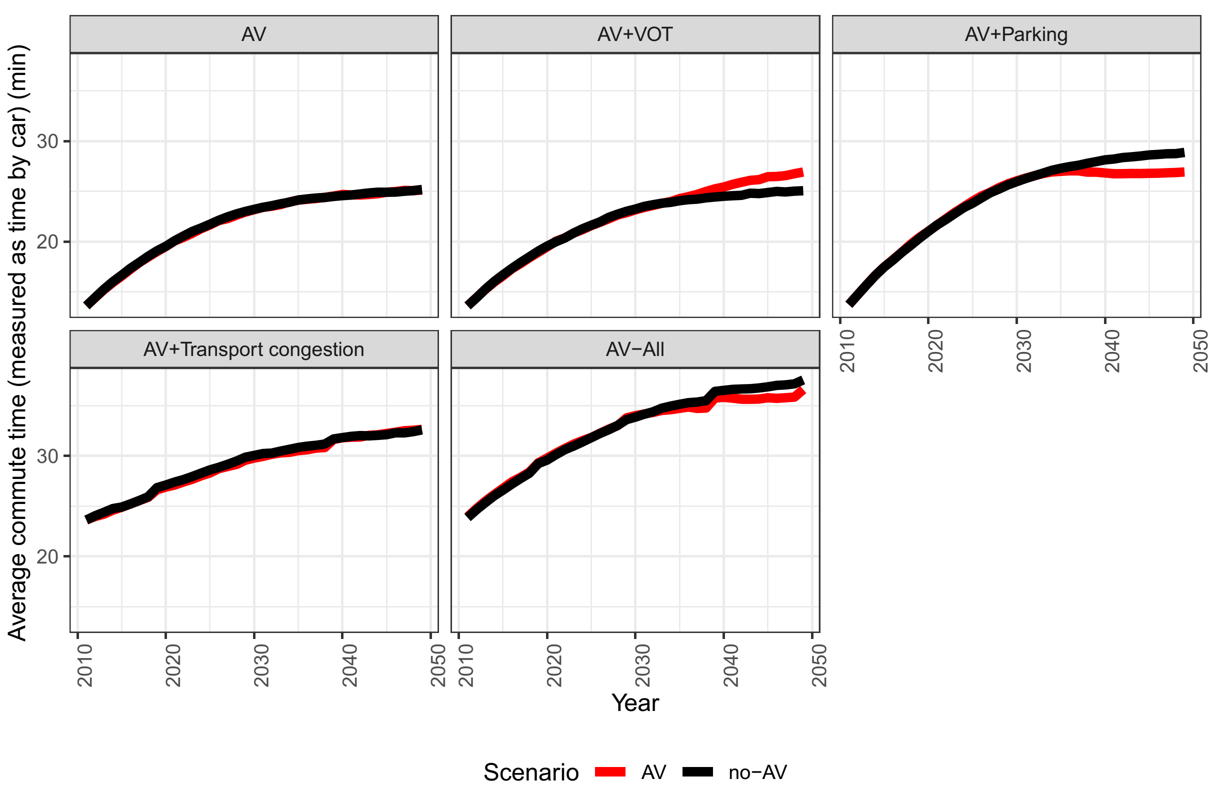

Fig. 10. Average commute time by scenario. Note that the no-AV line differs in the scenarios AV + Parking and AV + Transport, as these model setups affect all users, not only AV users.

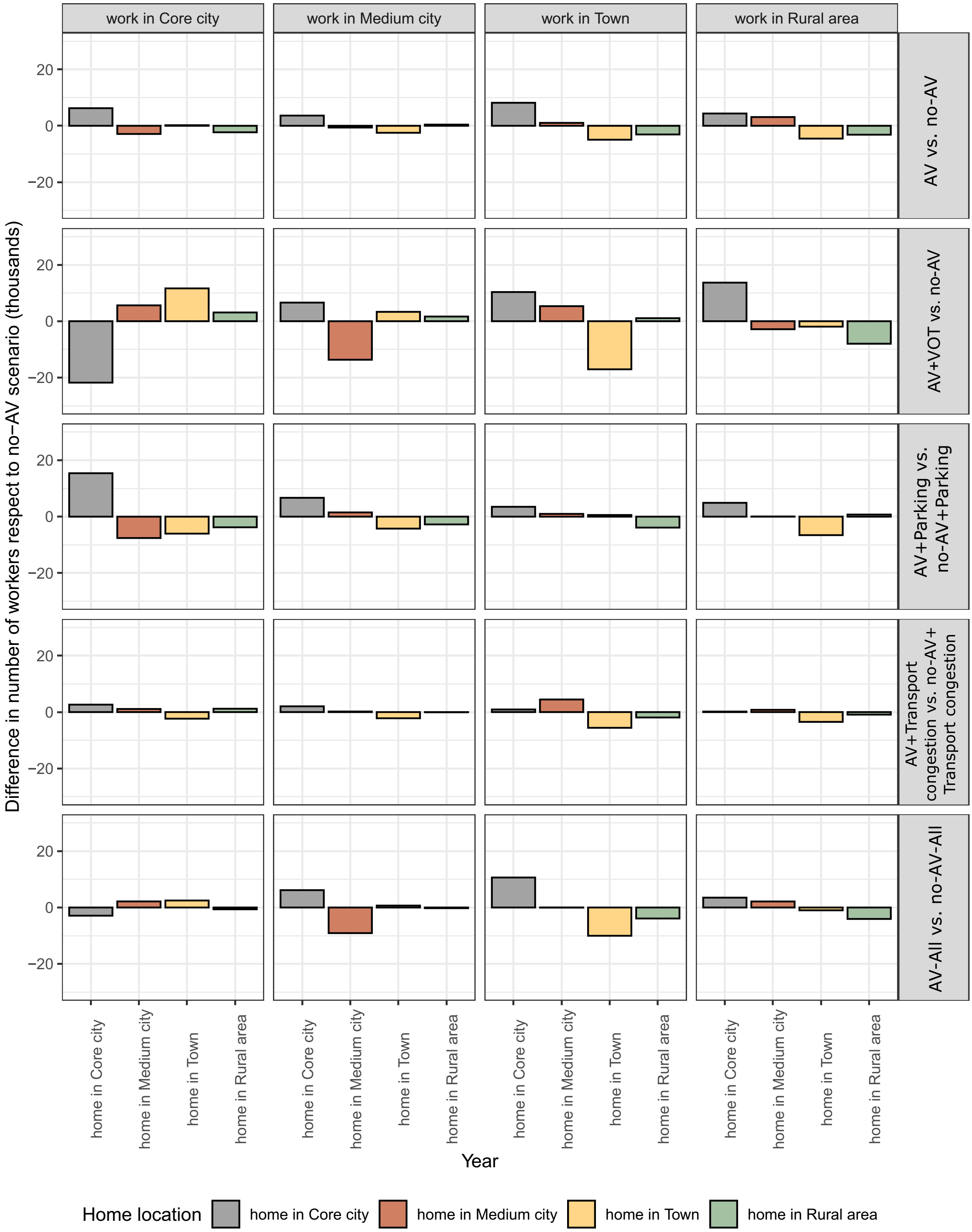

Fig. 11. Differences in the number of households by home area type (color) and work area type (column) and scenario (row). Each row shows the difference in the number of households with respect to the no-AV scenario.

represents an optimistic scenario based on Milakis and Snelder (2017) and was chosen for demonstration purposes in this paper.

One of the first effects of AVs is to provide access to travel by car to users who do not own a license, e.g. younger and elderly people (Harper et al., 2015). Also, AVs can reduce the limited car availability within a household (Zhang & Guhathakurta, 2018), as we assumed that AVs can be used by multiple household members for separate trips. As a result, the share of public transport is likely to decrease substantially and only public transport captive households and commuters to city center, where public transport commonly is faster than the car, would continue to use it. The reduction of public transport usage shown in this paper is also caused by the fact that the public transport network was not extended during the simulated period. It is perceivable that some loss in public transport ridership could be mitigated by offering fast rail service in congested areas. AV technology also has the potential of improving traditional public transport services by serving the access and egress trip for public transport. This may compensate for some increase in distance traveled by CV or AV.

One of the effects of AVs that has been investigated before is the change of VOT. Many authors propose or quantified reductions in VOT that cause longer commutes, and therefore, are likely to result in urban sprawl. The model SILO/MITO/MATSim introduced a reduction of 40% (a large reduction based on previous research, in line with public transport reductions reported by Malokin et al. (2019) for business-related trips). When this effect was simulated independently (without taking into account parking restrictions or additional congestion) the effects on urban sprawl were visible but relatively moderate, with around 8% increase of the average commute time of all workers (from 25 to 27 min). The reasons behind the moderate impact are that in the period from 2025 to 2050 (simulation period where AVs are present), only a certain proportion of households relocate, and only for some of them the reduction of VOT motivates a change in the selected home location, since mode choices are only one component (of many) of household relocation factors.

Moreover, in the study area of Munich, households with no workers represent 46% of the total population. Their household relocation is not affected by AV commute times, and therefore, is not encouraged to increase urban sprawl (note that this group is not even analyzed in the paper). Au contraire, 33% of all households have one worker only and are likely to be affected strongly by AVs on their relocation mode and VOT. The rest of households (21%) have multiple workers, and as consequence, their home locations are the result of a combination of multiple commute trips. For those households, the effects of AVs are less immediate (every location placed between two job locations has approximately the same marginal utility, and therefore, a similar probability of being chosen by a two-worker household).

In another scenario, the SILO/MITO/MATSim model simulated the changes due to AVs when parking restrictions are included into the model (those strongly affect CVs and to a smaller degree AVs). This model improvement reflects that commuters to city centers prefer public transport and AVs, as parking is expensive and limited. As a result, the population in core cities increases significantly after the introduction of AVs, and the average commute times are lowered from 29 to 27 min. The effect counterbalances the increase of urban sprawl motivated by the increases of VOT.

In the third scenario, the model represented the impact of additional congestion due to AVs, which contributed to an increase of person-kilometers traveled. For this scenario, we ran the full integrated land use/transport model, where travel times are fed back to the land use model every ten years. Despite a high share of AV commuters that increase person-kilometers traveled, the changes in average commute time are not visible (both AV and no-AV simulations result in the almost same average commute times).

Lastly, when all the effects were simulated together, the effects of VOT and parking restrictions more or less cancelled out each other. In any case, and given the strong assumptions made in the paper, all simulated scenarios with AVs revealed that the changes in population within the study area, due to the introduction of private AVs, are very moderate.

Apart from the assumptions already mentioned (which cannot be entirely supported by observations yet), we identified additional limitations in the simulated scenarios that affect the transport model results. Firstly, the trips made by AVs are not explicitly simulated with respect to intra-household coordination and empty trips. This prevented us from representing the additional waiting or times or detours of pooled AV trips. Secondly, the transport model only runs every 10 years due to computational runtime. This could affect the feedback loop from the transport model to the land use model when there are drastic changes in travel demand or supply. However, this limitation appears to be minor, as no abrupt changes in the average commute time during the simulated period were observed (compare Fig. 10).

6. Conclusion

Integrated land use/transport models allow to simulate the impact of new technologies, such as AVs. A common critique is that the results of the simulation are highly influenced by the assumptions. If assumptions are set in favor of AVs, model results are likely to show the benefits of AVs, and vice versa. However, the real strength of models is the representation of capacity limits and the representation of unexpected effects. For example, it is often hypothesized that AVs would increase urban sprawl. While we could observe some increase in sprawl, the effect was rather minor. An agent-based model can represent congestion and resulting slower travel times on the street network quite well. AVs will add a lot of congestion to the network and increase the travel time. Consequently, there is a natural limit how far households are willing to move out. While congestion in an AV is likely to be less burdensome than in a CV, it is still time that I could spend playing, working out, dining, or work with better focus in an office. AVs will not increase the acceptance of congestion indefinitely. While a simulation model cannot forecast how people will travel on AVs, simulation models are arguably very good at representing the level of congestion and the resulting counterbalance to limit AV usage.

The role of agent-based models for the study of AVs is to provide a framework in which behavioral models can be integrated and expanded to the entire population. Various examples were provided in the paper, including the effect of VOT, the mode choice module or the parking restrictions. We limit the study to private AVs and exclude shared AVs. With such tools, we facilitate the simulation scenarios to anticipate potential impacts. As seen in the paper, it is possible to understand the marginal impacts of a certain factor (e.g. isolate the effect of a reduction of VOT, without taking into account the changes in parking behavior). Although those scenarios are based on assumptions, they are very well suited to measure the sign and magnitude of the expected impacts. Even with very strong assumptions regarding VOT or parking, we observed that the impacts of AVs on relocation are of a relatively low magnitude, in absence of additional land use policies that are out of the scope of this paper.

We showed that for particular households, private AVs can motivate strong changes in commute mode or home location choice. However, there are also household types for which the introduction of private AVs may be less relevant for household relocation (in particular for households with multiple workers, households without cars and households without workers). Accordingly, the influence of AVs on the relocation of households might be smaller than often hypothesized.

CRediT authorship contribution statement

Carlos Llorca: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Visualization, Writing – original draft, Writing – review & editing. **Ana Moreno:** Conceptualization, Investigation, Methodology, Writing – original draft. **Ghassan Ammar:** Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Rolf Moeckel:** Conceptualization, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

None.

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Appendix A. Sensitivity analysis of the relocation model

The sensitivity analysis was carried out calculating the utility for multiple combinations of regions (and dwellings) varying every independent variable in the ranges observed in the model implemented for the metropolitan area of Munich.

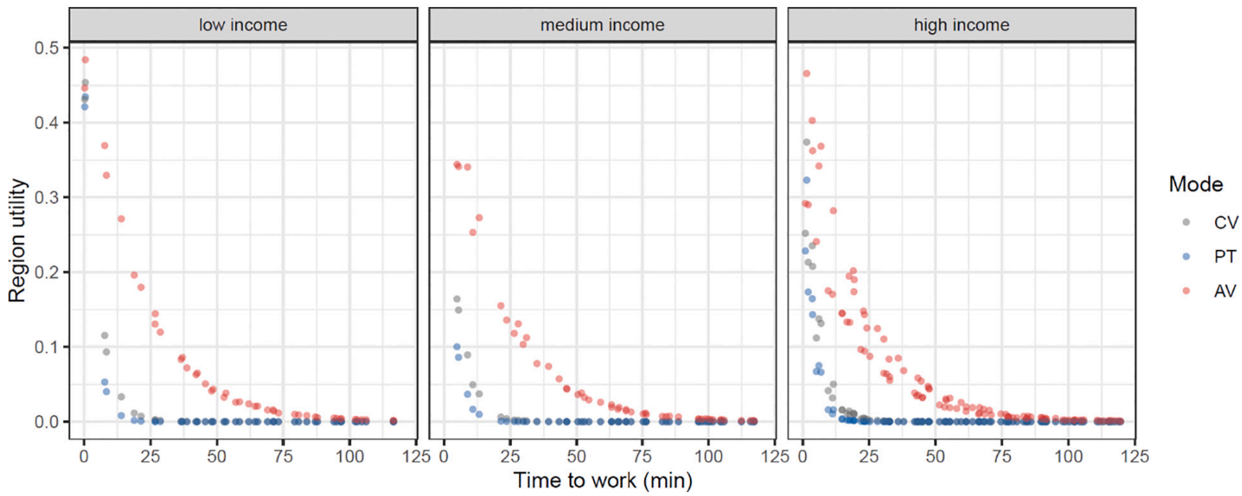

Fig. A-1. Utility of regions as a function of the transport mode from home to work (color), travel time from home to work (horizontal axis) and income level (subplot). The household has one worker and one car, being all their members German. The candidate regions have an average accessibility of 50 (in a scale from o to 100) and an average price in the range 1300–1700 EUR, and a share of foreign under 25%.

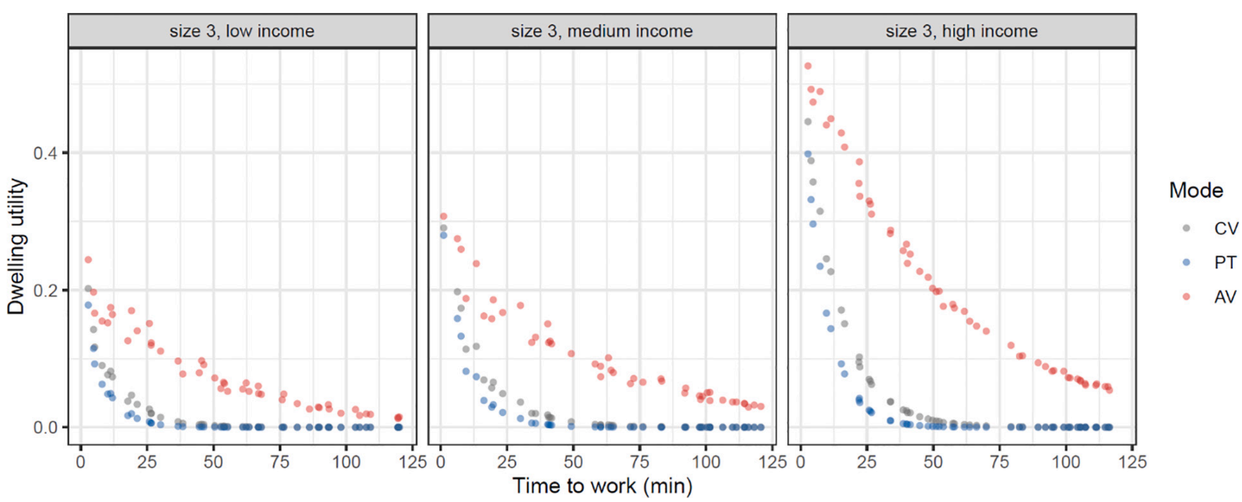

Fig. A-2. Utility of dwellings as a function of the transport mode from home to work (color), travel time from home to work (horizontal axis) and income level (subplot). The household has 3 members. The candidate dwellings have 2 bedrooms, high quality (4 in a scale of 5), an accessibility in the range 30–70 and a price between 1300 and 1700 EUR.

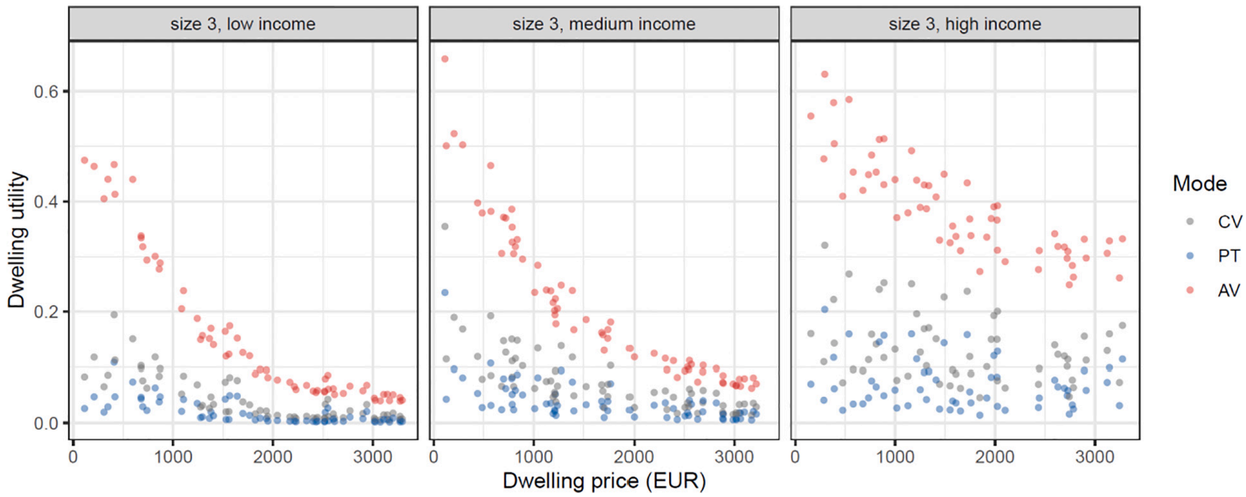

Fig. A-3. Utility of dwellings as a function of the transport mode from home to work (color), price (horizontal axis) and income level (subplot). The household has 3 members. The candidate dwellings have 2 bedrooms, high quality (4 in a scale of 5), an accessibility in the range 30–70 and the distance to work in the range 10–30 min.

References

Bagloee, S. A., Tavana, M., Asadi, M., & Oliver, T. (2016). Autonomous vehicles: Challenges, opportunities, and future implications for transportation policies. *Journal of Modern Transportation, 24*, 284–303.

Bansal, P., & Kockelman, K. M. (2016). Are we ready to embrace connected and self-driving vehicles?A case study of Texans. *Transportation (Amsterdam)*, 1–35.

Becker, F., & Axhausen, K. W. (2017). Literature review on surveys investigating the acceptance of autonomous vehicles. *Transportation (Amsterdam), 44*, 1–12.

Carrese, S., Nigro, M., Patella, S. M., & Toniolo, E. (2019). A preliminary study of the potential impact of autonomous vehicles on residential location in Rome. *Research in Transportation Economics, 75*, 55–61.

Deutschen Zentrums für Luft- und Raumfahrt (DLR). (2017). Mobilität in Deutschland [WWW Document]. http://www.mobilitaet-in-deutschland.de/ accessed 12.1.17.

Faisal, A., Yigitcanlar, T., Kamruzzaman, M., & Currie, G. (2019). Understanding autonomous vehicles: A systematic literature review on capability, impact, planning and policy. *Journal of Transport and Land Use, 12*, 45–72.

Fraedrich, E., Heinrichs, D., Bahamonde-Birke, F. J., & Cyganski, R. (2019). Autonomous driving, the built environment and policy implications. *Transportation Research Part A: Policy and Practice, 122*, 162–172.

Franco, S. F., & Khordagui, N. (2017). *Parking prices, parking availability and work commute mode choices: Evidence from Los Angeles County*.

Gelauff, G., Ossokina, I., & Teulings, C. (2019). Spatial and welfare effects of automated driving: Will cities grow, decline or both? *Transportation Research Part A: Policy and Practice, 121*, 277–294.

Gurumurthy, K. M., & Kockelman, K. M. (2020). Modeling Americans' autonomous vehicle preferences: A focus on dynamic ride-sharing, privacy & long-distance mode choices. *Technological Forecasting and Social Change, 150*.

Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Planning Association, 25*(2), 73–76. https://doi.org/10.1080/01944365908978307

Harper, C., Mangones, S., Hendrickson, C. T., & Samaras, C. (2015). Bounding the potential increases in vehicles miles traveled for the non-driving and elderly populations and people with travel-restrictive medical conditions in an automated vehicle environment. In *Transp. Res. Board 94th Annu. Meet*.

Hawkins, J., & Nurul Habib, K. (2019). Integrated models of land use and transportation for the autonomous vehicle revolution. *Transport Reviews, 39*, 66–83.

Henao, A., & Marshall, W. E. (2019). The impact of ride-hailing on vehicle miles traveled. *Transportation (Amsterdam), 46*, 2173–2194.

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

Lavieri, P. S., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Astroza, S., & Dias, F. F. (2017). Modeling individual preferences for ownership and sharing of autonomous vehicle technologies. *Transportation Research Record, 2665*, 1–10.

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.

Martínez-Díaz, M., Soriguera, F., & Pérez, I. (2019). Autonomous driving: A bird's eye view. *IET Intelligent Transport Systems, 13*, 563–579.

Meng, Z., Le, D. T., Zegras, P. C., & Ferreira, J. (2019). Impacts of automated mobility on demand on long-term mobility choices: A case study of Singapore. In *2019 IEEE Intell. Transp. Syst. Conf. ITSC 2019* (pp. 1908–1913).

Milakis, D., & Snelder, M. (2017). Development and transport implications of automated vehicles in the Netherlands: Scenarios for 2030 and 2050. *European Journal of Transport and Infrastructure Research, 1*, 63–85.

Moeckel, R. (2017). Constraints in household relocation: Modeling land-use/transport interactions that respect time and monetary budgets. *Journal of Transport and Land Use, 10*, 1–18.

Moeckel, R., Llorca, C., Moreno, A. T., & Rayaprolu, H. (2020). Agent-based simulation to improve policy sensitivity of trip-based models. *Journal of Advanced Transportation, 2021*, 1–13, 2020.

Molloy, J., & Moeckel, R. (2017). Automated design of gradual zone systems. *Open Geospatial Data, Software and Standards, 2*, 19.

Moore, M. A., Lavieri, P. S., Dias, F. F., & Bhat, C. R. (2020). On investigating the potential effects of private autonomous vehicle use on home/work relocations and commute times. *Transportation Research Part C: Emerging Technologies, 110*, 166–185.

Okrah, M. B., Moreno, A. T., Llorca, C., & Moeckel, R. (2018). Modeling household car ownership level changes in an integrated land use/transport model. In *Transp. Res. Board Annu. Meet. Washingt. DC*.

Parida, S., Franz, M., Abanteriba, S., & Mallavarapu, S. (2019). Autonomous driving cars: Future prospects, obstacles, user acceptance and public opinion. In N. Stanton (Ed.), *Advances in human aspects of transportation* (pp. 318–328). Springer.

Singleton, P. A. (2019). *Discussing the "positive utilities" of autonomous vehicles: Will travellers really use their time productively?*.

Soteropoulos, A., Berger, M., & Ciari, F. (2019). Impacts of automated vehicles on travel behaviour and land use: An international review of modelling studies. *Transport Reviews, 39*, 29–49.

Vyas, G., Famili, P., Vovsha, P., Fay, D., Kulshrestha, A., Giaimo, G., & Anderson, R. (2019). Incorporating features of autonomous vehicles in activity-based travel demand model for Columbus,OH. *Transportation (Amsterdam), 46*, 2081–2102.

Weinberger, R. (2012). Death by a thousand curb-cuts: Evidence on the effect of minimum parking requirements on the choice to drive. *Transport Policy, 20*, 93–102.

Weis, C., Vrtic, M., Widmer, P., & Axhausen, K. W. (2012). Influence of parking on location and mode choice: A stated choice survey. In *Transportation Research Board Annual Meeting*.

Zakharenko, R. (2016). Self-driving cars will change cities. *Regional Science and Urban Economics, 61*, 26–37.

Zhang, W., & Guhathakurta, S. (2018). Residential location choice in the era of shared autonomous vehicles. *Journal of Planning Education and Research*, 1–4.

Zhang, W., Guhathakurta, S., & Khalil, E. B. (2018). The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation. *Transportation Research Part C: Emerging Technologies, 90*, 156–165.