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Impact of vehicle automation and electric propulsion on production costs for mobility services worldwide

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ABSTRACT

Automated driving technology along with electric propulsion are widely expected to fundamentally change our transport systems. They may not only allow a more productive use of travel time, but will likely trigger completely new business models in the mobility market. A key determinant of the future prospects of both existing and new mobility services will be their production costs. Hence, in this research the production costs of various transport modes both today and in an automated-electric future are analyzed. To account for different local contexts, the study is conducted for 17 cities across the globe. The results indicate that high-income countries will benefit the most from vehicle automation, while only smaller changes can be expected in lower-income countries. This is due to the different relative contribution of labor cost to the total cost of current taxi and bus operations. In a likely final state, transportation costs will be largely decoupled from a country's income level, which will favor productivity in higher-income

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locations. While this research provides valuable first insights into potential future developments, the underlying assumptions will need to be updated as better information becomes available.

1. Introduction

Automated driving technology is widely expected to fundamentally change our transport systems. Driverless vehicles do not only allow today's drivers of private vehicles to use their travel time more productively, but – in combination with modern information technology – they may enable new mobility services and vehicle types (Burns, 2013; Cervero, 2017). Offering seamless trips between any two points within an area, autonomous mobility services may substantially change the accessibility landscape (Meyer et al., 2017), triggering changes to the urban form, potentially comparable to the invention of elevators or to the mass-production of cars.

Since we are still in the early stages of the autonomous driving revolution, it is largely unclear how the future of transportation may look like. Open questions include what type of vehicles will be on the road (Burns, 2013), which services people will prefer to travel on (Cervero, 2017), or how these systems may affect road capacities (Le Vine et al., 2015). Moreover, it is hard to predict which regulations and policies will be put in place. Yet, from a travel demand perspective, even future services can be abstracted to private vehicles, line-based public transport and (pooled) taxis with their key attributes being access/egress time, frequency/reliability, travel time, comfort and cost/fare.

While the operational characteristics of the different future modes (such as levels of service or travel times) can be modeled using simulation experiments (Alonso-Mora et al., 2017; Liu et al., 2017; Hörl et al., 2019b), user preferences are commonly studied using stated-preference approaches (Krueger et al., 2016; Haboucha et al., 2017). Yet, the results of both methods strongly depend on the cost/price levels assumed for the different modes. Despite their importance, sound estimates of the prices are still scarce.

To address this research gap, a methodology to produce sound cost estimates for future taxis, private cars and public transportation (Bösch et al., 2018) is applied to a number of cities around the globe. By conducting this research for various different case study locations, it is acknowledged that travel behavior is substantially shaped by local factors, too (Cervero and Kockelman, 1997). Although limited to the current state of knowledge, the results allow a glimpse on the potential roles of the different modes in the future and will be helpful to inform subsequent simulation experiments and survey approaches with realistic cost/price assumptions.

2. Background

Fully-autonomous driving technology will disrupt the transport system in many ways. Not only will it make existing modes of transport, such as cars, taxis and public transport, more attractive by reducing (perceived) travel times and costs, but it will also enable the emergence of new modes and vehicle types (Burns, 2013; Cervero, 2017) as well as ownership concepts (e.g. Mobility as a Service (Mulley, 2017)). Yet, rebound effects in form of increased congestion can be expected if this leads to a substantial shift towards private modes (Meyer et al., 2017; Hensher, 2018). Although the actual features of future services are difficult to predict, the number of attributes relevant in mode choice decisions are limited (Krueger et al., 2016). Starting from operational models suggested until now, four main modal categories can be identified:

- private vehicles,
- individual taxis,
- pooled taxis/ dynamic on-demand public transport,
- line-based public transport.

Here, *private vehicles* mean private use of an autonomous vehicle similar to today's private car, but potentially shared among household members. *Individual taxis* refer to the known taxi or ride-hailing services, simply without the human driver, whereas *pooled taxis* include ride-sharing, where strangers share the vehicle for at least a part of their trips.[1] In this sense, they are very similar to suggested forms of *dynamic public transport* (Mulley and Nelson, 2009), although for the latter, one could imagine larger vehicle types and requiring passengers to walk to consolidated pick-up points. Eventually, the differences between them may be shaped by potential contractual frameworks, such as concessions and/or subsidies (Hensher, 2017). Finally, *line-based public transport* systems, i.e. bus, light rail and rail lines, may likely prevail in their current fashion on certain corridors, minus the human driver.

Apart from first attempts to estimate consumers' willingness to pay for automation technology in their private car (Daziano et al., 2017; Bansal and Kockelman, 2017; Hörl et al., 2019b), earlier research has mostly addressed the case of individual or pooled autonomous taxis, finding that such systems may allow to reduce total fleet sizes by as much as 90%, hence freeing up valuable parking space for more efficient uses (International Transport Forum, 2015; Bösch et al., 2016; Alonso-Mora et al., 2017; Fagnant and Kockelman, 2018). However, smaller fleets do not necessarily go hand in hand with a reduction in vehicle-kilometers traveled (VKT). Due to demand from new user groups (Meyer et al., 2017; Truong et al., 2017), vehicle relocations as well as potential detours in shared rides (among other factors), the total kilometers traveled may likely increase (International Transport Forum, 2015; Fagnant and Kockelman, 2018), potentially leading to a suboptimal system state (van den Berg and Verhoef, 2016) and enlarging the

[1] For simplicity, less common arrangements such as peer-to-peer car-sharing are not considered here.

ecological footprint of the transport system (Wadud et al., 2016).

Most of the analyses undertaken so far consider all-or-nothing scenarios, in which either the whole travel demand or full segments of it (e.g. all taxi trips) are assigned to the new mode. A more realistic outcome is that autonomous taxis will be in competition with other modes, or as a complement offering first/last mile connections. Consequently, much of their modal share - and thus their impact on the transport system - will likely depend on the price difference between taxis and other modes of transport (Krueger et al., 2016; Chen and Kockelman, 2016; Liu et al., 2017; Simoni et al., 2019; Hörl et al., 2019b).

Various estimates of future fares for autonomous taxis have been proposed for the United States. For example, Burns et al. (2013) used travel survey data in combination with an agent-based optimization model to find that a system of pooled autonomous taxis could offer trips at 0.41 US-$ per mile (compared to 1.60 US-$ for a privately owned conventional car) and that fares could decrease further to 0.15 US-$ per mile for purpose-built vehicles. Using a similar approach, Fagnant and Kockelman (2018) found that a pooled autonomous taxi scheme could offer trips at 1.00 US-$ per mile, which already includes a 19% profit margin. Using an agent-based simulation as well, Loeb and Kockelman (2019) put a special emphasis on the detailed calculation of the costs for the charging infrastructure for electric automated taxis. For the Austin area, their results suggest that the costs for the latter amount to 59 Cents per mile versus 45 Cents for the gasoline counterpart. Stephens et al. (2016) analyzed how the single cost components of today's taxi schemes may be affected by autonomous vehicle technology for average utilization patterns. Depending on the scenario, they project a lower bound of operating costs of 0.20–0.30 US-$ per passenger-mile. Taking up a similar methodology for individual autonomous taxis, Johnson and Walker (2016) expect fares of 0.35 US-$ by 2035. Unlike Stephens et al. (2016) and Johnson and Walker (2016), Lim and Tawfik (2019) also look at the effect of advertising during the ride. Their results suggest that the costs for electric and automated taxis will amount to between 8 and 29 Cents per mile, three cents lower than without any advertising. In a different approach using NHTS trip distance and time of day distributions to generate realistic demand patterns for Austin, TX, Chen et al. (2016) estimated that a fleet of shared electric automated vehicles could potentially serve the demand at a cost of 0.42 US-$ to 0.49 US-$ per occupied mile traveled. While those estimates are mostly within the same ballpark, most of the above approaches rely on strong assumptions on travel demand and utilization patterns, neglecting potentially important factors such as maintaining and cleaning the fleet or sometimes do not make all their assumptions transparent. Moreover, mostly only single modes (pooled autonomous taxis) were considered, ignoring that they will be only one among several evolving options.

Estimates for other countries have been rare so far. For Germany, Friedrich and Hartl (2016) estimated a fare of 0.34 US-$ per mile for a pooled autonomous taxi scheme. However, other future modes were not considered in their research. Dandl and Bogenberger (2018) use an existing free-floating car-sharing scheme as a reference and find that the same service could be offered for about one third lower fares. For the case of DriveNow in Munich, this would mean about 0.25 US-$ per minute. For Switzerland, Bösch et al. (2018) followed the component-based approach and extended it to cover all four main categories of future autonomous modes mentioned above. Their results indicate that fares for individual taxis in Switzerland (0.58 US-$ per mile) may only be twice as expensive as for autonomous public transportation, with the difference becoming negligible for pooled autonomous taxis. In contrast to all other studies reviewed, Wadud (2017) calculate the total cost of ownership for different income groups in the UK. Even when monetizing gains in available time, he finds that costs rise for those people who belong to the lower 80% of the income distribution. Only for the upper 20% costs decrease by 6.4%. Yet, for many countries, sound estimates are still missing.

This research paper aims to address this research gap by providing cost estimates for modes of future, automated transportation for different countries across the globe. A comparison of the results for the different cities will then provide a glimpse on the potential future market position of the different modes.

3. Methodology

As it allows the most comprehensive analysis both with respect to cost components and types of modes, the approach of Bösch et al. (2018) is used in this research. The approach presents a bottom-up calculation of the cost and price structures of the respective modes. It divides the task into four parts:

1. single vehicle cost structures,
2. impact of fleet operation, electrification and (full) automation,
3. external parameters,
4. vehicle operations (and average trip characteristics).

In the first step, the individual cost components of a conventional vehicle (i.e. not electric and not automated) are determined. Cost components are given per year (fixed cost) or per km (variable cost) and cover all vehicle-related costs from acquisition and insurance to parking and fuel. Values are obtained for private ownership of the vehicles, but are assumed independent of their actual utilization.

Second, the impact of electric propulsion and driver-less technology is defined for each cost component. These cost modifiers are based on earlier literature and given in relative or absolute numbers. In addition, cost reductions or increases due to fleet operation are accounted for in this step (mostly economies of scale). Hence, together with the input from above this allows to obtain fixed and variable cost for automated, electric and automated-electric vehicles, too.

The third input are external parameters, which comprise relevant economic factors such as wages for drivers, interest rates or typical lifetime of a vehicle. Combined with the two previous stages, this allows a determination of the cost structures of the respective vehicle types for any operational model.

In the fourth step, the different operational models (private car, individual/pooled taxi, line-based public transport) are defined by providing their respective operations attributes such as average speeds, trip lengths or occupancy levels. The values were set to describe a well-established, efficient service with a substantial fleet (tailored to the demand). Lacking any general transport model covering all the locations in this study, daily averages (mostly from travel surveys, taxi data and/or traffic assignment models) had to be used. In reality, there will also be an interplay between fares and demand patterns, which could not be accounted for in this research.[2]

A detailed description of the methodology is presented in Bösch et al. (2018). It is therefore not presented here. Specific assumptions made in this research are described in more detail in Appendix A.

Case studies were conducted for 17 locations in 14 countries across the globe (c.f. Fig. 1). The locations were selected to cover major cities with different degrees of (public) transportation infrastructure and services, travel patterns, congestion and wealth. Ideally, the variety of case studies analyzed in this research can be used for predictions of operating cost for other cities beyond the sample. The case study locations are briefly introduced in the supplementary material. In addition, key indicators of city characteristics are presented in Table 1.

Research has been conducted to define the input values for each of the case study locations for all of the four steps. However, due to limited availability of dis-aggregated information and for better comparability, some assumptions were fixed for all case studies. To provide better understanding to the source of differences in the results, two comparisons are made:

- In a first step, parameters for step 4 (i.e. vehicle operations assumptions including average speed, trip length and vehicle occupancy levels) are fixed and assumed to be equal across all 17 cities. For the sake of illustration, vehicle operations parameters for Zurich (reference city) were used in all cases.[3] Consequently, impacts of electrification and automation can be observed without confounding elements like different trip lenghts or vehicle occupancy rates between cities.
- In the second set of analyses, all parameters froms steps 1 to 4 are city-specific.

Detailed information about the assumptions for each of the case study locations is provided in Appendix A. To allow comparability, analyses of the different case study locations used the same underlying assumptions:

- The reference time horizon is the present. However, cost assumptions on technologies are based on future mass-market prices in today's US-$ (e.g. sensors are prohibitively expensive today, but prices are expected to plummet in the near future; hence, the latter have been used in the calculation).
- For simplicity, only one vehicle type was used to estimate costs for private cars and taxi services. For each location, a specific midsize vehicle was chosen, which matches the average price of all new vehicle registrations. Often, this also corresponds to the most-sold vehicle.
- Analyses were conducted at the city level. For most European locations, the case study area comprises the whole urban area (also beyond municipal borders). In most other cases (in particular mega-cities such as Tokyo), the definition includes the urban core and its surroundings. In the vehicle operations parameters (step 4), all trips with origin and/or destination in the target area are considered. For parking prices (part of step 1), values for the city center were used.[4]
- It is assumed that current policy regimes (e.g. Singaporean import taxes and registration charges or tax-exemption for electric vehicles in Zurich) remain unaltered. While this may be a strong assumption, changes in regulation are hard to predict. Hence, the current analysis provides an estimate of the effect of automation and electrification on cost structures previous to any (additional) policy intervention.
- Public transport operations are represented by *city bus* (regular bus lines operating in the case study area). For the service, full operational costs are considered (including capital costs of vehicles and applicable fees for the use of infrastructure), but not construction costs of the roads/tracks or stops/stations.

Multiple iterations of internal reviews were conducted to ensure comparability of the results across locations.

While assumptions and cost analyses were made in local currency units (LCU), all results were converted to US-$ at 2016 exchange rates (marked as *EXCHR*; see Table A.10) to allow better comparability.[5] It is important to note that only two propulsion types are considered in this research: internal combustion engines and battery-electric vehicles. Other promising solutions exist (such as hybrid-electric vehicles or fuel-cell approaches) (Chen et al., 2016), but would exceed the scope of this research.

To further limit the number of dimensions, analysis is focused on midsize cars with private ownership, individual taxis and pooled taxis as operational modes. Regular, line-based public transport was also analyzed to understand the relative market position of automated taxis in the transport system. In particular, dynamic transit systems using minibuses as well as (right-sized) one-seater micro-vehicles are not considered here. However, earlier research has demonstrated that at current demand levels larger vehicles may not necessarily bring additional benefits compared to pooled taxi schemes (International Transport Forum, 2015). As for micro-

[2] It is generally possible to combine the approach of Bösch et al. (2018) with a transport simulation tool to study how fares affect demand patterns and vice versa (Hörl et al., 2019a). However, for most case study locations, no suitable transport model was available.

[3] Zurich was chosen as a reference city, because it offered a high data availability and was also subject of earlier research (Bösch et al., 2018).

[4] In fact, parking prices may vary substantially within the case study area. The reader will need to keep this in mind when interpreting the results.

[5] In addition, selected results were converted at purchasing power parity (PPP) and presented in the appendix.

Fig. 1. Case study locations (adapted from: http://techcenter.jefferson.kctcs.edu/).

vehicles, predictions would substantially depend on unreliable assumptions since their actual design and potential cost structures are largely unclear. Moreover, using current technology, they do not appear to be more efficient than regular taxis on a fleet level (Bösch et al., 2018). Hence, despite those restrictions the analyzed modes can be expected to cover most of the future modes conceivable today.

4. Results

The results allow various forms of comparisons and analyses. For the sake of brevity, only the most important aspects are presented in this section.[6] Three aspects are analyzed sequentially: First, the production cost of the four modes are studied using operational characteristics for a reference city. This allows a direct comparison of the unit production cost in the different markets. Second, the corresponding operational characteristics for each of the cities are applied, so that the effective production cost in the different cities can be compared. This setup is then also used for an assessment of individual impacts of automation and electrification as well as an in-depth analysis of the cost structures of taxis. As a third main part, a simple regression analysis is presented which allows to identify the main driver of production costs across the different case study locations.

4.1. Analysis for a reference city

To better understand the drivers of differences in costs, the analysis has first been performed using Zurich as a reference case. This means that Zurich's demand patterns and network characteristics were used for all locations (compare Section 3). This first analysis allows a direct comparison of the unit production costs for the different cities.

The results are presented in Fig. 2. It shows in grey the production costs of conventional modes and in colors the production costs of the corresponding automated-electric modes.[7] As expected, there is substantial variation in costs between cities. Europe and North America are the most expensive, whereas China and India show the lowest costs.

Moreover, the relative differences between the modes vary substantially. In particular, cities with generally high mobility costs also show a larger gap between conventional taxi services and private car costs. Another interesting observation is that in Zurich, production cost for private car travel is slightly lower than for bus, whereas it is substantially more expensive than public transport e.g. in China, India or Brazil. Singapore presents a special case, in that private car ownership and use is particularly expensive.

To derive the cost estimates for autonomous-electric operations, the production costs for the corresponding conventional mode are modified by the factors presented in Table A.5. As shown in Fig. 2, introduction of automation and electrification slashes operating costs for taxi services, whereas only little change is observed for the operating costs of private vehicles.[8] Public transport services tend to get more cost-efficient, too. However, on the right side of the spectrum, reductions in taxi and bus costs are smaller.

As a general result, locations with high transportation costs see a convergence of the cost level for the different modes, whereas in cities with lower transportation costs, a certain relative cost gap between (individual) taxi services and buses remains. As costs for private car travel remain largely constant, it becomes the most expensive travel mode in almost all locations (when fixed costs are included). Hence, it appears more economical to share a vehicle than to own it.

[6] Detailed results are presented in Appendix B allowing further analyses at the reader's discretion.
[7] It is important to note that the values shown rely on (estimated) true production costs. Especially for public transport, this does not reflect the fares paid by travellers, which are often highly subsidized.
[8] Singapore is a notable exception as the prevailing duties and taxes enlarge the effect of increasing acquisition cost.

Table 1
List of case study locations.

Location	Population size (metro area) (million)	Population density (city center/ metro area) (residents per km^2)	Number of cars per 1 k residents	Mode share by distance (car/ moto/ PT/ active modes)	Median household income (US-$ at PPP)	Median per-capita income (US-$ at PPP)	Household size (average)
Austin	0.93	1229 / 181	797	93% / 1% / 2% / 4%	43,585	15,480	2.5
Beijing	21.71	8759 / 1291	260	36% / – / 50% / 12%	6180	1786	2.6
Berlin	4.47	4166 / 1194	323	45% / 1% / 42% / 12%	33,333	14,098	1.8
Cape Town	4.43	1100 / 1500	274	38% / 3% / 34% / 25%	5,217	1217	–
Chongqing	30.48	1556 / 370	146	40% / – / 59% / 1%	6,180	1,786	2.7
Copenhagen	1.32	7081 / 1718	339	36% / 1% / 12% / 51%	44,360	18,262	2.1
Delhi	16.79	11,320 / 11,320	162	9% / 16% / 29% / 34%	3,168	616	4.9
Jakarta	32.43	15,517 / 4,383	343	12% / 43% / 20% / 25%	2,199	541	3.8
Johannesburg	5.49	2900 / 2300	308	36% / 2% / 37% / 24%	5217	1217	–
San Francisco	7.15	7282 / 426	494	48% / 4% / 25% / 23%	43,585	15,480	–
Santiago	6.30	17,485 / 2587	273	24% / 2% / 24% / 38%	8098	2040	3.2
São Paulo	20.86	7727 / 2624	516	32% / 3% / 58% / 7%	7522	2247	3.1
Singapore	5.61	7796 / 7796	149	37% / – / 63% / –	32,360	7345	3.2
Sydney	4.45	6161 / 1060	609	79% / – / 17% / 2%	46,555	15,026	2.8
Tel Aviv	3.70	8192 / 2436	365	54% / 1% / 17% / 28%	30,364	7847	3.1
Tokyo	37.76	14,796 / 2310	432	29% / 2% / 33% / 36%	33,822	10,840	2.2
Zurich	1.33	4514 / 1022	510	57% / 1% / 32% / 9%	50,124	20,635	2.2

Household and per-capita income values used from Gallup survey[a] *and are only available on coutry-level (at purchasing power parity).*
All other values are based on local sources, which are provided in supplementary material.
Mode share information was not always available for all four modes.

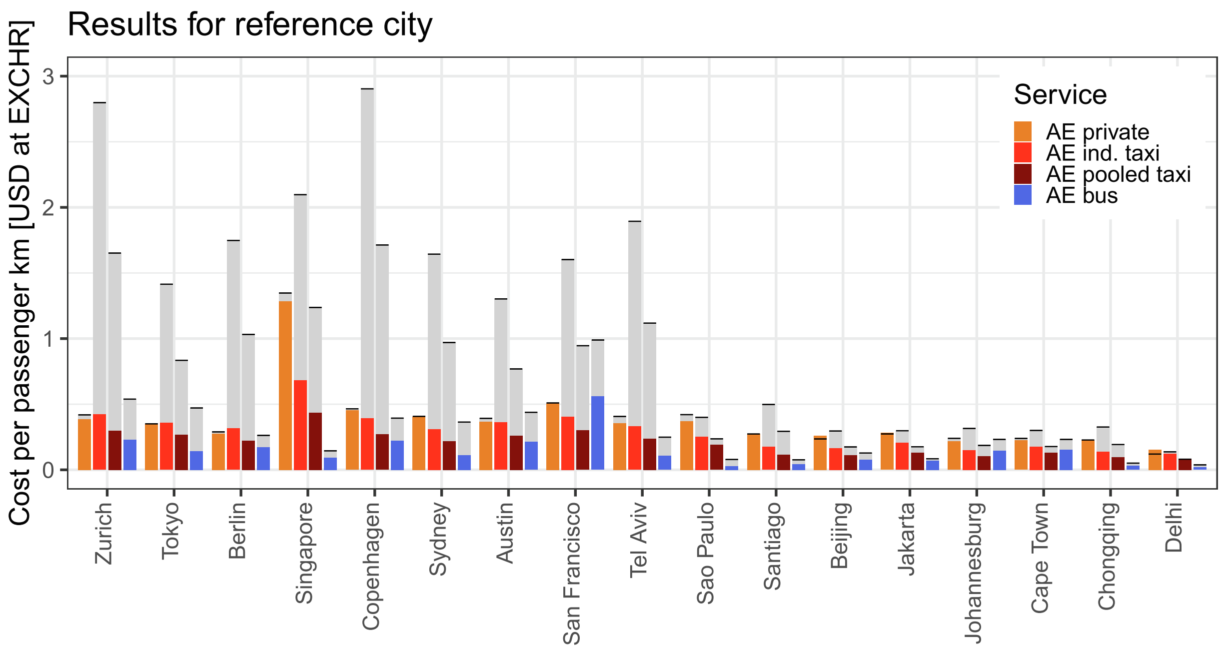

Fig. 2. Comparison of costs for autonomous-electric services (colors) and conventional services (light grey with black whiskers) assuming operational characteristics for Zurich (converted to US-$ at 2016 exchange rates). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2. Local case study areas

The impact of the new technologies on production cost also depends on the city characteristics. Especially the achievable passenger load factors, network speeds and trip distances affect the shares of fixed and variable cost components. In consequence, the shape of the current transport system also determines the future market potential of the different automated services.

4.2.1. Full production cost

Fig. 3 shows the production costs of conventional and automated-electric modes for the local case study characteristics. When comparing the results with Fig. 2, it becomes obvious that including the local operations characteristics substantially changes the production costs both within and across case study areas.

A prominent example is Tokyo, for which conventional taxi costs now are about 1 US-$ (70%) higher compared to the reference case. On the other hand, Copenhagen sees a decrease of a similar order of magnitude. Moreover, for Santiago de Chile, using the local operational characteristics suggests that the impact of automation and electrification will actually be lower than for the reference city. The differences in the operating cost between the reference city (Fig. 2) and localized assumptions (Fig. 3) can also be interpreted as cost of congestion. It can thus serve as an indicator, how much improvements in built-environment factors or travel demand management could potentially help to lower cost of operations.[9]

Also when accounting for city-specific operational characteristics, there is substantial variation in the cost impacts of automation and electrification. As shown in Fig. 3, autonomous-electric technology mostly results in reduced costs of taxi and bus services, but not for private cars. In contrast, autonomous-electric technology increases the cost of private car travel in various locations like Beijing, Delhi, Jakarta, and Santiago.

4.2.2. Impact of automation and electrification

Although it is often assumed that the two innovations of electric propulsion and vehicle automation will coincide to revolutionize the transport system, Table B.11 indicates that vehicle automation has a much more profound impact on the cost levels than electric propulsion. While the latter may provide cost reductions of a few percent, vehicle automation may reduce costs by as much as 84% in the case of Berlin.

Furthermore, Table 2 shows that the impacts are not homogeneous across cities, but vary substantially in their size. While there are several cities with potential reductions in taxi costs[10] in the same order of magnitude as Berlin, the effect is much lower in other cities, down to 29% in the case of Delhi. For buses, a similar pattern applies, but with a generally lower impact of new technologies. In contrast to the clear and substantial impact on taxi and bus costs, the impact on production costs of private car travel is ambiguous. While lower costs can be expected in Berlin or Tel Aviv, costs may even increase in places like Delhi, Beijing, Santiago, and Jakarta.

4.2.3. Taxi cost structures

As described by Bösch et al. (2018), vehicle automation and electrification impact the cost structures in three ways: they increase acquisition cost of the hardware, they decrease marginal operating costs (maintenance, fuel, insurance) and they allow more flexible operations, because they remove the need of a driver (who takes shifts and breaks). Because taxi operations are the most labor-intense (per passenger carried), they will be affected the most by this innovation (as also indicated by Table 2). To understand better the key drivers of their cost levels, Fig. 4 shows the cost structure for conventional and automated-electric individual taxis.[11]

The figure indicates that in all cities, the driver's salary is the single most important cost driver, accounting for 40% (Jakarta) to 87% (Zurich) of the total operating cost. Depending on the local context, fuel, depreciation, maintenance and parking/tolls are other relevant factors (although mostly contributing less than 5–10% each). Again, in those countries with generally higher transportation costs, also the share of salaries of the overall costs is the highest.

With the driver's salary as a main cost component gone after automation, relative contribution of the other remaining cost components increases. However, vehicle automation and electrification have further implications: Because of increased efficiency, the relative contribution of fuel costs increases only slightly or even decreases in some cities. Also, cleaning constitutes a substantial share of the operating costs of automated taxis.[12]

Hence in general, Fig. 4 confirms that for automated-electric operations, hardware costs (depreciation, battery, maintenance) and operations cost (cleaning and fuel) play a much more relevant role than for conventional taxi services, the cost structures of which are dominated by salaries. In addition, there is substantially more variation between the cities, e.g. in the relative importance of hardware cost, cleaning, tolls and taxes. For example, the relative importance of hardware costs are particularly high in China, which should be a result of relatively low costs for services and fuel. In Copenhagen and Singapore, taxes and registration charges attached to any vehicle purchase are particularly high, which also results in a high share of hardware-related costs. For all cities, the cost

[9] System-level benefits may even be higher given that efficiency gains go beyond savings in production cost.

[10] For simplicity, individual taxis and pooled taxis are considered the same except for occupancies and trip distances.

[11] Cost structure decompositions for the other modes are available from the authors upon request.

[12] Increases in cleaning costs are based on two effects: Because there is no driver on board, he cannot perform these tasks during any incidental idle time anymore, but the vehicle has to drive to a service point regularly. In addition, in the spirit of the tragedy of the commons, passengers may take less care about keeping the car clean when they are not watched by a human driver. And since such cleaning services cannot necessarily be automated, they are cheaper in low-wage countries.

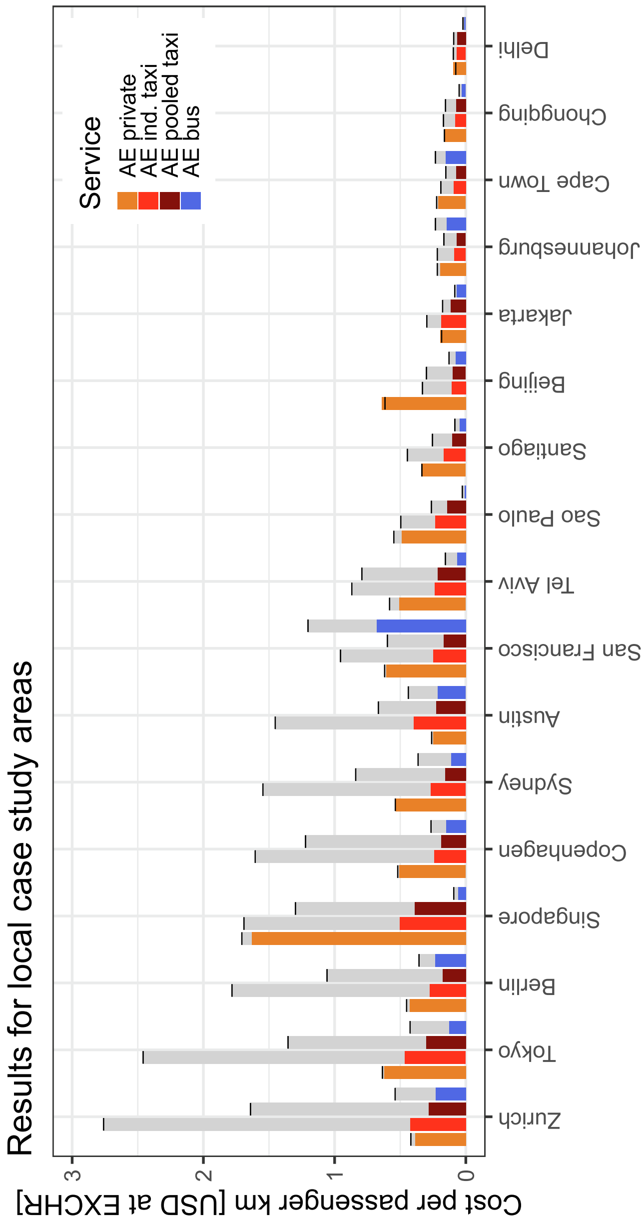

Fig. 3. Comparison of costs for autonomous-electric services (colors) and conventional services (light grey with black whiskers) for the local case study locations (converted to US-$ at 2016 exchange rates). Raw data is provided in Table B.11.

Table 2
Impact of electrification and automation on the cost levels (data provided in Table B.11).

Location	priv. car	ind. taxi	Pooled taxi	Urban bus
Austin	−4%	−73%	−66%	−52%
Beijing	4%	−67%	−67%	−40%
Berlin	−5%	−84%	−83%	−34%
Cape Town	−6%	−52%	−51%	−33%
Chongqing	−2%	−52%	−53%	−40%
Copenhagen	−3%	−85%	−85%	−43%
Delhi	27%	−29%	−30%	−51%
Jakarta	5%	−36%	−35%	−17%
Johannesburg	−10%	−60%	−59%	−37%
San Francisco	−2%	−74%	−72%	−44%
Santiago	1%	−63%	−60%	−45%
Sao Paulo	−11%	−53%	−46%	−65%
Singapore	−4%	−70%	−70%	−36%
Sydney	0%	−83%	−81%	−70%
Tel Aviv	−13%	−73%	−73%	−57%
Tokyo	−2%	−81%	−78%	−70%
Zurich	−8%	−85%	−83%	−57%

component for the battery (lease) is quite large, indicating a considerable potential for savings in operating costs, once cheaper battery options become available.[13]

Observations from the cost structure analysis help to interpret the different impacts, automation and electrification have on the taxi cost structures: In locations, where the salary is the main cost component of individual taxi services, the impact is strongest, whereas it is weakest for locations, where also hardware, fuel and tolls are important cost drivers. A similar (although weaker) relationship can also be observed for bus operations.

4.3. Drivers of costs

The results of the above analyses indicate substantial differences in the size of the impact of vehicle automation and electrification on production costs. Especially for taxi services, the differences can at least partly be explained by the role salaries play in the cost structure of conventional services. To generalize these insights, Fig. 5 shows a scatterplot of production costs of taxis and bus services vs. the median per-capita income for the given country.[14] Production costs are converted at purchasing power parity (compare Table A.10).

Despite substantial local variation, Fig. 5 provides three main insights:

- Relative to other goods and services current transportation costs are more expensive in high-income countries,
- This effect is stronger for taxi services than for bus services,
- In an automated-electric regime, the relation of transport costs to the cost of other goods and services is constant across countries.

The lines in Fig. 5 show the result of a simple linear regression of the production cost vs. income data.[15]

$$cost = \alpha + \beta \cdot inc + \epsilon$$

Relationships with other city characteristics (c.f. Table 1) were also studied, but no significant effect was found. This notion is further supported by the high R^2 of the simple models, indicating that they can already explain about 50% of the variation in the data for the conventional taxis (15% for buses). Detailed regression results are presented in Table 3.

The results also shed some light on the way vehicle automation may influence the future market position of the two modes. Although automation and electrification generally reduce production costs for mobility services, the effects are stronger for taxis than for buses and are stronger in high-income locations than in low-income locations. As a result, in lower income locations, operations costs for taxi services will remain higher than for buses, and this difference is still substantial, in particular considering the low income level. In contrast, in higher-income locations, the production costs of taxi and bus services will converge and - in particular given the high income levels, the remaining absolute difference may likely become irrelevant.[16]

While the general trend shown in this analysis is clear and can be expected robust, the analysis relies on 2013 income data. Hence, especially for emerging countries like China, the current income levels are likely higher than reflected in the data. Moreover, private cars will also play a role in the equation. However, they were not considered in this partial analysis, because values may be biased by current policies (from very soft regulations in Austin, TX to the massive tolls and registration charges in Singapore), which may be different in the future.

[13] If, however, battery prices do not decrease as expected in this research, the contribution of the battery to the total cost will be even higher.
[14] City-level data was not available from consistent sources.
[15] The regression results have to be treated carefully given the heteroscedasticity in the taxi data and can thus only be used as a rough orientation.
[16] Note that externalities (such as pollution or congestion) cannot not be captured here. They would likely tip the balance in favor of public transportation if they were incorporated.

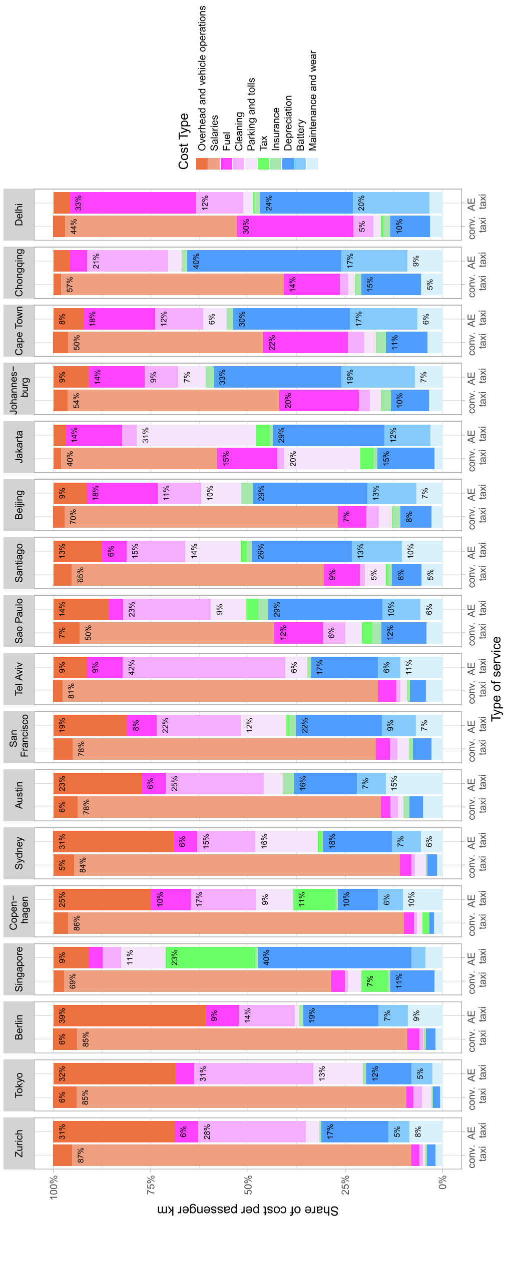

Fig. 4. Comparison of cost structures for (individual) taxi services (data provided in Table B.12).

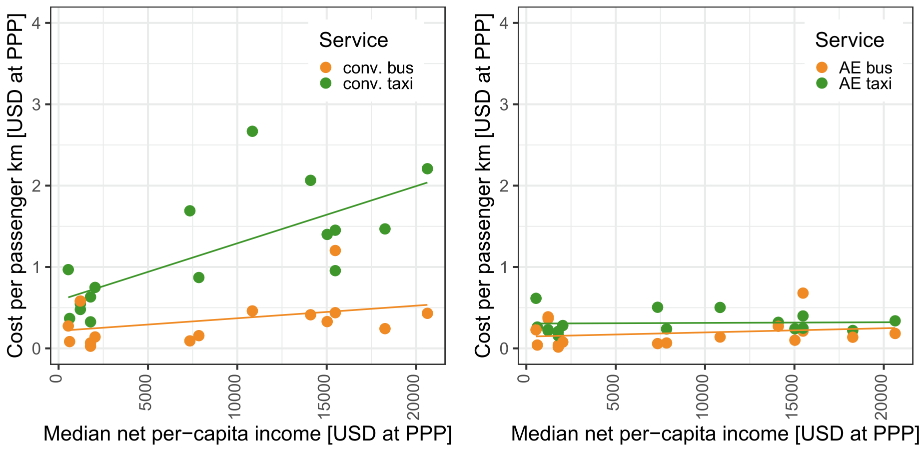

Fig. 5. Production cost of individual taxi and bus services vs. median net per-capita income.

Table 3
Regression results as plotted in Fig. 5.

	Conventional		Automated	
Parameter	Bus	Taxi	Bus	Taxi
α	0.21 *	0.59 **	0.14 *	0.30 ***
$\beta \cdot 10^{-6}$	15.48	70.26 ***	5.12	0.81
R^2	0.15	0.52	0.05	0.00

Significance codes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5. Discussion

Travel time, comfort and cost usually are the key determinants of short-term mode choice decisions (Wardman, 2004). Given that travel times depend on the capacity impacts of automated vehicles as well as their induced demand, they can hardly be predicted today. Moreover, comfort levels will depend both on service characteristics and future vehicle design, which are also still under development. Hence, estimating their cost structures can be assumed the next-best thing to predict the market position of generic future mobility services. In this research, such an estimation is done using a bottom-up approach. In this approach, cost components of current mobility services were sized and their relative changes in case of electric propulsion and vehicle automation were estimated. Along with projected operational characteristics and external economic factors this allows to estimate current and future production costs of different mobility services for a number of cities across the world.

Naturally, future operational characteristics (occupancy levels, speeds, trip lengths etc.) or policies (e.g. taxes, tolls, parking fees) are largely uncertain and were therefore assumed to remain the same as today. Hence, the results reflect the levels of production cost if vehicle automation and electrification were introduced into today's transport systems. Moreover, for the costs of batteries and automation technology only rough estimates are available today. Anyway, the framework is flexible and can always be updated as more accurate information becomes available (Bösch et al., 2018).

The results suggest that the impact of vehicle automation and electrification will be different for the various case study locations. In general, two clusters can be identified: In high-income countries, production costs for taxi services will approach the ones for buses to a degree that the relative cost differences between the modes become negligible. Hence, with their production costs plummeting, taxi services can be expected to become highly popular. And given the small differences, individual taxis will likely be the preferred mode. However, as shown earlier, urban road networks will not be able to accommodate a shift of all travel demand towards automated taxis (Meyer et al., 2017), at least not in cities with a substantial public transport mode share today. Therefore, policy interventions (e.g. subsidies, road pricing, limits on empty travel) will be required to steer the development towards a system optimum. Such measures will be important, also because there is almost no change in the costs for private cars, which may (with features of a personal mobility robot) become even more attractive than today.

For lower-income locations, changes in the transport system may not be that profound. Although costs for bus and taxi services will be reduced, the respective price gaps will not change substantially. And the relatively small absolute savings by automation may even be too small to outweigh the additional benefits of a human driver (in terms of service, safety and reaction to unforeseen circumstances). Besides taxis and formal buses, in many such locations informal transit by minibuses or jitneys has emerged (Cervero and Golub, 2007), offering mobility at even cheaper prices and towards locations under-served by formal public transportation. Although a detailed analysis of such systems was beyond the scope of this research, it can safely be assumed that the impact of automation and electrification would lie between those of taxis and formal buses, so that the fare spacing and thus the general structure of demand between the service types may not change dramatically.

Also within the two groups of higher-income and lower-income locations, certain differences can be observed. For example, in Beijing, all modes are substantially more expensive than in Chongqing. The reason for the differences may less be the size of the respective cities, but the general price level (and especially parking prices) as well as policy measures (tolls and taxes). Moreover, different performance levels in the transport systems can amplify differences in certain cost components. For Cape Town and Johannesburg, only small differences occur since their transport systems and price levels are very similar.

Given the substantial uncertainties in the future development and deployment of electric propulsion and automated driving, validating the results was only possible using empirical data of current services and other predictions of future production costs. For the former, results of this research have been validated against data from car owners' associations as well as taxi/ Uber fare estimates. For the latter, only few alternative approaches are available. As discussed above, in earlier research usually certain cost levels were assumed, but not derived. A rare exception is the approach presented by Chen et al. (2016), who use synthetic trip data for Austin, TX, to design an optimal automated taxi scheme to serve this demand. They estimate a cost of 0.42 US-$ per occupied trip mile (0.26 US-$ per km) for an automated-electric individual taxi. The estimate is substantially lower than the result of this research for Austin, TX (0.40 US-$ per km). However, the gap can be mostly explained by two key methodological differences: First, Chen et al. (2016) did not include (substantial) cleaning costs and second, they assume a 100% shift of travel demand towards automated individual taxis. In this research, however, trip characteristics of today's taxi and Uber trips were used, which may lead to a slight underestimation of the operational efficiency of such a large-scale automated taxi scheme (w.r.t. empty travel and idle times).

It has to be stressed that the results presented in this research rely on various assumptions and predictions which reflect the current state of knowledge. Hence, the analysis should be updated as more reliable information becomes available. Uncertainties do not only pertain to advances in technology and business models, but to a large degree also on future transport policies. While a thorough sensitivity analysis is unfeasible given the large number of dimensions, the disaggregated results in Table B.12 allow the reader to assess how relevant (changes in) certain cost components are. Additional disaggregated results are available from the corresponding author upon request.

The main aim of this research was to estimate actual production costs for different mobility services. It is important to note that the prices paid by travellers are usually biased by policy (in the case of public transport subsidies) or relate more to customers' willingness to pay (Uber's surge pricing). Yet, only using actual production costs, system-optimal states can be identified, thus allowing integrated planning. In this light, it may be worthwhile to study further, to what extent and in which situations e.g. dynamic automated ridesharing/ pooled taxi schemes may provide accessibility more efficiently than formal bus lines, hence calling for an extended definition of public transportation (Hensher, 2017; Cervero, 2017) and in consequence, a revised approach in public transport subsidies and pricing.

6. Conclusion

The analyses presented in this paper provide several contributions. It provides a comprehensive comparison of production costs for different generic mobility services, which - even for currently existing modes - has rarely been presented. In addition, estimates for future production costs in an era of automated-electric vehicles are produced. Obviously, the results only reflect current knowledge and will have to be updated once better data becomes available. Despite such uncertainties, the results have multiple implications. Not only do they allow first insights on the role the different mobility services may play in a future transport system, but they also inform subsequent studies with realistic cost assumptions, so that e.g. stated-preference experiments or simulation models can provide even more powerful outcomes.

In this research, median income was found to be the key factor to determine production costs for conventional modes. For automated services however, we could not observe an effect of the income level on production costs. We therefore conclude that transportation costs will become more similar across different countries and that the highest impact of automation is to be expected in high-income countries (also compare Tirachini and Antoniou (2020)). Other city characteristics used in this research did not show significant effects for both conventional and automated modes. Yet in light of earlier research indicating that spatial characteristics of a location do affect travel demand (Cervero and Kockelman, 1997) and the small sample used in this study, a more detailed analysis with respect to such impacts on production costs may be worthwhile. Given that most studies so far (including this one) have addressed the case of dense urban environments in and around major cities, such future research may also help to shed more light on the question, how vehicle automation and electrification may affect transport supply and demand in exurban or rural environments or smaller cities.

As a general result, the analyses suggest a decline in production costs across most modes. Hence, apart from modal shift, the effect of induced demand may be substantial. Moreover, cheaper taxi services may trigger profound changes in land-use patterns in higher-income cities, thus further increasing negative externalities of private transportation. But beyond that, newly emerging mobility will contest the role of line-based formal public transport as single provider of accessibility. Hence, automation and electrification may allow transit agencies to substantially lower fares. Alternatively, they may re-allocate subsidies to emerging modes and lower-density areas, where automated-electric taxis may allow to provide the required level of service more efficiently. In another scenario, political stakeholders may even demand an overall reduction in the level of subsidies. Further research will be needed to understand the impact of the possible responses on system performance.

7. Final thoughts

We are extremely grateful for the valuable time and feedback provided by three anonymous reviewers. Two of them expressed strong concerns about the accuracy of the predictions in this paper and we would like to acknowledge this problem here.

Reviewers' concerns

First, that the success of our exercise depends on the ability to achieve consistency in the measurements made in all the cities considered, and – unfortunately – not all cities around the world follow the exact same standards. All our indices are highly dependent on the utilization of the various modes and on best guesses by the analysts, as there is no formal process of calibration and internal consistency. Second, the costs caused by changes in propulsion type, and also vehicle automation, can be regarded as wild guesses, especially when it comes to electrification as we do not know what will be the costs if electromobility becomes a mass market reality.

Authors' reflections

With regard to these concerns we wish to comment that, in our case, the accuracy of the predictions is determined by three factors: the methodology, the data, and our assumptions:

- *Methodology*: we need to project the changes in individual cost components for the different modes. One of the aims of this study was to provide inputs for simulation models aimed at predicting counterfactual scenarios. For this reason, we implemented the cost calculator as a dynamic component to be used in simulation studies. This ensures that the prices reflect a given occupancy level rather than a given arbitrary baseline for every city. Regarding calibration, we want to emphasize that the costs of public transport reflect the information provided by the transport agencies. Finally, with regards to internal consistency, we want to note that we used strict guidelines and multiple rounds of internal reviews to arrive at the same assumptions.
- *Data*: we used the best information sources available for each city. However, given that the transport system is organized locally, standards of data collection and preparation are obviously not the same across the globe. This is why all input data were picked and reviewed by co-authors with a deep knowledge about the local situations. Moreover, several rounds of internal reviews were conducted to ensure comparability of input data across locations. In addition, following scientific best practice, we are making all sources and assumptions transparent in the supplementary material.
- *Assumptions*: the strongest hypothesis in this paper refers to the use of parameters for the different vehicle services. In fact, it is almost impossible to predict how the different transport services will be used in the future. Hence, we strongly suggest to combine the results of this research with simulation tools (which usually lack valid cost estimates) in a next step. Vehicle automation may fundamentally disrupt the whole transport system. Hence, any kind of predictions – be it in vehicle-miles-travelled, future fleet sizes, or (as in this case) production costs - can only be made with uncertainty. In this sense, the goal of this paper is not to provide perfectly accurate forecasts of future production costs. It is, rather, a first attempt to do so, which would also capture differences across various locations across the globe.

While the paper does operate in uncertain territory by attempting to project consequences of autonomous technology at a global scale, the finding that transportation costs will become more similar across different countries and that the highest impact of automation is to be expected in high-income countries, cannot easily be rejected however, as it is persistent across a range of scenarios. This insight is valuable to understand the global perspective of autonomy although precise impacts cannot be measured.

To end, we sincerely hope that this paper will only be the beginning of a longer scientific discussion, and invite other researchers to validate or question our results with their approaches. Hence, the two reviewers' concerns highlight a fundamental challenge of long-term planning: uncertainty.

Author contributions

R. Abe contributed the analysis for the Tokyo case; S. Bekhor and Y. Shiftan for Tel Aviv; P.F. Belgiawan and R.A. Nasution for Jakarta, Indonesia; J. Compostella and L.M. Fulton for San Francisco, CA; K. Marczuk and E. Frazzoli for Singapore; D. Guggisberg Bicudo for Sao Paulo, Brazil; Y.Z. Wong and D.A. Hensher for Sydney; K.M. Gurumurthy and K.M. Kockelman for Austin, TX; J.W. Joubert for Cape Town and Johannesburg, South Africa; D. Shen and S. Le Vine for Chongqing, China; L. Kröger for Berlin, Germany; J. Malik and L.M. Fulton for Delhi, India; M. Zhang and F. Becker for Beijing, China; J. Rich and A. Papu Carrone for Copenhagen, Denmark; A. Tirachini for Santiago de Chile; H. Becker, F. Becker and K.W. Axhausen for Zurich, Switzerland based on Bösch et al. (2018). H. Becker and F. Becker provided technical assistance with the tool (Bösch et al., 2018), compiled the results from the individual case studies, and conducted the analyses. H. Becker coordinated the collaboration and prepared the manuscript. All authors contributed to the analysis and interpretation of the joint results and reviewed the final manuscript.

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Appendix A. Assumptions

In the following, the input data used for the algorithm (Bösch et al., 2018) is presented for the different case study areas. To

Table A.4
Fixed and variable vehicle costs in US-$ at EXCHR.

	Acquisition	Registration tax	Insurance [per year]	Annual tax [per year]	Parking [per year]	Other [per year]	Battery [per km]	Maintenance [per km]	Tires [per km]	Fuel [per km]	Other [per km]
Austin	20,914	63	2,662	15	1,926	0	0.041	0.055	0.039	0.040	0.000
Beijing	22,575	0	632	63	903	0	0.041	0.018	0.009	0.057	0.000
Berlin	27,654	29	885	88	299	0	0.041	0.038	0.022	0.082	0.000
Cape Town	14,460	0	1,074	41	775	231	0.041	0.011	0.007	0.084	0.000
Chongqing	22,575	19	632	45	722	0	0.041	0.018	0.009	0.057	0.000
Copenhagen	14,484	12,255	783	98	4,457	0	0.041	0.077	0.013	0.089	0.000
Delhi	7,330	0	298	95	244	0	0.041	0.007	0.002	0.068	0.000
Jakarta	19,724	2,404	410	394	793	11	0.041	0.002	0.008	0.066	0.069
Johannesburg	14,460	0	1,074	41	775	231	0.041	0.011	0.007	0.086	0.000
San Francisco	25,000	0	1,645	387	4,200	1,200	0.041	0.050	0.000	0.052	0.000
Santiago	19,334	69	709	300	532	0	0.041	0.035	0.009	0.061	0.023
São Paulo	25,856	139	1,189	1,078	1,124	611	0.041	0.036	0.000	0.086	0.000
Singapore	134,405	49,720	1,612	1,629	6,400	1,143	0.041	0.072	0.004	0.106	0.000
Sydney	25,275	297	558	297	2,974	3,085	0.041	0.036	0.007	0.074	0.000
Tel Aviv	32,547	0	1,302	417	65	260	0.041	0.096	0.013	0.096	0.026
Tokyo	22,629	0	662	363	3,265	69	0.041	0.016	0.009	0.057	0.000
Zurich	35,519	0	1,015	254	1,522	41	0.041	0.065	0.020	0.081	0.000

reduce complexity, analyses have been conducted for regular, 4-seater midsize cars only.[17] The authors have taken great care to find reliable numbers in a web-based search or to make reasonable assumptions where necessary. Due to the large number of different sources and the fact that many of them are not available in English, references for the individual assumptions are not provided in the paper, but are available from the supplementary material of this paper and from the authors upon request.

Table A.4 presents the fixed and variable cost components for the respective midsize vehicles. Values are given as gross prices for private customers and for conventional vehicles (no automation, no electric propulsion). Acquisition cost is deprecated by vehicle lifetime. Since local data was not always available, the same values were assumed for all locations:[18] For private vehicles, it is assumed that the value of an average-aged car drops by 6.7% each year, independent of the mileage.[19] Economic lifetime for commercially used vehicles was assumed 300 000 km.[20]

For each cost component, the effect of electrification (transition to battery-electric vehicles) and vehicle automation (change towards driverless technology) is determined separately. Moreover, discounts (or price increases) for commercial fleet services are provided, which mostly represent economies of scale for larger fleets.[21] It is assumed that the three factors are linearly independent. To ensure comparability between cities, some assumptions were aligned:

- Impact of automation on acquisition cost: It is assumed that eventually, sensors and computers required for vehicle automation will come at 5’000 US-$ per vehicle[22] (converted to local currency via exchange rate).
- Impact of automation on tax levels: A wide range of new taxes and congestion charges will likely be required to manage future travel demand (also compare Meyer et al. (2017)). However, their actual form can hardly be predicted. Hence, a zero-effect was assumed for all case study locations, acknowledging that this should be adjusted as soon as more reliable information becomes available.
- Impact of automation on insurance: While there is the general expectation of a disruption of the vehicle insurance industry, it is not clear, how it will affect premiums. Yet, given that automated vehicles are expected to drive more safely than humans, a 50% reduction is assumed.
- Impact of automation on parking: It is well conceivable that self-driving vehicles will avoid parking costs by driving out of town for parking. Yet, it can be expected that cities will design policies to prevent this behavior. Given such uncertainties, no change was assumed.
- Impact of automation on fuel consumption and tires: Lacking any more detailed data, it is assumed that due to smoother driving, automated vehicles will reduce fuel consumption and by 10% for all case studies (Stephens et al., 2016); the same effect was assumed for tires.
- Impact of automation on maintenance cost: Despite some promises of a more efficient and conservative driving behaviour, there have not been any reports yet that automation leads to a reduction in maintenance cost. If anything, it could even be assumed that

[17] In Bösch et al. (2018) different vehicle types were analyzed.
[18] In reality, vehicle lifetime may be affected by different road conditions, driving behaviour and maintenance standards.
[19] This corresponds to an economic lifetime of 15 years, assuming linear depreciation (also compare Bento et al. (2018)).
[20] BMW press statement according to http://www.spiegel.de/auto/aktuell/bmw-setzt-maximal-laufleistung-von-150-000-km-voraus-a-855355.html (accessed on December 4th, 2018).
[21] Actually, the modifier would depend on the fleet size. For simplicity, in this research fleet sizes comparable with today’s car rental agencies are assumed. Results of larger public transport operators further indicate that economies of scale almost exclusively arise through a better bargaining power towards suppliers (White, 2017), so that there is a natural limit given by the supplier’s production cost.
[22] https://www.reuters.com/article/us-autos-delphi/self-driving-costs-could-drop-90-percent-by-2025-delphi-ceo-says-idUSKBN1DY2AC (accessed on May 4th, 2018)

Table A.5
Relative impact on cost components [%].

	Automated	Electric	Fleet
Acquisition	+5000 US-$	–	−30%
Insurance	−50%	see Table A.6	−20%
Tax	–	see Table A.6	see Table A.6
Parking	–	see Table A.6	–
Maintenance	–	−35%	−25%
Tires	−10%	+20%	−25%
Fuel	−10%	see Table A.6	−5%

Table A.6
Relative impact on cost components [%] – location-specific modifyers.

	Electric ⟶ Insurance	Electric ⟶ Tax	Electric ⟶ Parking	Electric ⟶ Fuel	Fleet ⟶ Tax
Austin				−25	
Beijing		−100		−10	
Berlin	−20	−100		−50	
Cape Town	−35	−100		−55	
Chongqing		−100	−10	−83	
Copenhagen	−13			−37	
Delhi		−60		−14	
Jakarta		−100		−34	
Johannesburg	−35	−100		−69	
San Francisco	20	−5		−40	
Santiago				−72	
São Paulo		−47		−85	
Singapore	−35			−65	
Sydney	−25			−60	
Tel Aviv		−100		−40	
Tokyo	−3	−100		−44	−76
Zurich	−35	−100		−50	

Table A.7
Public transport parameters.

	Urban bus capacity	Urban bus full cost [US-$/km]	Urban bus effect of electrification	Urban bus effect of automation
Austin	60	5.90	−12%	−45%
Beijing	60	0.07	−16%	−29%
Berlin	94	5.53	−6%	−30%
Cape Town	60	3.12	−20%	−17%
Chongqing	60	1.01	−15%	−35%
Copenhagen	70	6.18	−6%	−40%
Delhi	60	0.51	−30%	−30%
Jakarta	100	1.90	−5%	−13%
Johannesburg	60	3.12	−24%	−17%
San Francisco	50	11.09	−6%	−40%
Santiago	90	1.54	−14%	−36%
São Paulo	99	1.75	−19%	−57%
Singapore	100	3.25	−6%	−32%
Sydney	60	4.89	−5%	−68%
Tel Aviv	70	3.91	−6%	−55%
Tokyo	72	7.61	−6%	−68%
Zurich	60	7.25	−6%	−55%

the sensors and computers require more frequent or more expensive maintenance efforts. Acknowledging a lack of information, at this point a zero-effect was assumed across all case study locations.

- Impact of fleet operation on acquisition cost, insurance, maintenance, tires and fuel: Again, disaggregate information was not available. Therefore a reduction of 30% in acquisition cost, 20% in insurance, 25% in maintenance and tire cost and 5% in fuel is assumed for all case studies (Bösch et al., 2018).
- Impact of fleet operation on parking: values could only be obtained for a subset of cities and varied greatly. Hence, for consistency across the different cases it was assumed that there is no difference in parking cost between private and commercial vehicles.
- Impact of electrification on acquisition cost: Currently, electric vehicles are usually more expensive than their combustion-engine counterparts. However, the price-difference is mostly driven by the battery cost. Following Bösch et al. (2018), a zero-impact on

Table A.8
External parameters.

	Cleaning price per instance [US-$]	Hourly wage of drivers [US-$]	Annual interest rate (private)	Annual interest rate (commercial)	General sales tax/ VAT
Austin	15.00	15.00	4.5%	5.0%	8%
Beijing	4.52	2.54	5.2%	5.2%	17%
Berlin	10.95	21.57	5.9%	1.9%	19%
Cape Town	8.16	2.37	10.0%	8.0%	15%
Chongqing	4.52	3.01	5.2%	5.2%	17%
Copenhagen	11.88	37.29	4.8%	2.0%	25%
Delhi	3.72	0.79	9.0%	13.5%	12%
Jakarta	3.01	1.74	5.7%	11.9%	10%
Johannesburg	5.44	2.63	10.0%	8.0%	15%
San Francisco	19.00	19.00	4.0%	5.0%	8%
Santiago	4.26	4.92	18.0%	3.4%	19%
São Paulo	12.89	2.80	19.9%	13.0%	21%
Singapore	9.52	20.69	2.8%	1.7%	7%
Sydney	11.15	25.27	8.4%	1.5%	10%
Tel Aviv	13.02	23.43	5.0%	2.0%	17%
Tokyo	17.92	16.97	2.6%	1.5%	8%
Zurich	15.22	35.52	8.0%	1.5%	8%

acquisition cost is assumed, while battery costs are presented separately (compare Table A.4).

- Impact of electrification on maintenance cost: According to earlier research, vehicle electrification is expected to reduce maintenance cost by 35% (Diez, 2016). Since no country-specific values were found, this modifier was used for all case studies. However, a key cost driver of electric vehicles will be the battery with approximately 0.04 US-$/km (Bösch et al., 2018). Assuming a global market for supply of batteries, the same cost value was used for all case study areas.
- Impact of electrification on tire cost: An increase of 20% is assumed given that electric vehicles tend to be heavier than their conventional counterparts.[23]

All modifiers are provided as relative changes. Aligned modifyers are presented in Table A.5. Location-specific modifiers are shown in Table A.6.

Since for public transport (Table A.7), cost values were only available on an aggregate level for most case study locations, analyses were performed using the full operating costs only. In addition, the relative impact of automation and electrification was determined. The full operating costs are meant to include all expenses of operators of public transport services and include capital costs, management, salaries, vehicle maintenance and depreciation, fuel etc. Not included in the full operational cost are construction costs (e.g. for dedicated infrastructure), but only infrastructure usage fees if paid by the respective operator. It is important to note that the production costs presented in the table usually do not correspond to the (politically or commercially defined) prices paid by travelers.[24]

Table A.8 presents the external parameters (step 3), which capture aspects of travel behavior and economic indicators relevant for the operating costs of any business model. To reduce complexity, certain parameters were fixed for all locations. These include the cleaning frequency (8 times per year for private cars, every second day for conventional taxis, every fourtieth ride for automated taxis), credit periods (5 years for private and 3 years for commercial borrowers), payment handling fees (0.5%). For overhead and vehicle management cost, the value of 24 CHF per vehicle per day was used from the Swiss analysis (Bösch et al., 2018) and scaled by hourly compensation cost for manufacturing (c.f. Table A.10).[25]

Table A.9 presents the assumptions for the behavioral parameters relevant in step 4 of the algorithm (c.f. Section 3). Parameters were obtained from household travel surveys, current taxi data or assignment models. Hence, they describe large-scale and mature mobility services. It is assumed that these operational characteristics do not change through automation or electrification.

Since detailed data was not available for all cities, differences were expressed in terms of occupancy, speed and passenger trip distance only. To reflect the generally lower data availability, only daily averages were used.[26] On the same note, for pooled taxis, the same speed and operations hours were assumed as for individual taxis. Moreover, passenger trip length was assumed 15% longer due to potential detours (Alonso-Mora et al., 2017) and vehicle occupancy was fixed to 60% of the vehicle capacity. For both individual and pooled taxis it was further assumed that they carry passengers only during 46% of their operating hours (54% idle time) across all case study locations (compare Bösch et al. (2018)).

[23] http://www.modelcenter.transport.dtu.dk/Noegletal/Transportoekonomiske-Enhedspriser

[24] In Beijing and Chongqing, operating costs were not available on the vehicle level. Instead, the presented values already are the full operating costs per passenger km.

[25] The assumed value for overhead and vehicle management cost is the same for conventional and automated fleets. It can be expected that automated vehicles may demand more remote management (or even backup drivers) than human driven vehicles, but in turn management of drivers is not required anymore. Lacking any more detailed information, it is assumed that these effects will cancel out.

[26] The original approach allowed a further temporal disaggregation (Bösch et al., 2018).

Table A.9
Key indicators of vehicle operations.

	Operating hours [h] private car	Average occupancy [%] private car	Average speed [km/h] private car	Average passenger trip length [km] private car	Relative active time [%] individual taxi	Average occupancy [%] individual taxi	Average speed [km/h] individual taxi	Average passenger trip length [km] individual taxi	Relative active time [%] pooled taxi	Average occupancy [%] pooled taxi	Average speed [km/h] pooled taxi	Average passenger trip length [km] pooled taxi	Operation hours per day urban bus	Duty time [% of operation hours] urban bus	Average occupancy [%] urban bus	Average speed [km/h] urban bus
Austin	1.8	41.8	37.0	11.5	46.1	27.5	26.1	3.7	46.1	59.9	26.1	4.3	19.0	85.0	22.4	18.4
Beijing	0.8	35.6	15.9	13.9	46.1	54.4	10.9	9.2	46.1	59.9	10.9	10.6	19.0	85.0	22.4	21.3
Berlin	0.9	32.3	27.6	11.1	46.1	35.5	21.7	6.8	46.1	59.9	21.7	7.9	20.0	85.0	16.5	19.4
Cape Town	1.8	35.0	29.9	24.6	46.1	48.0	27.9	18.0	46.1	59.9	27.9	20.7	19.0	85.0	22.4	21.3
Chongqing	1.3	54.6	29.2	25.2	46.1	54.4	30.7	6.7	46.1	59.9	30.7	7.7	16.0	85.0	66.7	15.2
Copenhagen	1.2	34.3	35.1	7.9	46.1	45.6	32.0	7.3	46.1	59.9	32.0	8.4	19.0	85.0	33.3	22.4
Delhi	1.6	58.0	26.0	7.6	46.1	58.0	17.5	11.3	46.1	59.9	17.5	12.9	19.0	85.0	41.3	21.3
Jakarta	3.6	40.7	22.2	20.5	46.1	35.6	22.2	10.4	46.1	59.9	22.2	12.0	19.0	85.0	22.4	21.3
Johannesburg	2.0	35.0	28.0	19.6	46.1	46.0	26.1	18.0	46.1	59.9	26.1	20.7	19.0	85.0	22.4	21.3
San Francisco	1.1	38.1	29.0	16.7	46.1	37.5	36.9	8.9	46.1	59.9	36.9	10.2	19.0	85.0	18.4	13.0
Santiago	1.4	29.2	31.0	8.3	46.1	34.2	27.0	4.2	46.1	59.9	27.0	4.8	22.8	85.0	23.5	24.2
São Paulo	1.5	31.7	24.5	9.7	46.1	31.7	19.2	6.1	46.1	59.9	19.2	7.0	19.0	85.0	65.0	20.5
Singapore	1.1	33.8	31.3	12.2	46.1	46.0	20.9	10.0	46.1	59.9	20.9	11.5	24.0	85.0	35.2	18.6
Sydney	1.1	32.0	33.0	9.6	46.1	32.5	26.0	7.0	46.1	59.9	26.0	8.0	19.0	85.0	22.4	14.0
Tel Aviv	1.1	29.7	30.0	15.2	46.1	54.6	33.0	3.3	46.1	59.9	33.0	3.8	16.5	85.0	35.7	19.3
Tokyo	1.3	27.6	21.9	15.3	46.1	33.0	13.4	3.2	46.1	59.9	13.4	3.6	19.0	85.0	26.2	11.0
Zurich	1.3	35.6	34.1	12.1	46.1	35.6	22.4	3.2	46.1	59.9	22.4	3.7	19.0	85.0	22.4	21.3

Table A.10
Exchange rates, purchasing power parities (PPP) and hourly compensation costs for manufacturing [US-$] for case study locations. Exchange rates and PPP displayed in national currency units per US-$ for 2016 (OECD, 2018).

Country	Local currency	Exhange rate	PPP	Hourly comp. cost
Australia	AUD	1.345	1.486	47.7
Austria	EUR	0.904	0.800	41.5
Brazil	BRL	3.491	1.995	11.2
Chile	CLP	676.958	402.571	10.6
China	CNY	6.644	3.474	3.1
Denmark	DKK	6.732	7.356	48.5
Germany	EUR	0.904	0.780	45.8
India	INR	67.195	17.447	1.6
Indonesia	IDR	13,308.327	4,091.834	2.6
Israel	NIS	3.841	3.833	20.1
Japan	JPY	108.793	100.279	35.3
Singapore	SGD	0.840	0.840	24.2
South Africa	ZAR	14.710	5.865	5.3
Switzerland	CHF	0.985	1.232	57.8
United States	USD	1.000	1.000	35.7

Data for Singapore was not available from OECD OECD (2018).
Therefore, the IMF's World Economic Outlook Database,
October 2016, was used in this case.

Appendix B. Detailed results

See Tables B.11 and B.12.

Table B.11
Production cost per passenger kilometer (in US-$ at EXCHR).

Location	Technology	Priv. car	Ind. taxi	Pooled taxi	Urban bus
Austin	conv.	0.26	1.45	0.67	0.44
	auton.	0.24	0.39	0.22	0.24
	auton. elect.	0.25	0.40	0.22	0.21
Beijing	conv.	0.62	0.33	0.30	0.13
	auton.	0.63	0.10	0.09	0.09
	auton. elect.	0.64	0.11	0.10	0.08
Berlin	conv.	0.45	1.78	1.06	0.36
	auton.	0.45	0.29	0.18	0.25
	auton. elect.	0.43	0.28	0.18	0.23
Cape Town	conv.	0.22	0.19	0.15	0.23
	auton.	0.22	0.10	0.08	0.19
	auton. elect.	0.21	0.09	0.07	0.15
Chongqing	conv.	0.16	0.17	0.15	0.05
	auton.	0.17	0.09	0.08	0.04
	auton. elect.	0.16	0.08	0.07	0.03
Copenhagen	conv.	0.52	1.60	1.22	0.27
	auton.	0.52	0.25	0.19	0.16
	auton. elect.	0.51	0.24	0.19	0.15
Delhi	conv.	0.08	0.10	0.09	0.02
	auton.	0.09	0.06	0.06	0.02
	auton. elect.	0.10	0.07	0.07	0.01
Jakarta	conv.	0.18	0.30	0.18	0.08
	auton.	0.19	0.18	0.11	0.07
	auton. elect.	0.19	0.19	0.11	0.07
Johannesburg	conv.	0.22	0.22	0.17	0.23
	auton.	0.21	0.10	0.08	0.19
	auton. elect.	0.20	0.09	0.07	0.15
San Francisco	conv.	0.62	0.96	0.60	1.20
	auton.	0.60	0.25	0.17	0.72
	auton. elect.	0.61	0.25	0.17	0.68
Santiago	conv.	0.33	0.45	0.25	0.08
	auton.	0.35	0.18	0.11	0.05
	auton. elect.	0.34	0.17	0.10	0.05
Sao Paulo	conv.	0.55	0.50	0.26	0.03
	auton.	0.55	0.27	0.16	0.01
	auton. elect.	0.49	0.23	0.14	0.01
Singapore	conv.	1.71	1.69	1.30	0.09
	auton.	1.68	0.53	0.41	0.06
	auton. elect.	1.63	0.51	0.39	0.06
Sydney	conv.	0.54	1.55	0.84	0.36
	auton.	0.55	0.28	0.16	0.12
	auton. elect.	0.54	0.27	0.16	0.11
Tel Aviv	conv.	0.58	0.87	0.79	0.16
	auton.	0.56	0.25	0.23	0.07
	auton. elect.	0.51	0.24	0.21	0.07
Tokyo	conv.	0.64	2.46	1.35	0.42
	auton.	0.64	0.46	0.30	0.14
	auton. elect.	0.62	0.46	0.30	0.13
Zurich	conv.	0.42	2.76	1.64	0.54
	auton.	0.42	0.44	0.29	0.24
	auton. elect.	0.39	0.42	0.28	0.23

Table B.12
Comparison of cost structures for taxi services (cost per 100 km in US-$ at EXCHR).

Service	variable	Zurich	Tokyo	Berlin	Singapore	Copen-hagen	Sydney	Austin	San Francisco	Tel Aviv	Sao Paulo	Santiago	Beijing	Jakarta	Johannesburg	Cape Town	Chongqing	Delhi
AE taxi	Overhead and vehicle operations	13.2	14.6	10.8	4.6	6.1	8.2	9.1	4.7	2.0	3.3	2.1	0.9	0.6	0.8	0.7	0.3	0.3
	Salaries	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Fuel	2.6	2.2	2.4	1.9	2.4	1.6	2.5	1.9	2.2	0.8	1.0	2.0	2.7	1.3	1.7	0.4	2.2
	Cleaning	11.7	14.2	4.0	2.4	4.1	4.0	10.0	5.4	10.0	5.3	2.5	1.2	0.7	0.8	1.1	1.7	0.8
	Parking and tolls	1.5	5.9	0.3	5.8	2.3	4.3	2.0	2.9	1.4	2.1	2.4	1.1	5.8	0.6	0.6	0.3	0.2
	Tax	0.0	0.0	0.0	11.6	2.6	0.3	0.0	0.2	0.0	0.7	0.3	0.0	0.6	0.0	0.0	0.0	0.0
	Insurance	0.2	0.4	0.3	0.3	0.1	0.1	1.1	0.4	0.2	0.6	0.2	0.3	0.2	0.2	0.2	0.1	0.1
	Depreciation	7.3	5.4	5.4	20.0	2.5	4.7	6.4	5.5	4.1	6.9	4.3	3.2	5.4	2.9	2.8	3.2	1.6
	Battery	2.3	2.5	2.1	1.8	1.5	2.0	2.9	2.2	1.4	2.3	2.1	1.4	2.2	1.7	1.6	1.4	1.3
	Maintenance and wear	3.6	1.2	2.5	2.2	2.4	1.5	5.8	1.7	2.6	1.3	1.7	0.7	0.6	0.6	0.6	0.7	0.2
Conv. taxi	Overhead and vehicle operations	13.2	14.6	10.8	4.6	6.1	8.2	9.1	4.7	2.0	3.3	2.1	0.9	0.6	0.8	0.7	0.3	0.3
	Salaries	240.9	208.6	151.5	116.3	138.5	129.6	113.2	74.5	70.4	24.9	28.9	23.2	11.9	11.9	9.6	9.8	4.2
	Fuel	5.8	4.3	5.3	5.9	4.3	4.5	3.7	3.5	4.1	6.1	4.1	2.5	4.6	4.5	4.1	2.5	2.8
	Cleaning	2.6	5.5	1.9	1.3	1.1	1.4	2.8	1.9	1.0	2.9	0.6	1.0	0.5	0.6	0.8	0.4	0.5
	Parking and tolls	1.5	5.9	0.3	5.8	2.3	4.3	2.0	2.9	1.5	2.1	2.4	1.1	5.8	0.6	0.6	0.3	0.2
	Tax	0.2	0.1	0.1	11.6	2.6	0.3	0.0	0.2	0.2	1.4	0.3	0.1	1.0	0.0	0.0	0.0	0.1
	Insurance	0.8	0.9	0.7	1.0	0.3	0.3	2.2	0.7	0.4	1.2	0.5	0.6	0.3	0.5	0.5	0.2	0.2
	Depreciation	6.4	4.4	4.6	19.3	1.9	3.9	5.2	4.5	3.6	5.7	3.4	2.6	4.4	2.1	2.0	2.6	1.0
	Battery	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Maintenance and wear	4.8	1.5	3.0	3.3	3.4	2.1	7.1	2.6	3.7	2.0	2.4	0.9	0.6	0.7	0.7	0.9	0.3

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.tra.2020.04.021.

References

Alonso-Mora, J., Samaranayake, S., Wallar, A., Frazzoli, E., Rus, D., 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. Proc. Natl. Acad. Sci. 114, 462–467.

Bansal, P., Kockelman, K., 2017. Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. Transp. Res. Part A 95, 49–63.

Bento, A.M., Roth, K.D., Zuo, Y., 2018. Vehicle lifetime trends and scrappage behavior in the U.S. used car market. Energy J. 39.

van den Berg, V.A.C., Verhoef, E.T., 2016. Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity. Transp. Res. Part B 94, 43–60.

Bösch, P., Becker, F., Becker, H., Axhausen, K.W., 2018. Cost-based analysis of autonomous mobility services. Transp. Policy 64, 76–91.

Bösch, P., Ciari, F., Axhausen, K.W., 2016. Autonomous vehicle fleet sizes required to serve different levels of demand. Transp. Res. Rec. 2542, 111–119.

Burns, L.D., 2013. Sustainable mobility: A vision of our transport future. Nature 497, 181–182.

Burns, L.D., Jordan, W., Scarborough, B., 2013. Transforming personal mobility. Technical Report The Earth. Institute Columbia University.

Cervero, R., 2017. Mobility Niches: Jitneys to Robo-Taxis. J. Am. Plann. Assoc. 83, 404–412.

Cervero, R., Golub, A., 2007. Informal transport: A global perspective. Transp. Policy 14, 445–457.

Cervero, R., Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. Transp. Res. Part D 2, 199–219.

Chen, T.D., Kockelman, K.M., 2016. Management of a shared autonomous electric vehicle fleet: implications of pricing schemes. Transp. Res. Rec. 2572, 37–46.

Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. Transp. Res. Part A 94, 243–254.

Dandl, F., Bogenberger, K., 2018. Comparing future autonomous electric taxis with an existing free-floating carsharing system. IEEE Trans. Intell. Transp. Syst. 1–11.

Daziano, R., Sarrias, M., Leard, B., 2017. Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. Transp. Res. Part C 78, 150–164.

Diez, W., 2016. Elektroautos mit deutlich niedrigeren Unterhaltskosten. Webpage (last accessed 08.11.2016). http://www.ifa-info.de/downloads/3241%2FPresseinformation%2520Elektromobilit%25C3%25A4t%252020.11.12.pdf.

Fagnant, D.J., Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation 45, 143–158.

Friedrich, M., Hartl, M., 2016. MEGAFON – Modellergebnisse geteilter autonomer Fahrzeugflotten des öffentlichen Nahverkehrs. Research report Universität Stuttgart, Institut für Strassen- und Verkehrswesen Stuttgart.

Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transp. Res. Part C 78, 37–49.

Hensher, D., 2018. Tackling road congestion – what might it look like in the future under a collaborative and connected mobility model? Transp. Policy 66, A1–A8.

Hensher, D.A., 2017. Future bus transport contracts under a mobility as a service (MaaS) regime in the digital age: Are they likely to change? Transp. Res. Part A 98, 86–96.

Hörl, S., Ruch, C., Becker, F., Frazzoli, E., Axhausen, K.W., 2019a. Fleet operational policies for automated mobility: A simulation assessment for Zurich. Transp. Res. Part C 102, 20–31.

Hörl, S., Becker, F., Dubernet, T., Axhausen, K.W., 2019. Induzierter Verkehr durch autonome Fahrzeuge: Eine Abschätzung. Technical Report. Research project SVI 2016/001 upon request of the Swiss Association of Transport Engineers and Experts (SVI).

International Transport Forum, 2015. Urban mobility system upgrade: How shared self-driving cars could change city traffic. Technical Report OECD.

Johnson, C., Walker, J., 2016. Peak Car Ownership. Research Report Rocky Mountain Institute.

Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transp. Res. Part C 69, 343–355.

Le Vine, S., Zolfaghari, A., Polak, J., 2015. Autonomous cars: The tension between occupant experience and intersection capacity. Transp. Res. Part C 52, 1–14.

Lim, L., Tawfik, A., 2019. Estimating the Future Travel Costs Using Shared Autonomous Vehicle (SAV) Systems. In: International Conference on Transportation and Development 2018 Proceedings, pp. 119–131. Philadelphia. doi:10.1061/9780784481530.012.

Liu, J., Kockelman, K., Bösch, P., 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. Transp. Res. Part A: Policy Pract. 121, 374–385. https://doi.org/10.1016/j.tra.2019.01.025.. http://www.sciencedirect.com/science/article/pii/S096585641730112X.

Meyer, J., Becker, H., Bösch, P., Axhausen, K.W., 2017. Autonomous vehicles: The next jump in accessibilities? Res. Transp. Econ. 62, 80–91.

Mulley, C., 2017. Mobility as a Servicees (MaaS) – does it have critical mass? Transp. Rev. 37, 247–251.

Mulley, C., Nelson, J.D., 2009. Flexible transport services: A new market opportunity for public transport. Res. Transp. Econ. 25, 39–45.

OECD, 2018. Purchasing power parities (PPP). (accessed 12.02.2018). doi:10.1787/1290ee5a-en.

Simoni, M., Kockelman, K., Gurumurthy, K.M., Bischoff, J., 2019. Congestion pricing in a world of self-driving vehicles: an analysis of different strategies in alternative future scenarios. Transp. Res. Part C 98, 167–185.

Stephens, T., Gonder, J., Chen, Y., Lin, Z., Liu, C., Gohlke, D., 2016. Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles. Technical Report National Renewable Energy Laboratory, U.S. Department of Energy Golden, CO.

Tirachini, A., Antoniou, C., 2020. The economics of automated public transport: Effects on operator cost, travel time, fare and subsidy. Econ. Transp. 21, 100151.

Truong, L.T., De Gruyter, C., Currie, G., Delbosc, A., 2017. Estimating the trip generation impacts of autonomous vehicles on car travel in Victoria, Australia. Transportation 44, 1279–1292.

Wadud, Z., 2017. Fully automated vehicles: A cost of ownership analysis to inform early adoption. Transp. Res. Part A: Policy Pract. 101, 163–176. https://doi.org/10.1016/j.tra.2017.05.005.

Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transp. Res. Part A 86, 1–18.

Wardman, M., 2004. Public transport values of time. Transp. Policy 11, 363–377.

White, P., 2017. Bus economics. In: Cowie, J., Ison, S. (Eds.), The Routledge Handbook of Transport Economics. Routledge, London, pp. 31–47.