Spatial effects of automated driving: dispersion, concentration or both?[1]

George Gelauff*, Ioulia Ossokina**, Coen Teulings***

*KIM Netherlands Institute for Transport Policy Analysis

**Eindhoven University of Technology

***University of Cambridge and University of Amsterdam

18 September 2017

Abstract

This paper studies possible effects of automated driving technology on the concentration and dispersion of the population and on residential land prices in the Netherlands. We perform simulations with the Dutch spatial general equilibrium model LUCA. The simulations account for two possible effects of automation: (i) self-driving cars allow drivers to use their time in the car more productively; (ii) self-driving transport offers faster and more comfortable door-to-door transfers than traditional busses, trams and metro. We find that more productive time use during car trips results in population flight from cities. Residential prices converge: they fall in cities and rise in non-urban areas. The efficiency gain in public transport has an opposite effect. It leads to further population clustering in urban areas and an increase in residential price disparity between cities and rural areas. A combination of these two components may result in concentration of the population in the largest most attractive cities and their suburbs at the cost of smaller cities and non-urban regions. These results are in particular relevant for countries where public transport has a considerable share in urban mobility. Neglecting the impact of vehicle automation on public transport may result in biased policy recommendations.

Key words: Vehicle automation; Self-driving cars; Residential land market; General equilibrium.

JEL classification: H4, H54, R13, R23, R4

** Corresponding author: i.v.ossokina@tue.nl

[1] We thank Arjen Deetman for excellent research assistance. We thank Theo Arentze, Frank Hofman, Eric Molenwijk, Remko Smit, Taede Tillema and Jan van de Waard for useful discussions and suggestions. The second author gratefully acknowledges the hospitality of Erasmus School of Economics where some of the work was performed.

1 Introduction

This paper focuses on two major consequences of vehicle automation: a lower perceived cost of travel time by car[2] and the replacement of public transport by more efficient automated door-to-door mobility services. We call these two developments, respectively, *car (CAR) transport automation and public transport (PT) automation*. While both make travelling more efficient and more comfortable, they turn out to have offsetting effects on the concentration and dispersion of the population and on residential land prices. We analyse these effects in a number of simulations with the Dutch spatial general equilibrium model LUCA. The model computes shifts in location of homes and jobs, commuting patterns, housing prices, consumer benefits and landowner benefits for a densely populated country, the Netherlands.

Automated driving will radically change travelling experience and this is likely to have effects on land use. In a fully self-driving car, there is no need for the driver to concentrate on the road any more. Travel time can thus be used more efficiently, e.g. for working or relaxing, with, as a result, a less negative perception of the time cost of a car ride. This may lead to people living further away from their jobs and having longer commutes. Through this mechanism, automation technology may thus induce suburbanisation and dispersion of land use (Anderson et al., 2014).

Public transport travel experience is likely to drastically change too. Automated taxibots providing personal mobility services may replace bus, tram and part of metro (KiM, 2015, Yap et al., 2016). Using the new technology, individual or shared taxibots will offer door to door services and follow the most efficient routes for their passengers. With as a result large savings in access, egress and waiting time as compared to traditional public transport. Simulations for Lisbon (OECD, 2015) show that a system of shared automated mobility services has low waiting times and only limited roundabout travel as compared to a direct car trip. Mobility services are more efficient and less expensive in places with higher population density. Therefore, public transport automation will likely increase the attractiveness of cities and lead to further concentration of land use. [3]

Fully automated taxibots operating in cities require a considerable improvement in technology that may take quite some time. Once the stage of *full automation* has been reached, highly efficient and relatively cheap mobility services delivered by automated taxibots may not only replace bus/tram/metro, but also a large part of private car use, leading to an integrated system of mobility service provision. In an earlier stage, car

[2] In this paper the 'perceived cost of travel time by car' has the same meaning as the 'value of time in the car' and 'VOT in the car'. We will use these terms interchangeably.

[3] Car transport automation may also lead to concentration of land use by freeing up considerable parking space in city centres (Anderson et al., 2014) and thus attracting more people to cities. This impact of automation through parking in particular is relevant for cities in the United States where cars constitute the principal mode of commuting. In most European cities the impact of public transportation automation on land use may be more significant.

automation and public transport automation will likely develop next to each other without integrating with each other. In this *high automation* stage, cars will only be self-driving on highways, but not in cities. Automation will still lead to a less negative perception of the travel time in a car, yet only during highway trips and to a more limited degree. At the same time public transport will expand and become more efficient through driverless vehicles, information technology and investment by public authorities. Busses, trams and metro's will however still follow predetermined routes (KIM, 2015 and 2017).

We model these developments in automation using the Dutch spatial general equilibrium model LUCA (Teulings et al., 2017), which belongs to the type Land Use Transportation Interaction models. The model was constructed to study the impact of developments in transportation on the residential location choice of individuals and on land use in the Netherlands. LUCA models the individual choices of workers concerning their home location, job location and commuting mode, and the implications of these choices for the land use. The model distinguishes some three thousand possible home and job locations on the level of a four digit zip-code,[4] and four transportation modes, *viz.* car, train, bus/tram/metro and bike/walking. An important difference of LUCA from its peers is that it includes data on land prices and is able to model an equilibrium on the residential land market. Information on land prices allows to calculate the welfare effects of different developments in transportation. We exploit this feature of the model in this paper. Furthermore, in LUCA it is possible to distinguish effects that are due to modal shift changes only, from general equilibrium effects including changes in home and job location of individuals.

The car automation development (CAR) is modelled in LUCA through a reduction of the perceived cost of travel time in the car (i.e. lowering the "value of time" in the car). In the first place, this results in a higher share of the car in the modal split and in longer car commutes. The latter result arises because a car becomes a more attractive substitute for a train. In the second place, people relocate their homes and their jobs, commuting distances increase. Cities with their high cost of living lose population to cheaper non-urban regions. In this way the most urbanized Western part of the country becomes more interconnected with the less urbanized regions surrounding it. Residential prices converge: they fall in cities and rise in non-urban areas.

The public transport automation development (PT) is modelled through reducing the travel times of trips made by public transport. Under full automation, this reduction is large because shared vehicles do not follow predetermined routes any more. More efficient automated transport services compete with the train and with the bike, affecting the modal split. Higher public transport efficiency raises commuting distances within urban areas. Furthermore, densely populated areas, where mobility services can be provided most efficiently, attract

[4] A four digit zip code in the Netherlands contains some 1500 houses, in cities it covers an area of approximately one square kilometre.

population and jobs at the cost of less urbanized areas. Residential prices rise in urbanized parts of the country and decrease elsewhere. Land owners in cities get a considerable part of the total benefits of the transportation improvement.

When the impacts of car automation and public transport automation are combined, some of the previous effects cancel out. Now, spatial divergence arises between cities. Cities located in a densely populated urbanized region attract population; more isolated cities lose population. For the former the effects of the public transport component turn out to be prevailing, for the latter the effects of the car automation component are dominant.

The population relocation effects are most pronounced in the full automation scenario with an integrated system of mobility services. In this scenario, the average home-job distance grows with about 25% and the new integrated mobility services increase their cumulative modal share with almost 10 percentage points. In the high automation scenarios, the home-job distance grows with about 5% and the combined share of car and bus/tram/metro increases with 2 percentage point.

Our results are interesting for several reasons. First, they show that the effect of vehicle automation on the spatial distribution of economic activity can differ, depending on whether car automation or public transport automation is dominant. Second, our insights can help transportation experts and urban planners to develop policies that account for the possible effects of automated driving technologies. Third, our paper adds to the understanding of how spatial developments and transportation are interconnected. Of course, the quantitative effects that we present cannot yield an exact picture of a remote and highly uncertain future. Yet, since the model has been calibrated on current empirical data for the Netherlands, it provides a quantitative impression of two possible consequences of automation, which are highly relevant for both spatial and transport policy. Indeed, a policy focus on the impact of car transport automation only would erroneously direct policy at dispersion without taking into account the offsetting impact on concentration.

The rest of the paper has the following structure. Section 2 discusses the related literature. Section 3 deals with the main mechanisms and assumptions of the model LUCA. Section 4 explains how we implement the automation components in LUCA. Sections 5 and 6 report the quantitative results of the simulations. Section 7 discusses the policy implications and concludes.

2 Related literature

This paper is related to several streams of the literature. The first one studies the possible effects of self-driving cars. Chen et al. (2017) model how the equilibrium traffic operational capacity changes when traffic consists of both, automated vehicles and regular vehicles. Wadud et al. (2016) identify specific mechanisms through which automation may affect travel and energy demand and simulate the resulting changes in emissions. Fagnant and Kockelman (2015) examine the potential impact of the self-driving cars on safety, congestion and travel behaviour and discuss possible policy responses. However, we are not aware of studies that focus on the implications for the population distribution and for the land market. Correira and Van Arem (2016) and Berg and Verhoef (2015) are two studies that most closely relate to ours. They examine the implications of self-driving cars for mobility and find that urban congestion might increase. Our paper argues that this effect might be affected by changes in the urban population.

The second stream of related literature includes studies based on the land use transportation interaction (LUTI) models. These are mostly large applied models which are developed to analyse the implications of large-scale spatial developments in transportation - new highways or new railways - on land use and the conversion of land from an agricultural to an urban function. These models often integrate a separate transportation model and a separate land use model (see De Palma, 2005, et al. for Paris, Jones et al., 2017, for Brussels and Van Wee, 2015, for an overview). To our knowledge, land use transportation interaction models have not been applied yet to study the effects of automated driving technology. Furthermore, our approach with model LUCA differs from the standard models in three ways. First, LUCA has been developed as a single model in which agents simultaneously choose home location, job location and their transportation mode, so consistent behavioural assumptions have been made. Second, LUCA is a general equilibrium model in which transportation changes lead to a new equilibrium on the residential land market. In this way our model is closely related to Anas and Liu (2007) general equilibrium model RELU-TRAN. As compared to other spatial general equilibrium models, LUCA has a high degree of transparency as it is based on a very limited number of equations. Third, in LUCA residential land prices are one of the determinants of residential location choice, thus allowing to calculate endogenously the monetary welfare effects of transportation investments.

Our paper is also related to policy studies that use scenarios to simulate long-term economic and spatial developments. In the Netherlands and other developed countries this practice is widely used in policy analysis. The latest Dutch scenarios for economic and spatial developments were published in 2016 (CPB and PBL, 2016), but did not explicitly model the consequences of automated driving technology. The Netherlands Institute for Transport Policy Research (KiM, 2015) developed qualitative scenarios for self-driving cars that are used as a baseline for the research of this paper.[5] Rand Corporation (Rohr et al., 2016) developed non-quantitative transport scenarios for UK; in one of these automation technology plays a role.

Finally, a growing literature studies the effects of the developments in transportation on the spatial distribution of the population and economic activity. Desmet and Rossi-Hansberg (2013) explain the city size distribution from differences in congestion costs, amenities and productivity. Ahlfeldt et al. (2014) model the changes in residential density and land prices in Berlin after the fall of the Berlin wall. Baum-Snow (2007, 2010) empirically shows that the construction of highways in America in 1950-1980 led to suburbanization of the population and jobs. Garcia-Lopez et al. (2016) find a similar effect for Europe. Duranton and Turner (2012) estimate a model explaining the joint evolution of the highways and employment. Teulings et al. (2017) show that a better railway connection between the economic centre and its periphery can lead to a relocation of jobs to the centre and a relocation of people to the periphery. Our paper studies the possible effects of automated driving technology.

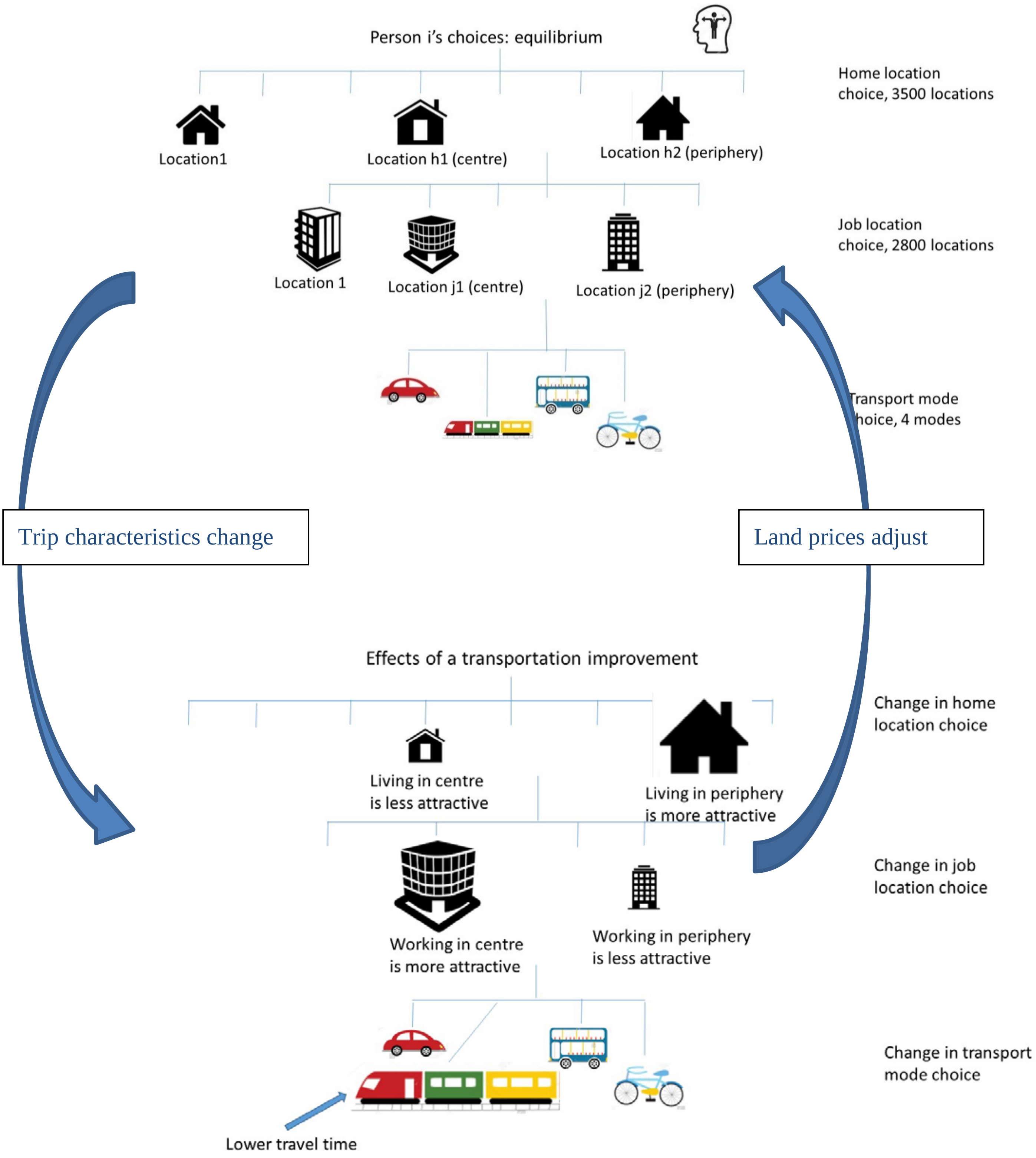
3. General equilibrium model LUCA

LUCA is based on micro-economic premises. It models the behaviour of four types of agents: three types of consumers who differ in their educational attainment (high, middle and low), and land owners. Land owners rent housing to consumers. Consumers choose (i) their home location and the size of the dwelling, (ii) their job location, (iii) the commuting mode between their home and job location. See Teulings et al. (2017) for a formal description of the model.

When making these choices, consumers take into account: (i) home location characteristics, including residential amenities (parks, nice sites, restaurants, etc.) and land and housing prices; (ii) job location characteristics such as e.g. wage; (iii) commuting costs. The discrete home-job-commuting choices are modelled as a nested logit, see upper panel of Figure 1. The choice of housing consumption is continuous and follows the Muth (1969) model.

[5] Milakis et al. (2017) develop alternative scenarios for self-driving cars in the Netherlands; these however do not allow for a spatial dimension.

Figure 1. Schematic representation of LUCA



Using the above inputs, LUCA allows to simulate the effects of transportation improvements on the spatial distribution of population and jobs, land use and land prices. To illustrate the working of the model consider as an example a better railway connection between the economic centre of a country and its periphery, reducing the commuting time between the two regions (see also Teulings et al., 2017). In LUCA, this connection leads to a modal shift from car to train and to a relocation of jobs from the periphery to the more productive centre (see lower panel of Figure 1). Indeed, as more people are willing now to commute to the centre, labour supply in the centre increases and so does the number of jobs. The periphery loses jobs, but becomes a more attractive location to live in due to the better accessibility of the centre. As the demand for living in the periphery rises, land prices and land intensity rise there. This counteracting force restricts further demand growth. The adjustment process continues until a new equilibrium on the land market is achieved. In this new equilibrium the periphery has a higher population than in the reference situation, but fewer jobs.

In a LUCA simulation, individual workers choose where they want to live, conditional on the land prices, transport accessibility of jobs and residential amenities. In each iteration, the model sums up individual demand for housing and land to total demand for land at each location, and confronts it with supply. Hence, demand for housing is endogenous and follows from the model. In this way, LUCA is perfectly suitable to model the effect of transportation improvements on the residential choice of people and the land market. Consecutive adjustment of land prices allows the model to converge to a new equilibrium, equalizing demand for and supply of land.

The geography of LUCA is modelled on a highly disaggregated level and consists of some 3000 home and job locations, defined on the level of a four-digit zip code. In the Netherlands, a four-digit zip code contains on average 1.5 thousand dwellings and covers in urban regions an area of approximately one square kilometre. The parameters of the consumer choice model have been estimated from real data on home, job and commuting choices of 60 thousand Dutch employees (see Teulings et al., 2017, for a detailed discussion), as well as zip code level data on land prices and amenities, provided by Statistics Netherlands.

For the purposes of this paper it is important to understand how the modal split works in LUCA. The modal choice includes four alternatives: car, train, bus/tram/metro and bike. The attractiveness of each mode on a specific home-job link depends on the travel time and the travel costs of this mode. The utility weights individuals attach to travel time and cost are estimated from real data; as usual the value of time equals the ratio of these estimated coefficients. For public transport, LUCA makes a distinction between the in-vehicle and the out-of-vehicle travel times allowing for different values-of-time between the two. For the train mode, access and egress times are modelled separately. Finally, for each mode, a mode-specific constant is included to account for the attractiveness of the mode that has not been controlled for by the time and cost elements.

These constants can differ by education level: for instance, high educated have a higher preference for commuting by train than other groups. Furthermore, for the bus/tram/metro mode the value of the constant differs by degree of urbanization; this accounts for the fact that public transport can be provided more efficiently and is of higher quality in densely populated urbanized areas.

4. Simulation design

The Society of Automotive Engineers distinguishes six levels of automation, ranging from 'no automation' (Level 0) via 'high automation' (Level 3/4) to 'full automation' (Level 5) (NHTSA, 2016). In this application we explore the high automation and the full automation levels. For these two levels of automation we distinguish a public transport and a car automation component. We simulate the effects of both components separately and in combination. The combinations yield a high automation and a full automation scenario. This makes a total of 6 different simulation variants as documented in Table 1. The table reports how the simulations are implemented in LUCA. The simulations were inspired by the scenarios on automated driving developed by KiM Netherlands Institute for Transport Policy Analysis (2015, 2017).

Table 1. Simulation design of four components of two automated driving scenarios in LUCA

	High automation	**Full automation, mobility as a service**
Public transport automation	**PT-1**	**PT-2**
In-vehicle travel time bus/tram/metro	unchanged	set to 1.2 times the travel time of the car
Out-of-vehicle travel time bus/tram/metro	reduced by 50%	set to 0
Access / egress time train	reduced by 20%	reduced by 50%
Car transport automation	**CAR-1**	**CAR-2**
Coefficient on travel time of the car	set to 0.95 times the current coefficient, for trips longer than 15 km	set to 0.8 times the current coefficient, on all routes
which reduces the perceived cost of time in a car (VOT in a car) by	5%, for trips longer than 15 km	20%, on all routes
COMBI	**COMBI-1 = PT-1 + CAR-1**	**COMBI-2 = PT-2 + CAR-2**

High automation

In the high automation scenario the technology allows cars to drive autonomously under well-defined circumstances. On roads with well-indicated, separate lanes, self-driving cars can adjust their speed to the flow of the traffic, shift lanes and take over, give way to merging traffic, etc. However, vehicles cannot function autonomously on narrow streets where other modes (pedestrians, bikes, busses) interact with the flow of cars, or in complex and unclear traffic situations. Hence, in this world a substantial number of people drive 'hands free' on highways, together with platoons of automated trucks. Once a car enters a city, the driver has to resume control.

While the car controls the actions in traffic, the driver can engage in other activities. As a consequence, on highways drivers may perceive a lower cost of driving time, but this is not the case in cities. Furthermore, drivers still need to be seated in a confined space behind a steering wheel. To account for this, we model the car transport component of high automation in LUCA by lowering the cost of driving time with 5% for trips longer than 15 km (see CAR-1 in Table 1).[6] This is a quarter of the travel time reduction in the full automation scenario discussed below.

High automation in public transport involves driverless trams and metros that travel on separate trajectories. Driverless pod-/bus-systems operate on fixed routes in cities and between main public transportation hubs, such as stations and university campuses. ICT systems support passengers with up-to-date personalised travel information. We simulate this shift to a more efficient public transport system in LUCA by reducing the out-of-vehicle time of bus/tram/metro trips by half. In addition, access and egress times of train trips are reduced with 20% (see PT-1 in Table 1).

To keep the simulations transparent, we assume the out-of-pocket (monetary) costs of the modes not to change in the automation scenarios. All adjustments take place through the travel time variables.

Full automation

In this scenario automation technology has reached the highest level of development one can think of today. Transportation looks quite different from what we are used to now. A considerable part of it has most probably been replaced by door-to-door mobility services delivered by automated vehicles and offered by fleet-owning companies (KiM, 2015). Only on very dense transport links scheduled services like trains and metros continue to operate. On all other links shared or non-shared taxibots have replaced buses, trams, and private cars. A traveller simply orders the automated vehicle which is most suited for her needs. For commuting during peak hours a shared six person taxibot is one of the cheapest options. If the commuter prefers more privacy and a larger working space, a one person taxibot is available at a higher price. In particular, high income earners increasingly prefer one person taxibots when commuting distances increase, because privacy considerations gain weight over time.

[6] In the Netherlands, the highway density is the highest in Europe and highways are widely used not only for intercity but also for intracity trips. Indeed, an average Dutch person lives within 2.5 kilometre from a highway ramp (Statistics Netherlands, 2012). However, for shorter trips it seems unlikely that people will find it worthwhile to switch to other activities when riding on the highway,

In this scenario vehicles operate without steering wheels and other driver controls. These vehicles are able to find their way autonomously and safely in all traffic conditions, both on highways and in cities. Several studies (see e.g. Kouwenhoven and De Jong, 2017 and the references therein) suggest that the perceived cost of time in a fully automated car may amount to 80% of its current level. We apply this value to model the car transport component of the full automation scenario in LUCA (see CAR-2 in Table 1).[7]

Shared mobility services (taxibots) are much more efficient than traditional public transport. Indeed, travelers no longer have to walk to a bus stop or change lines. Moreover, they travel along almost straight routes to their destination. The multi-person taxibot only makes a detour to pick up or drop off other passengers. These detours are relatively short though, especially in cities where ICT systems can very efficiently allocate passengers due to the high population density. Hence, in the LUCA simulation the public transport component of the full automation scenario is modelled by setting the in-vehicle travel time of the bus/tram/metro equal to the travel time of a car plus 20% detour time. Hence, the in-vehicle travel time equals 1.2 times the current car travel time.[8] The out-of-vehicle time is set to zero, and the access and egress times of train trips are set to half their current value (see PT-2 in Table 1).

Taxibots transport passengers to their destination and then proceed to pick up others or, alternatively, return to their parking places which are located outside the residential or working areas. Traditional parking lots in the city become redundant and the parking fees disappear. In this application of LUCA, we do not study the consequences of these developments. We assume that, to guard livability, cities will introduce other traffic reducing policies with a similar effect as the parking fees used to have, such as e.g. road pricing. Indeed, parking fees currently make up a considerable part of the municipal budgets and it is likely that the cities will try to compensate the disappearance of the fees with another similar policy. In addition, fleet providers will likely make taxibot trip fares time-varying and adjust them to transport demand and inner city capacity during rush hours.

Finally, the automation technology may have a positive impact on the capacity of roads as self-driving vehicles can be expected to make a more efficient use of road space (e.g. they drive closer to each other than traditional vehicles). This will likely result in travel time improvements on congested roads. It is however not clear how large this improvement will be and what level of technology adoption is required for it to occur. The resulting favorable impact on congestion and travel times will furthermore be counteracted by an

[7] In the base parametrization of LUCA travel time in a car is perceived more negatively than that in public transport. One of the reasons is that public transport is 'hands free'. In the full automation scenario the car and public transport merge into one system of automated door-to-door services. By reducing the perceived cost of travel time in a car with 20% in this scenario, the travel time perception in the former car mode and former public transport mode become similar, as should be in an integrated system.

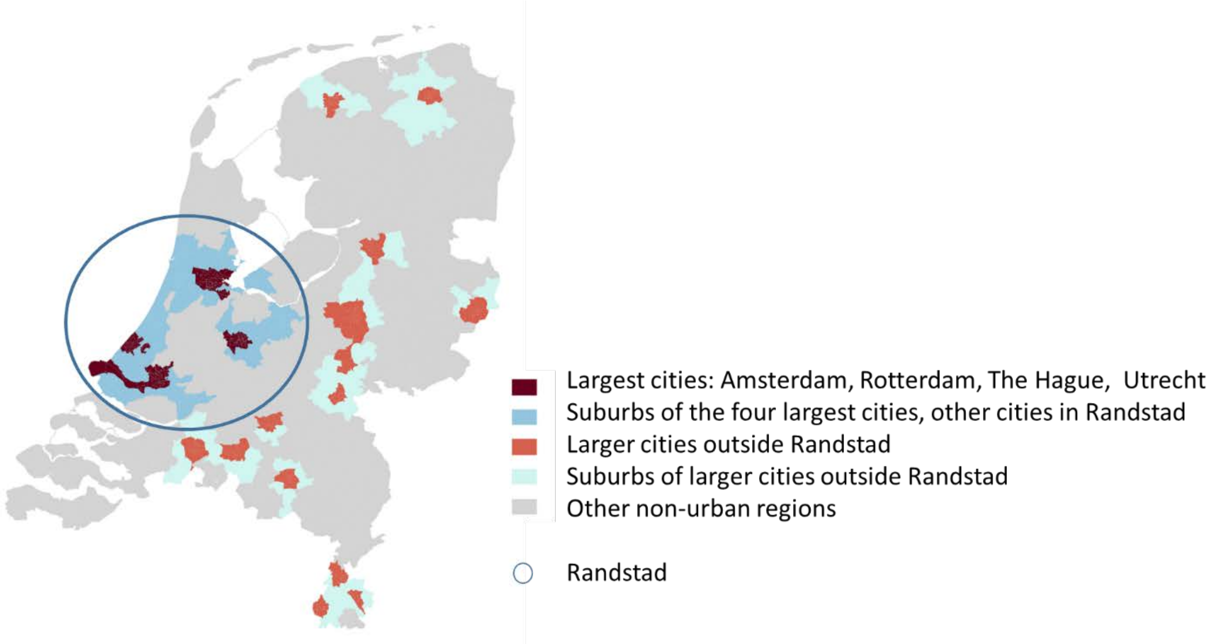
[8] This implies that the traditional bus, tram and some metro lines do not exist any more. Private cars, busses, trams and less intensively used metros merge into a system of automated mobility services.

increase of travel demand due to more efficient and more comfortable trips offered by automated vehicles. Therefore, in this paper we assume that the capacity effect and the demand effect on congestion offset each other, so that the automation technology will not lead to any second-order changes in travel times in addition to those discussed in Table 1.

5 Effects of automation on population distribution

In this Section we discuss the outcomes of the scenario components presented in Table 1. We will report the outcomes for two levels of aggregation. The first is a four digit zip code. The second level of aggregation consists of five non-contiguous regions, ordered by their degree of urbanization according to the classification of Statistics Netherlands: (i) 4 largest cities: Amsterdam, Rotterdam, The Hague and Utrecht; (ii) suburbs of these cities as well as other larger cities in the urbanized Western part of the country, called Randstad; (iii) larger cities outside the Randstad; (iv) suburbs of the larger cities outside the Randstad; (v) other, less-urbanized places. Figure 2 depicts these regions. The effects of automation are reported in comparison to the reference scenario, for which LUCA was estimated. This is the Netherlands in 2011.

Figure 2. Regional division of the Netherlands



5.1 High automation

Figures 3 and 4 report the population relocation effects in the high automation scenario, by zip code and aggregated for each of the five regions we distinguish. The public transport and the car components have opposite effects. An increase in the efficiency of public transport (PT-1) attracts population to the most urbanized regions. The reason is that in densely populated areas public transport can be provided more efficiently. As a result these areas benefit most from automation of public transport. The suburbs of the isolated cities and the non-urban regions experience a population loss. A decrease in the perceived cost of time in the car (CAR-1) leads to suburbanization: cities lose population to suburbs and non-urban areas. The reason for suburbanization is that longer commutes have become more acceptable. Smaller isolated cities and their suburbs experience the largest population loss, because they are surrounded by extended and attractive non-urban areas and because the urban amenities they offer are relatively limited. The combination of the car and public transport components (COMBI-1) results in concentration of the population in the urbanized part of the country. Cities and suburbs in highly urbanized regions gain population, isolated cities and their suburbs lose. The edges of the country experience the largest population loss.

Figure 3. Population changes in % by zip code: High automation. Left PT-1, middle CAR-1, right COMBI-1.

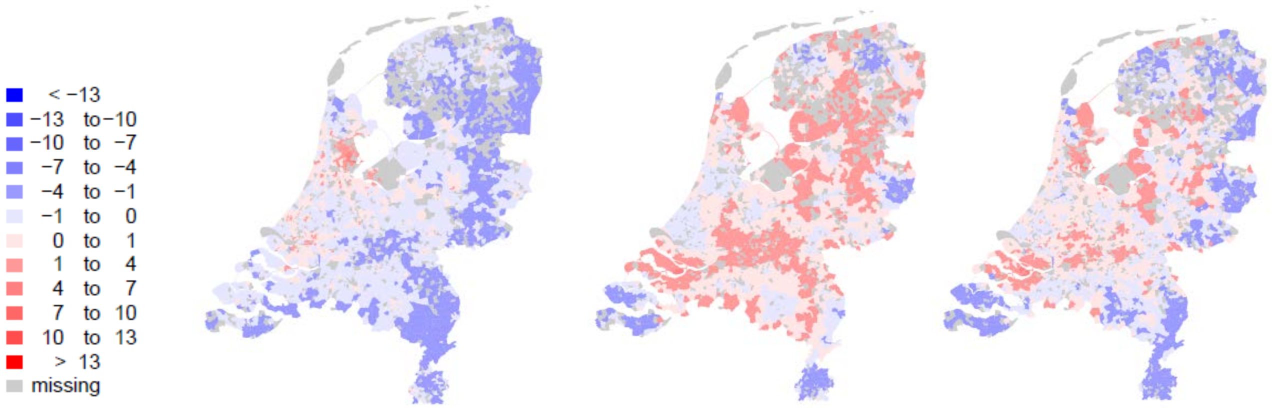
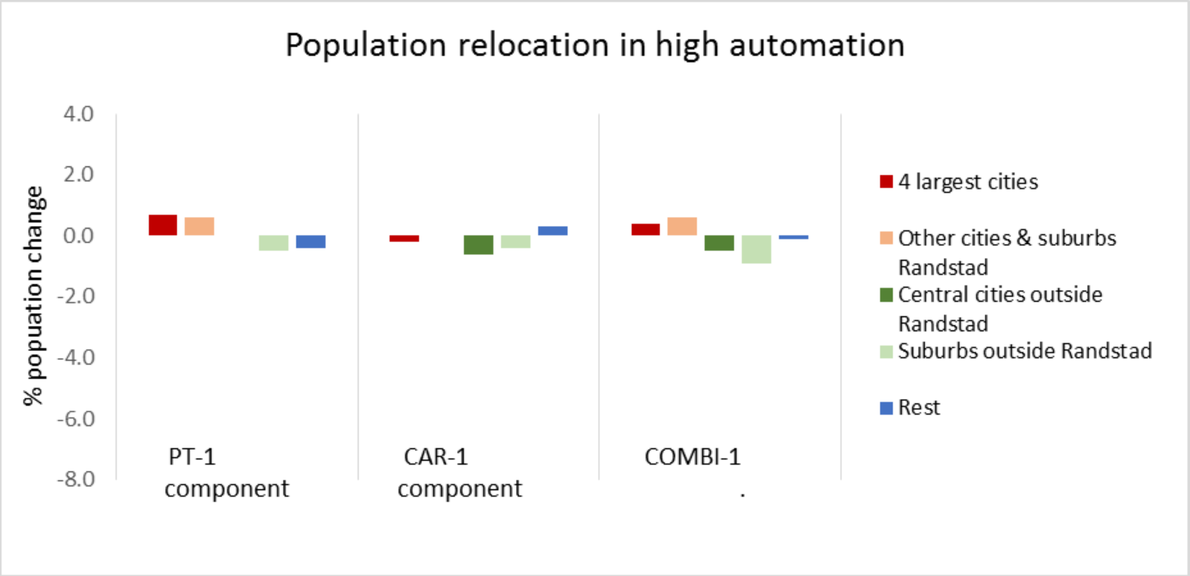


Figure 4. Population redistribution, changes in % compared to the current equilibrium



5.2 Full automation

In the full automation scenario the effects are three to four times larger than in the high automation scenario, but the general trend is the same (Figures 5 and 6). The public transport component (PT-2) attracts population to urbanized areas while the car component (CAR-2) leads to suburbanization. Combination of the two components (COMBI-2) results in relocation of the population from smaller isolated cities and their suburbs to the urbanized part of the country. The edges of the country lose the most.

Figure 5. Population changes in %: Full automation. Left PT-2, middle CAR-2, right COMBI-2.

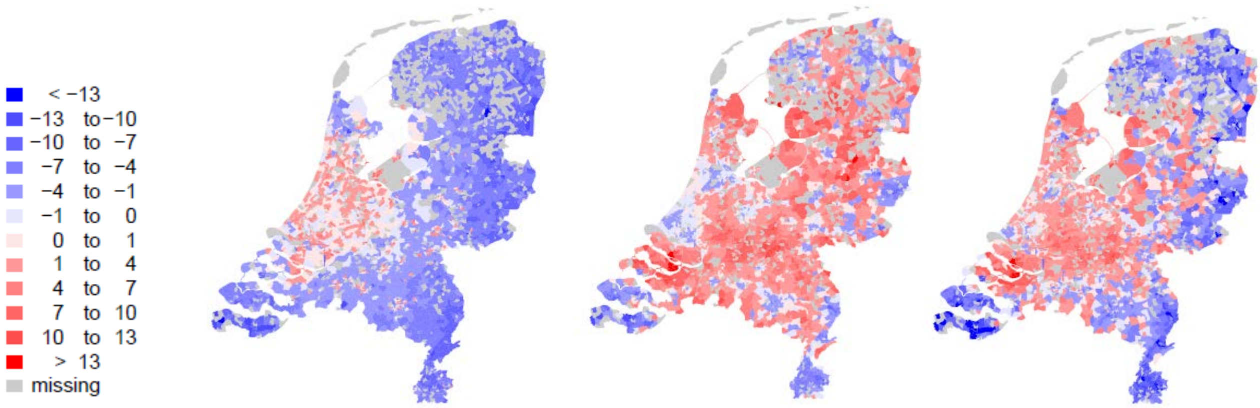
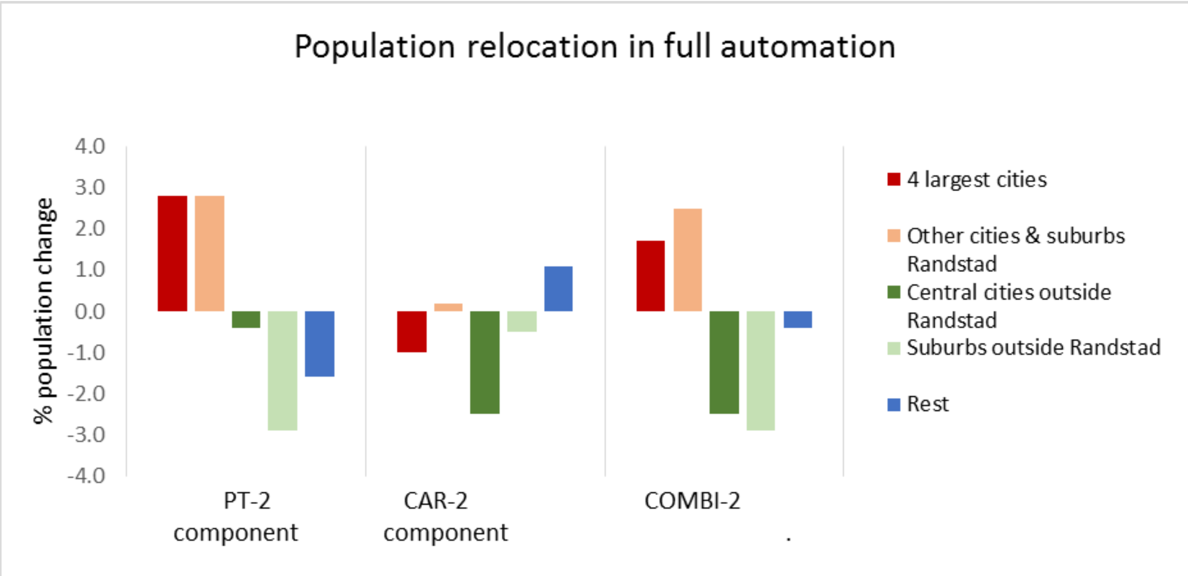


Figure 6. Population redistribution, changes in % compared to the current equilibrium



To put these effects into perspective we compare the above results with the scenarios of autonomous regional development for the Netherlands (CPB /PBL, 2015), which are widely used as input for policy analysis and debate in the Netherlands. In the CPB/PBL scenario's, population growth in the period 2012-2050 lies between -10% and +30%, depending on the region and the assumptions on economic growth and on regional concentration or dispersion. The cities are expected to grow the most, the non-urban areas the least. The regional effects of full automation in our calculation lie between -3 and 3%. Compared to the autonomous developments, these population shifts can make a difference. For instance, they may considerably increase the challenge the four largest cities and their suburbs face in accommodating population growth, and alleviate or eliminate this challenge for cities outside the Randstad.

6 Other effects

6.1 Consumer benefits and land price effects

In LUCA, automation affects the behaviour of economic agents through several channels (see also Section 3). In the first place, agents enjoy more comfortable and quicker trips. In the second place, demand for different residential locations may change. As discussed above, suburbs and non-urbanized locations become relatively more attractive due to the car automation component. Cities become relatively more attractive due to the public transport automation component. In the model, if the demand for a location rises, land and housing prices increase, thus providing a counteracting force and restricting further demand growth. This adjustment process continues until a new equilibrium in the model is reached. As shown in Section 5, in the new equilibrium quite a few people live in other places compared with the reference scenario.

On average, the introduction of automation technology increases welfare. Table 2 reports the welfare benefits, expressed in terms of yearly flows. We distinguish (i) benefits due to shorter travel time and more comfortable trips, computed conditional on people living and working in the same locations as in the reference scenario, and (ii) benefits due to relocation of homes and jobs. In the full automation scenario (COMBI-2) the total benefits amount to some 6 billion euro per year; this equals 0.8% of the Dutch BBP. In the high automation scenario the benefits are six times smaller. The largest part of this welfare improvement results directly from faster travel times and higher travel comfort. Benefits due to relocation to other home and job locations equal 3% of the total in the high automation scenario and 10% in the full automation scenario. Apparently, the large transportation improvements in full automation make it possible to achieve larger welfare gains by changing the home or job location.

In LUCA, we distinguish between welfare effects for consumers and land owners. A house owner is consumer and land owner at the same time, a house renter is consumer only. The total welfare effect is a sum of the effect for consumers and the effect for land owners. The latter is a direct consequence of the changes in land prices. Car automation leads to a convergence of land prices: they fall in cities and rise outside cities (see Appendix A for figures).[9] Because the land prices are much higher in cities than in non-urban areas, the

[9] This is a consequence of the suburbanization that comes together with a decreasing demand for land in cities and an increasing demand for land in less urban areas.

loss of land owners in cities cannot be compensated by the gain of land owners in other places. As a result, the average land price falls and land owners transfer part of their welfare to consumers. Under public transport automation, on the contrary, the land prices rise in the cities and in the urbanized centre – regions where they were already high. In this case the benefits of the better transport connections are divided between consumers and land owners; the latter get between 10% and 20% of the total pie.[10] When the impact of public transport automation and car automation is combined, the effect for the landowners largely cancels out.

Table 2. Consumer benefits and land price effects, compared to the reference equilibrium

in bln euro, yearly effects	**High automation**			**Full automation**		
	PT-1	**CAR-1**	**COMBI-1**	**PT-2**	**CAR-2**	**COMBI-2**
Total benefits transport improvement only	0.6	0.5	1.1	3.0	2.9	5.3
Total benefits including effects of relocation	0.6	0.5	1.1	3.4	3.1	5.9
of these:						
consumer part	0.5	0.6	1.1	3.0	3.5	6.0
land owner part	0.1	-0.1	0.0	0.4	-0.4	-0.1

LUCA allows to calculate welfare effects for different population groups (not in the table). Similar to other transportation improvements, the automation technology benefits the high educated most as this population group makes the longest commutes. Low educated furthermore suffer most from the increase in land prices in the cities. The gains of high educated are up to four times as large as the gains of low educated.

6.2 Effects on the transport market

Finally, Tables 3 and 4 report the effects of the scenarios that are related to the transportation market. Both, high automation and full automation scenarios result in more commuting. The average distance between the home and the job locations increases with some 5% in high automation and with some 25% in full automation. This occurs because vehicle automation lowers the generalized costs of transport and induces people to choose more remote home and job locations. Note that particularly in the full automation simulation more efficient public transport (PT-2) makes living in cities more attractive, yet at the same time raises commuting distances because within city areas people live further away from their job locations.

In high automation, the share of public transport increases considerably. When the impacts of the car and public transport components are combined (COMBI-1), the share of bus/tram/metro becomes almost twice as

[10] Note that the gain from automation technology is limited to the generation that is house owner when the technology is introduced. Future generations do not benefit from their landownership, because they have to buy the land at a higher price.

large as in the reference situation. This comes at the cost of the share of other transportation modes. In full automation, we do not distinguish any more between the car and the public transport modes as both then have merged into mobility services. As compared to the total share of car and bus/tram/metro in the reference situation, the share of mobility services rises with ten percentage points (COMBI-2). This comes mostly at the cost of the bike mode and can partly be explained by a considerable increase of commuting distances (see Table 3).

Table 3. Effects on home-job distance

in % change	**High automation**			**Full automation**		
	PT-1	**CAR-1**	**COMBI-1**	**PT-2**	**CAR-2**	**COMBI-2**
Modal shift + relocation						
average distance home-job	0.6	4.2	4.6	15.1	15.9	26.3

Table 4. Modal split (trips)

%	**Current situation (2010)**	**High automation**			**Full automation**		
		PT-1	**CAR-1**	**COMBI-1**	**PT-2**	**CAR-2**	**COMBI-2**
Modal shift only							
Car	64.0	62.2	64.8	62.6			
Bus/tram/metro	3.0	5.8	3.0	5.7			
Mobility services					69.8	69.7	71.4
Train	5.1	5.4	4.8	5.1	4.7	3.9	3.9
Bike	27.8	26.6	27.4	26.6	25.5	26.4	24.7
Modal shift + relocation							
Car	64.0	62.2	65.6	63.3			
Bus/tram/metro	3.0	6.0	2.9	5.9			
Mobility services					72.4	73.0	76.4
Train	5.1	5.5	4.9	5.3	5.5	4.2	4.6
Bike	27.9	26.3	26.6	25.5	22.1	22.8	19.0

7 Conclusions and discussion

In this paper we have applied the Dutch spatial general equilibrium model LUCA to study possible effects of vehicle automation on the concentration and dispersion of the population and on residential land prices in the Netherlands. We have accounted for two possible automation developments: *car transport* automation, where the technology reduces the perceived cost of travel time by car; and *public transport* automation where the new technology leads to more efficient public transport. We have considered scenarios with fast and slow development of the automation technology. We found that car automation results in population flight from cities and convergence of residential prices between cities and rural areas. Public transport automation has an opposite effect. It leads to further population clustering in urban areas, and an increase in residential price disparity between cities and rural areas. A combination of these two components leads to a concentration of the population in the largest most attractive cities at the cost of smaller cities.

We have focused on some main mechanisms through which automation technology can affect the intensity of land use and the distribution of population and jobs over the country. This allows to keep the analysis transparent and easily tractable but comes with a number of simplifications. For example, we did not account for the option of transferring parking places in cities to other use nor did we account for the possible feedback of automation technology on congestion. Also, we excluded welfare gains from improvement of traffic safety by automated vehicles. Ignoring these margins of adjustment leads to some underestimation of the benefits of transportation improvements, but does not change the general direction of the results. Extending the analysis along the discussed dimensions is a topic for further research.

The quantitative effects that we have presented are based on simulations and cannot of course yield an exact picture of a remote and highly uncertain future. Yet, since the LUCA-model has been calibrated on current empirical data for the Netherlands, it provides a quantitative impression of two possible consequences of automation, which are highly relevant for spatial and transport policy. Indeed, a policy focus on the impact of car transport automation only would erroneously direct policy at dispersion without taking into account the offsetting impact of more efficient public transport on concentration.

Our results are in particular interesting in the light of the ongoing discussions about the growth and decline of cities, in the past, present and future. The most influential transportation technology development of the last century – construction of the highways – has led to suburbanization of population and jobs (see Baum-Snow, 2007, 2010 and later studies). Vehicle automation may well be the next large transportation technology jump. Our results suggest that it might lead to a further concentration of population in already highly urbanized areas and a further divergence of housing prices between attractive and less attractive places. Given that in many developed countries attractive cities have recently been growing at a higher speed than the rest of the country (see e.g. Duranton and Puga, 2014, Gyourko et al., 2013), this poses additional challenges to policy makers at the local and national level.

References

Ahlfeldt, G.M., Redding, S.J., Sturm, D.M., Wolf, N., 2016. The economics of density: Evidence from the Berlin Wall, Econometrica.

Anas, A., Liu, Y., 2007. A regional economy, land use, and transportation model (RELU-TRAN): Formulation, algorithm design, and testing, Journal of Regional Science 47, 415-455.

Anderson, J. M., Nidhi, K., Stanley, K. D., Sorensen, P., Samaras, C., and O.A. Oluwatola, 2014. Autonomous vehicle technology: A guide for policymakers. Rand Corporation.

Baum-Snow, N., 2007. Did highways cause suburbanization? Quarterly Journal of Economics 122 (2), 775-805.

Baum-Snow, N., 2010. Changes in transportation infrastructure and commuting patterns in US metropolitan areas, 1960-2000, American Economic Review 100, 378-382.

Berg, V.A.C. van den and E.T. Verhoef, 2015. Robot Cars and Dynamic Bottleneck Congestion: The Effects on Capacity, Value of Time and Preference Heterogeneity. Tinbergen Institute Discussion Paper TI 2015-062/VIII.

Chen, D., Ahn, S., Chitturi, M. and D. A. Noyce, 2017. Towards vehicle automation: Roadway capacity formulation for traffic mixed with regular and automated vehicles. Transportation research part B 100: 196-221.

Correia, G.H., and B. van Arem, 2016. Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. Transportation research part B 87: 64-88.

CPB/PBL, 2015. Nederland in 2030-2050: twee referentiescenario's: Toekomstverkenning Welvaart en Leefomgeving. PBL Netherlands Environmental Assessment Agency / CPB Netherlands Bureau for Economic Policy Analysis (in dutch).

Desmet, K., Rossi-Hansberg, E., 2013. Urban accounting and welfare, American Economic Review 103 (6), 2296-2327.

Duranton, G. and D. Puga, 2014. The growth of cities. In Durlauf, S.N. and Ph. Aghion (eds.), Handbook of Economic Growth, Elsevier.

Duranton, G. and M.A. Turner 2012. Urban growth and transportation, Review of Economic Studies 79 (4), 1407-1440.

Fagnant, D.J. and K. Kockelman, 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transportation research part A 77: 167-181.

Garcia-López, M.A., I. Pasidis en E. Viladecans-Marsal, 2015, Express delivery to the suburbs: the effects of transportation in Europe's heterogeneous cities, IEB Working Paper 2015/30.

Gyourko, J., Mayer, Ch. and T. Sinai, 2013. Superstar cities. American Economic Journal: Economic Policy 2013, 5(4): 167–199.

Jones, J., Peeters, D. and I. Thomas, 2017. Scale effect in a LUTI model of Brussels: challenges for policy evaluation. European Journal of Transport and Infrastructure Research 17: 103-131.

KiM Netherlands Institute for Transport Policy Analysis, 2015. Driver at the wheel? Self-driving vehicles and the traffic and transport system of the future.

KiM Netherlands Institute for Transport Policy Analysis, 2017. Paths to a self-driving future.

Kouwenhoven, M. and G. de Jong, 2017. Waardering van reistijd als functie van comfort. Research report Significance.

Kyriakidis, M., Happee, R. and J.C.F. de Winter, 2015. Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. Transportation research F 32: 127-140.

Milakis, D., Snelder, M., Arem, B. van, Wee, B. van, and G.H. de Almeida Correia, 2017. Development and transport implications of automated vehicles in the Netherlands: scenarios for 2030 and 2050. European Journal of Transport and Infrastructure Research 17: 63-85.

NHTSA/ US Department of Transportation 2016. Federal Automated Vehicles Policy: accelerating the next revolution in road safety.

OECD/ International Transport Forum, 2015. Urban Mobility System Upgrade. How shared self-driving cars could change city traffic.

Palma, A. de, Motamedi, K., Picard, N. and P. Waddell, 2005. A model of residential location choice with endogenous housing prices and traffic for the Paris region. European Transport 31: 67-82.

Rohr, Ch., Ecola, L., Zmud, J., Dunkerley, F., Black, J. and E. Baker, 2016. Travel in Britain in 2035: Future scenarios and their implications for technology innovation. Rand Europe.

Teulings, C.N., Ossokina, I.V. and H.L.F. de Groot, 2017. Land use, worker heterogeneity and welfare benefits of public goods. Second revision submitted at Journal of Urban Economics.

Wadud, Z., MacKenzie, D. and P. Leiby, 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. Transportation research part A 86: 1-18.

Wee, B. van, 2015. Viewpoint: Toward a new generation of land use transport interaction models. The Journal of Transport and Land Use 8: 1-10.

Yap, M. D., Correia, G., and B. van Arem (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. Transportation Research Part A: Policy and Practice 94, 1-16.

Appendix

Figure A1. Land price changes in %: High automation. Left PT-1, middle CAR-1, right COMBI-1.

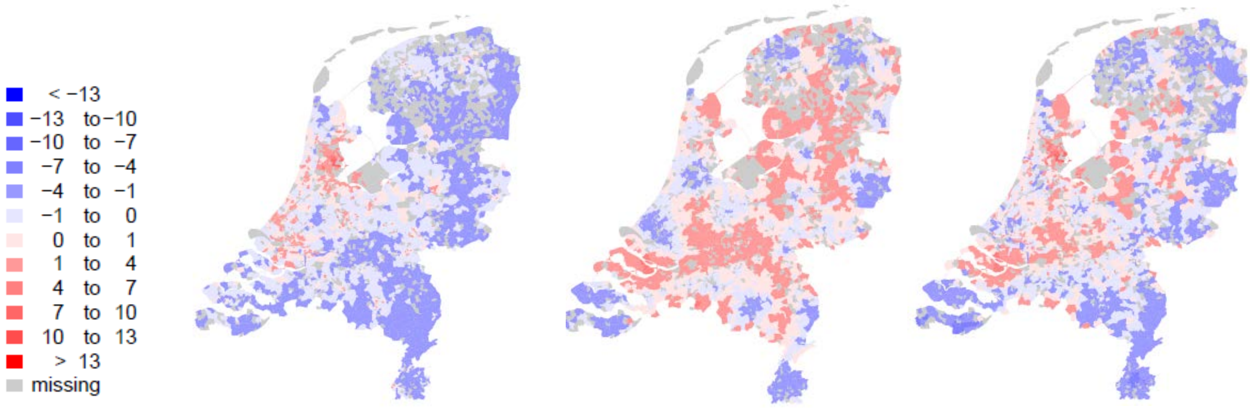


Figure A2. Land price changes in %. Full automation. Left PT-2, middle CAR-2, right COMBI-2.