This is a preprint of the article in
Transportation Research Part A,
121 (2019) 277-294

Spatial and welfare effects of automated driving: will cities grow, decline or both?[1]

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29 December 2018

Abstract

This paper shows that automated driving can lead both, to growth and decline of cities. We simulate spatial effects of automated driving for the Netherlands using LUCA, the Dutch spatial general equilibrium model. Two components of automation are accounted for: (i) more productive time use during car trips; (ii) fast and comfortable door-to-door automated public transit. We find that the car component results in population flight from cities, while the public transit component leads to population clustering in urban areas. A combination of the two may result in the population concentrating in the largest, most attractive cities, at the expense of smaller cities and non-urban regions. The simulations suggest that welfare benefits of automation are considerable, with up to 10% coming from population relocation and changes in land use. Our results are particularly relevant for countries where public transit claims a considerable share of urban mobility. Neglecting the impact of vehicle automation on public transit could result in biased policy recommendations.

Key words: Autonomous vehicles; Self-driving technology; Regional migration; Urban growth; Residential land market; General equilibrium; Wider benefits of transportation

JEL classification: R13, R23, R31, R4

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[1] We thank Arjen Deetman for his excellent research assistance. We thank the editor and referees of this journal, and also Theo Arentze, Frank Hofman, Eric Molenwijk, Remko Smit, Taede Tillema and Jan van de Waard for useful suggestions. The second author gratefully acknowledges the hospitality of the Erasmus School of Economics, where part of the work on this paper was done.

1 Introduction

Automated and autonomous driving will radically change the travel experience and likely have far-reaching consequences for mobility patterns, population distribution and land use. Self-driving cars – which we term *Privately-Ridden Automated Vehicles (PAV)* – relieve their occupants of the burden of driving, allowing them to spend the travel time on other activities, like working or relaxing.[2] PAV enhances the travel experience and may lead to longer commutes, population suburbanization and land use dispersion (Anderson et al., 2014, Heinrichs, 2016, Bansal et al., 2016, Zakharenko, 2016, Meyer et al., 2017, Litman, 2018). Automated transit – which we term *Shared-Ride Automated Vehicles (SAV)* – provides shared door-to-door rides and offers savings in access, egress and waiting time, as compared to conventional transit. Being inexpensive, fast and demand-responsive, especially in densely populated areas[3], SAV may replace buses, trams and some metro lines (KiM, 2015, ITF/OECD, 2015, 2017a, 2017b, Yap et al., 2016, Chen and Kockelman, 2016, Stocker and Shaheen, 2017). This could lead to cities becoming more attractive and to concentration of land use. [4] [5] The discussed trends in, and consequences of, automation have been examined separately in other papers. However, this study is the first to analyze them within a single formalized framework, which allows to examine both the spatial and the welfare effects of the automation.

This paper applies LUCA,[6] the Dutch spatial general equilibrium model, to study the possible effects of vehicle automation on population concentration and dispersion. We compute shifts in the location of homes and jobs, commuting patterns, land prices and welfare for a densely populated country, the Netherlands. We account for two possible automation developments: *car* automation, whereby technology enhances the travel experience in PAV; and *public transit* automation, whereby new technology results in fast and inexpensive SAV. Further, we use scenarios in which the automation technology is at differing levels of development. The first is *high automation* in which vehicles are able to drive autonomously under well-defined circumstances (inspired by Level 4 SAE International, 2014). The second is *full automation* in which vehicles are driving autonomously under all circumstances (inspired by Level 5 SAE International, 2014). Finally, two types of welfare effects of automated driving are computed: (i) benefits due to changes in generalized transportation costs and modal split, while keeping population distribution unchanged, and (ii)

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[2] In this paper we focus on car use and disregard ownership issues.

[3] We follow Litman (2018) in assuming that SAV's will be cheaper and faster – thus of higher quality - in higher density areas, where there are more people to share rides with. In this sense we expect SAV's to resemble public transit, which has a lower cost per passenger kilometer in higher density areas (e.g. Guera and Cervero, 2011). Simulations for the city of Lisbon (ITF/OECD, 2015) reveal that in a city, a system of shared automated mobility services does indeed have short waiting times and only limited roundabout travel, as compared to a direct car trip.

[4] Public transit plays a key role in European cities, and its modal share is considerable, reaching 40% of the journeys in some cities (PBL,2016). In Dutch cities the modal share of public transit is somewhat smaller - 15% - because bicycle plays an important role in urban transportation (KIM, 2018). The automation of public transit can have important effects on the attractiveness of cities.

[5] Car transport automation may also lead to concentration of land use by freeing up considerable parking space in city centers (Anderson et al., 2014, Zakharenko, 2016) 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 primary mode of commuting. In most European cities the impact of public transit automation on land use may be more significant.

[6] LUCA is described in detail in Teulings et al. (2018). This LUTI model was specifically designed to study the effects of transportation developments on population distribution, land prices and welfare in the Netherlands. LUCA is a computable general equilibrium model in which all parameters have been estimated from real data. The model was applied to analyze the effects of (i) railway tunnels under a waterway that cuts the Amsterdam region in two parts (Teulings et al., 2018); and (ii) a car tunnel connecting two islands in the West of the Netherlands (Ossokina et al., 2014).

benefits due to relocation of population and changes in land use. The latter effects are related to the so-called wider benefits of transport infrastructure (e.g. Laird and Venables, 2017).

This paper relates to several streams of the literature. The first examines the possible effects of vehicle automation on various aspects of mobility. Meyer et al. (2017) provide a comprehensive literature overview of the impact that autonomous vehicles could have on aspects such as travel experience, generalized travel costs, road capacity, travel demand, road safety, energy demand, emissions and accessibility. Additionally, some recent papers examine the implications for operational capacity (Chen et al., 2017), traffic delays and congestion (Correira and Van Arem, 2016, Berg and Verhoef, 2016). For the subject of this paper, the most relevant studies are those that focus on how automation technology impacts land use. Zakharenko (2016) considers a single city and shows how self-driving cars lead to longer commuting distances, a larger sized city due to urban sprawl, increases in property rents in the city center and decreases in the periphery. Anderson et al. (2014) predict that car automation will compel people to travel more, increase city sizes and reduce residential density. Litman (2018) and Heinrichs (2016) suggest that automation will lead to suburbanization, similar to how highways did in the 20th century. We contribute to this literature by (i) quantitatively analyzing the effects of automation for the entire country (not only for a single city), and (ii) comparing the effects of car automation and public transit automation trends, using a unified formal framework with parameters based on real data.

Second, a growing body of literature examines the effects that developments in transportation have on economic activity and the spatial distribution of population. Desmet and Rossi-Hansberg (2013) show that while better amenities and higher productivity lead to larger sized cities, higher congestion costs lead to smaller sized cities. Baum-Snow (2007, 2010) empirically reveals how highway construction in the United States in 1950-1980 led to the suburbanization of population and jobs. Garcia-Lopez et al. (2016) find that a similar effect occurred in Europe. Duranton and Turner (2012) estimate a model explaining the co-evolution of highways and employment. Teulings et al. (2017) detail how better railway connections between an economic center and its periphery can lead to relocation of jobs to the center and people to the periphery. Our paper examines the possible effects of automated driving technology.

Third, this paper is related to various studies based on LUTI (land use transportation interaction) models. These are primarily large, applied models that were developed to analyze the implications that large-scale investments in transportation infrastructure - new highways or new railways – have for land use and conversions of land from agricultural to urban functions. LUTI models often integrate a separate transportation model and separate land use model (for Paris, see De Palma, 2005, et al.; for Brussels, Jones et al., 2017; and for an overview, Van Wee, 2015). To the best of our knowledge, land use transportation interaction models have not yet been applied to studying the effects of automated driving technology. Further, the LUCA model differs from the standard models in four ways. First, LUCA was developed as a single model, in which agents simultaneously choose their home location, job location and transportation mode; consequently, consistent behavioral assumptions were made. Second, LUCA is a general equilibrium model, in which transportation changes result in a new equilibrium on the residential land market. As such our model is closely related to RELU-TRAN, the Anas and Liu (2007) general equilibrium model. Compared to other spatial general equilibrium models, LUCA is highly transparent, 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, thereby allowing the monetary welfare effects of transportation developments to be calculated endogenously. Fourth, LUCA allows to clearly distinguish the effects of transportation developments that are due to changes in generalized transportation costs and modal split, from those due to relocation of population and changes in land use.

Finally, our paper is related to policy studies that use scenarios to simulate long-term economic and spatial developments, a practice widely used in policy analysis in the Netherlands and other developed countries. The most recent Dutch scenarios for economic and spatial developments were published in 2015 (CPB/PBL, 2015), but they did not explicitly model the consequences of automated driving technology. The KiM Netherlands Institute for Transport Policy Analysis (KiM, 2015) has developed the qualitative scenarios for self-driving cars that are used as a baseline for the research in this paper. Rand Corporation (Rohr et al., 2016) has developed qualitative transport scenarios for the UK; automation technology plays a role in one of those scenarios. Milakis et al. (2017) developed scenarios for self-driving cars in the Netherlands; however, they do not allow for a spatial dimension.

Summarizing, our main contribution to the literature is as follows. We show what effects vehicle automation can have on population distribution and welfare, quantifying these effects by means of a computable general equilibrium model. We compare the implications of car automation and public transit automation forces, and study the effects of their interaction.

The remainder of the paper is structured as follows. Section 2 discusses the conceptual background, scenarios and assumptions. Section 3 explains the methodology and formally describes the LUCA model's main mechanisms and assumptions. Section 4 explains the simulation design. Section 5 presents the simulations' quantitative findings. Section 6 presents a discussion, and Section 7 provides final conclusions.

2 Conceptual background: scenarios and assumptions

The six different scenarios used in this paper were inspired by various KiM Netherlands Institute for Transport Policy Analysis (2015, 2017) research studies. The scenarios differ according to:
- the level of automation technology: (1) high automation and (2) full automation,
- the main automation component: (A) CAR automation, (B) PT - Public Transit - automation, (C) a combination of CAR and PT.

This section discusses the definitions and assumptions of the six scenarios presented in Table 1.

Table 1. Six scenarios

	High automation (1)	Full automation (2)
Public Transit component	**PT1** Faster PT trips, lower access, egress and waiting times	**PT2** Fully autonomous SAV, door-to-door mobility service
Car component	**CAR1** Hands off the wheel outside city, enhanced travel experience in extra-urban situations	**CAR2** Fully autonomous PAV, enhanced travel experience all trips
COMBI	**COMBI1** = **PT1 + CAR1**	**COMBI2 = PT2 + CAR2**

SAE International (2014) distinguishes five levels of automation: driver support (Level 1), partial automation (Level 2), conditional automation (Level 3), high automation (Level 4) and full automation (Level 5). The higher the level of automation, the less important the role of the human driver. Our scenarios focus on Level 4, in which automated vehicles are able to drive autonomously under well-defined circumstances, and Level 5, in which the automated driving system can perform all driving tasks under all circumstances without any human intervention. The scenarios combine these two levels of automation and additional assumptions about car and public transit automation, as based on the literature.

<u>High automation (based on Level 4 SAE)</u>

The car component in high automation is similar to Meyer et al. (2017), with technology allowing cars to drive autonomously under well-defined circumstances. On roads with well-marked, separate lanes, self-driving cars can adjust their speeds to the flow of the traffic, change lanes and overtake, give way to merging traffic, etc. However, vehicles cannot operate autonomously on narrow streets where other modes (pedestrians, bicycles, buses) interact with the flow of cars, or in complex, unclear traffic conditions. We therefore assume that in this world substantial numbers of people drive ‘hands free’ in extra-urban situations, both on highways and other roads. The driver must resume control when outside the city in exceptional cases the automated system signals that it falters, and once the car enters the city. When the car is controlling the driving actions in traffic, the driver can engage in other activities. Consequently, in extra-urban situations, drivers may perceive a lower cost of driving time, although this is not the case in cities. Further, drivers must remain seated in confined spaces behind steering wheels.

High automation in public transit pertains to driverless trams and metros travelling on separate trajectories. Driverless pod-/bus-systems operate on fixed routes in cities and between main public transit hubs, such as stations and university campuses. ICT systems support passengers with up-to-date, personalized travel information. Lower costs allow for higher frequency, which, when combined with better travel information, considerably reduces the out-of-vehicle (waiting) time. Similar to the conventional public transit, automated transit is of higher quality in cities than in less urban environments.

Full automation (based on Level 5 SAE)

In this scenario automation technology has reached the highest level of development imaginable today. Transportation looks quite different from what we are used to at present, with considerable parts of it likely having been replaced by door-to-door mobility services delivered by autonomous vehicles and supplied by fleet-owning companies (KiM, 2015). Scheduled services, like trains and metros, only continue to operate on very dense transport links. On all other links, shared-ride or privately-ridden autonomous vehicles (SAVs or PAVs) have replaced buses, trams and private cars. In cities where bicycles claim a considerable modal share, autonomous vehicles also compete with bicycles. In this scenario, automated vehicles operate without steering wheels and other driver controls, and these vehicles are able to navigate autonomously and safely in all traffic conditions, both on highways and in cities.

We model the car component here as a PAV and the public transit component as a SAV.[7] Compared to conventional cars, PAVs offer an enhanced travel experience, because drivers no longer need to participate in the driving process, and consequently can use the time spent in the vehicle for other tasks or leisure. A SAV offers much faster and more frequent transportation than conventional public transit. It is not restricted by fixed schedules and routes, but is demand-responsive and door-to-door. Travelers no longer need to walk to bus stops or make line transfers. Moreover, SAVs travel along largely direct routes to their destinations, only making detours to pick up or drop off other passengers. Such detours are relatively short, especially in cities, where the high population density allows ICT systems to very efficiently allocate passengers (ITF/OECD, 2015). SAVs can offer faster and more frequent trips in more densely populated areas than in less densely populated areas.

Other assumptions

In full automation, PAVs and SAVs take passengers to their destinations and then proceed to pick up other passengers, or, alternatively, to return to their designated parking places, which are situated outside of residential or working areas. In the cities, conventional parking lots and parking fees disappear. In this paper we assume that, in order to ensure quality of life, cities will introduce other traffic reducing policies - such as e.g. road pricing schemes[8] - that will have similar effects to the parking fees currently used today. Additionally, fleet owners will likely make trip fares time-varying, adjusting them according to transport demand and inner city capacity during peaks hours, which will also serve to limit the growth of urban traffic.

Automation technology will likely have a positive impact on road capacities and relieve congestion. This effect on congestion and travel times will however be counteracted by an increase in travel demand, particularly among the user groups currently lacking access to cars (the elderly, handicapped, children, etc.) Using the Swiss national transport model, Meyer et al. (2017) found that when non-urban roads are filled with cooperative, fully self-driving vehicles, road capacity might improve by 80% to 270%. The reason is

[7] This paper does not consider ownership issues, but it is logical to assume that SAV's will be owned by fleet owners, while PAV's can be both owned by fleet owners and by individuals (see e.g. Stocker and Shaheen, 2017).

[8] Another reason why cities might want to introduce such policies is that parking fees currently account for a considerable part of the municipal budgets and it is likely that cities will try to compensate for the disappearance of the fees.

that cooperative vehicles can drive closer to each other than traditional vehicles, thus increasing road capacity. The LUCA model used in this paper abstracts from modelling road capacity and congestion, while disregarding the feedback effects that automation has on travel times. In Section 6.2 Limitations, we discuss how relaxing this assumption would impact our findings. Further, with its focus on land use, our paper can be regarded as complementary to the analysis in Meyer et al. (2017), who focus on accessibility.

Finally, assumptions are needed about the autonomous developments in population towards a future in which vehicle automation is fully developed. KiM (2017) argues that this may take quite some time. A recent scenario study, 'Welfare and physical environment' (CPB/PBL, 2015), models the spatial developments in the Netherlands for 2012-2050 in two scenarios, high and low. In these two scenarios, population growth and urban growth vary: population increases in the high scenario, and decreases in the low scenario. Urban population increases in both scenarios, but more in the high scenario. Because of the large degree of uncertainty, in our research we set the autonomous developments in population to zero. To keep the calculations transparent, we also set urban dynamics to zero, with the current situation (base year 2011) serving as the simulations' starting point. We compare the size of our population relocation effects with the effects from the mentioned scenario study (CPB/PBL, 2015).

3 Methodology

To simulate the effects of automated driving on population distribution and land use, we use LUCA, the Dutch spatial general equilibrium model (Teulings et al., 2018) that belongs to the type Land Use Transportation Interaction models. LUCA models the individual choices that workers make pertaining to their home locations, job locations and commuting modes, and the implications such choices have for land use. The model distinguishes some 3,000 home and job locations (four-digit postal codes),[9] and four transportation modes, namely, car, train, bus/tram/metro and bicycle/walking. A key difference between LUCA and its peer models is that LUCA includes data on land prices and is capable of modelling an equilibrium in the residential land market. Information about land prices allows to calculate the welfare effects of various developments in transportation. Furthermore, LUCA allows to distinguish between (i) welfare benefits that are due to modal split and improvements in generalized transportation costs, keeping the distribution of the population fixed, and (ii) the benefits due to changes in population distribution and land use.

LUCA, which is based on micro-economic premises, models the behavior of four types of agents: three types of consumers who differ in their levels of educational attainment (low, middle and high), and land owners. Consumers choose where to live and work and how to commute, and land owners rent housing to consumers. Below we discuss: the model's setup (3.1), the main equations (3.2), the equilibrium, counterfactual simulations and calculation of welfare effects (3.3), and the model's parameters (3.4).

[9] A four-digit postal code in the Netherlands contains some 1,500 houses, and in cities spans an area of approximately one square kilometre.

3.1 Model set up

We consider a country with N individuals i. Each individual is endowed with an education level s: low, middle or high. There are N_s individuals of education level s, so that $\sum_s N_s = N$. The country contains H locations that are either indexed h for the home location of an individual, or j for her job location. Each individual has exactly one job. Within each location h, there are K_h houses. The number of houses is determined endogenously. Individuals choose to live in one of the houses $k \in K_h \text{ x } H$. Hence, by choosing a house k, an individual implicitly chooses to live in the home location h where that house is located and she chooses land consumption L_{ih}. Individuals also choose job location j. Finally, they choose a mode of transport m. It is convenient to define the combination of the three choices for a home, a job location and a mode of transport as one vector: $x = \{h, j, m\}$. The choice of x has a nested discrete structure, as described in Figure 1. Table A1 in Appendix A summarizes the main notation of the model.

When making the choice of x, the individual maximizes her indirect utility:

$$lnV_i[(x)] = \mathrm{v}(R_h) + \mu_{Ks}(\alpha'_s a_h + z_h) + \mu_{Ks}\mu_{Js}y_{sj} - \mu_{Ks}\mu_{Js}\mu_{Ms}\gamma'_s c_{shjm} + \varepsilon_{ikjm} \qquad (1)$$

where:

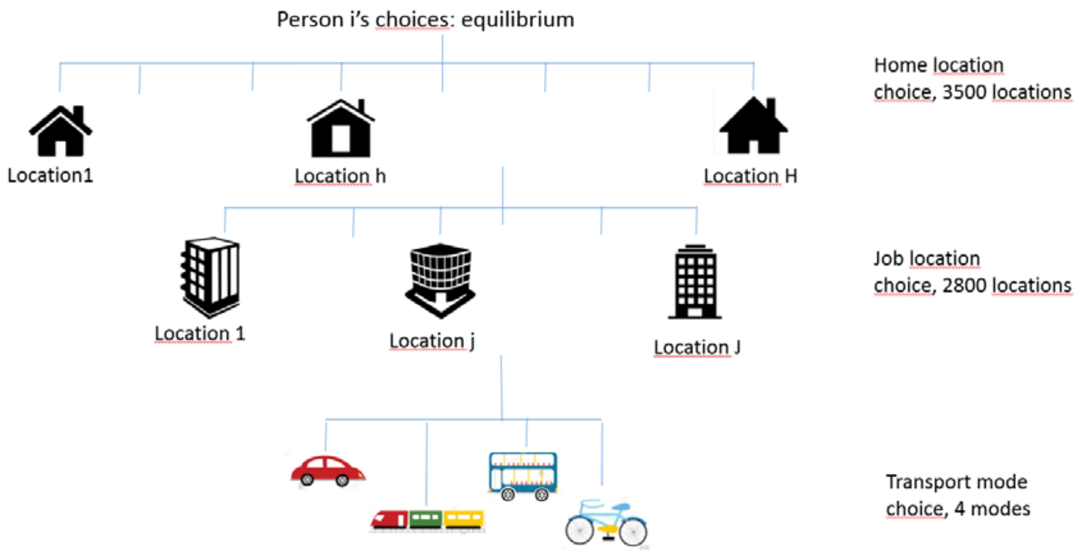
- R_h is the land price in location h and $\mathrm{v}(R_h)$ is a function of the land price,
- a_h and z_h are observed and unobserved home location amenities (such as e.g. parks, restaurants, cultural amenities, etc.),
- y_{sj} are job location amenities (such as e.g. availability of cafes or supermarkets near the office),
- c_{shjm} are characteristics of a trip between h and j with mode m (including time, cost, etc.),
- α, γ are parameters indicating the utility weight of home amenities, respectively commuting variables,
- $\mu_{Ks}, \mu_{Js}, \mu_{Ms}$ are parameters connected to the nested logit structure of the model,
- ε_{ikjm} is a Gumbel distributed error term that supports the nested structure described in Figure 1.

The land consumption L_{ih} in home location h is described by the following equation:

$$L_{ih} = -\mathrm{v}'(R_h)W_i(x) \qquad (2)$$

where $W_i(x)$ is the wage – net of commuting costs – of person i choosing a choice set x. For formal derivation of equations (1) and (2) from primitives, see Teulings et al. (2018).

Figure 1. Schematic representation of LUCA



3.2 Main equations of the model

Equation (1) allows for a simple interpretation of the utility function. Utility positively depends on the amenities an individual can enjoy in her home and job location, and negatively on the land price and commuting costs. Maximizing the indirect utility function (1) with respect to *x = {h,j,m},* we can derive the optimal value of the choice variable *x*. In a nested logit, nests can be solved sequentially (Ben-Akiva and Lerman, 1985); hence, we start with the choice of the transportation mode and then proceed to job location and home location choice.

Transportation mode choice

The probability of choosing transportation mode *m* from the set *M*, given that a person lives in *h*, works in *j* and has education *s*, is described by a standard multinomial logit (MNL) model:

$$\Pr[m|h,j,s] = \frac{\exp(-\gamma_s' c_{shjm})}{\exp(-c_{shj})} \tag{3}$$

$$c_{shj} = -\ln\left[\sum_{m\in M} \exp\left(-\gamma_s' c_{shjm}\right)\right] \tag{4}$$

where $-c_{shj}$ is the logsum of the transportation mode choice model. The logsum reflects the expected value of the generalized commuting costs for an individual of education *s* living in *h* and working in *j*. Note that for all modes, c_{shjm} are modelled in terms of travel time- and cost- related attributes of a trip. To keep the model transparent and to be able to incorporate the welfare analysis and the land market equilibrium, LUCA does not make explicit assumptions about specific routes, vehicle capacity, etc.

Job location choice

The probability of choosing job location *j* from the set H, given that the agent lives in *h*, is described by a standard MNL model:

$$\Pr[j|h,s] = \frac{\exp(y_{sj} - \mu_{Ms} c_{shj})}{\exp(g_{sh})} \tag{5}$$

$$g_{sh} = \ln\left[\sum_{j \in H} \exp\left(y_{sj} - \mu_{Ms} c_{shj}\right)\right] \tag{6}$$

where $\mu_{Ms} c_{shj}$ is the contribution of the generalized commuting costs c_{shj} to the utility of working in *j*, and g_{sh} is the logsum of the job location choice model. The logsum measures the option value of finding a job for someone living in *h* and is thus a generalized job accessibility measure.

Home location choice

The third logit model describes the probability of choosing home location *h* from the set *H*:

$$\Pr[h|s] = \frac{\exp(v_{sh} + lnN_h)}{\exp(v_s)} \tag{7}$$

$$v_{sh} = \mu_{Ks}^{-1} v(R_h) + \alpha_s' a_h + z_h + \mu_{Js} g_{sh} \tag{8}$$

$$v_s = \ln\left[\sum_{h \in H} \exp(v_{sh} + lnK_h)\right] \tag{9}$$

where K_h is the number of houses in *h*.

3.3 Land market equilibrium, counterfactuals and welfare analysis

Using (3)-(9) one can predict the demand for houses in each location *h*:[10]

$$N_h = \sum_{s \in S} N_s \Pr[h|s] \tag{10}$$

Similarly, the model can also predict the number of jobs per job location *j*, and the total number of kilometers travelled using different transportation modes.

In equilibrium the land prices R_h must be such that the total demand for land at location *h* equals the total supply of land. The supply of residential land in each location is exogenously given as: A_h. The demand for land can be calculated from equations (2) and (10) as: $N_h \bar{L}_h$, where $\bar{L}_h$ is the average land consumption in *h*.

The initial (current) equilibrium is described by the observed values of N_s, R_h and A_h. Starting with these and using the model's parameter estimates (see Section 3.4), we can run counterfactual simulations. In this paper the transportation modes' characteristics are adjusted in the counterfactuals. In the first place this affects $\Pr[m|h,j,s]$ in equation (3) and $W_i(x)$ in equation (2). Ultimately, it has an impact on the demand

[10] In equilibrium, this demand for houses in *h* equals the – endogenously determined - number of houses in location *h*, K_h.

for land $N_h\bar{L}_h$ in different locations *h*, resulting in a wedge between demand and supply of land. To arrive at a new equilibrium, land prices are adjusted until the demand and supply for land in each location *h* becomes equal again. The new equilibrium yields a new number of houses K_h in location *h.*

Using the above inputs, LUCA allows for simulating the effects that transportation improvements have on the spatial distribution of population and jobs, land use and land prices. In this simulation, individual workers choose where they want to live, conditional on land prices, residential amenities and the transport accessibility of jobs. In each iteration the model sums up individual demand for housing and land to the total demand for land at each location, and confronts it with supply. Hence, demand for housing is endogenous and follows from the model. LUCA therefore is perfectly suited for modelling the impact that transportation improvements have on land markets and people's residential choices. Consecutively adjusting land prices allows the model to converge to a new equilibrium, equalizing the demand for and supply of land.

LUCA allows for calculating the welfare effects of transportation developments. Table 2 reports formulae for these effects, where superscripts *n/o* indicate the values of the variables in the new/old equilibrium, and W_s is the wage of education level *s*. The first line reports the welfare benefit from the changes in modal split and from the improvement in generalized transportation costs, keeping the location of homes and jobs fixed. The second line also includes the effect from people choosing other home and job locations that yield them higher utility, and from the consecutive changes in land use and land prices. The difference between the two lines is equal to the (wider) benefits from changes in the population distribution and land use. For further details see Teulings et al. (2018).

Table 2. Welfare effect calculation

Effect	Expression
Transportation improvement only	$\mathrm{W}_s\mu_{Ks}\mu_{Js}\mu_{Ms}\sum_{h\in H}\sum_{j\in H}\Pr[hj\|s]\,\gamma_s\,(c^n_{shj}-c^o_{shj})$
Total effect including relocation of population and jobs	$\mathrm{W}_s\mu_{Ks}(v^n_s-v^o_s)$

3.4 Parameters of the model

The model's parameters were estimated based on the home, job and commuting choices data of 60,000 Dutch employees (see Teulings et al., 2018, for a detailed discussion), as well as postal code data pertaining to land prices and amenities, as provided by Statistics Netherlands. The model distinguishes some 3,000 home and job locations, defined on the level of a four-digit postal code, and four modes: car, train, bus-tram-metro and bicycle/walking. The base year is 2011.

Table 3 details the estimated parameters of the modal split equations (3)-(4) and Table 5 the estimated parameters of the home location choice logit (7)-(9). These parameters are most relevant for this study, as some will be adjusted in the simulations. For the model's other parameters, see Teulings et al. (2018).

In the modal split equations, the main parameters are coefficients of the variables time and cost of the trip. These are mode-specific. The general time coefficient in panel A of Table 3 can be interpreted as the coefficient by the car mode. Coefficients by other modes are reported in deviations from the car coefficient. Further, the coefficients for bus-tram-metro and train differ between in-vehicle time and out-of-vehicle time.

Table 3. Parameters modal split

Panel A: General variables	Coef	t-val						
Cost in % of net wage	-12.24	(8.6)						
Time (minutes/10)	-0.26	(20.0)						

Panel B: Alternative specific variables	Car[a]		Train		Bus		Bike	
	Coef	t-val	coef	t-val	Coef	t-val	coef	t-val
Δ time in vehicle (minutes/10)	--	--	0.18	(15.5)	0.07	(5.6)	-0.19	(13.7)
Δ time out of vehicle (minutes/10)	--	--	0.00	(0.0)	-0.15	(4.8)	--	--
Intercept	--	--	-1.57	(14.7)	0.03	(0.3)	0.62	(19.2)
Δ intercept high educated	--	--	0.58	(11.6)	-0.00	(0.1)	0.53	(16.9)
Δ intercept low educated	--	--	-0.48	(6.7)	0.01	(0.1)	-0.11	(3.4)
Parking cost at home[b]	-4.18	(15.8)	--	--	--	--	--	--
Parking cost at job[b]	-2.54	(18.0)	--	--	--	--	--	--
Access distance train (km/10)	--	--	-0.40	(9.7)	--	--	--	--
Egress distance train (km/10)	--	--	-0.52	(7.8)	--	--	--	--
Urbanization at home location	--	--	--	--	0.26	(15.2)	--	--
Urbanization at job location	--	--	--	--	0.29	(17.0)	--	--

[a] Car mode is taken as a reference. So the coefficient by time in a car is equal to the general coefficient by time reported in panel A of the table; the intercept (mode-specific constant) for a car is set to zero. Coefficients by time in other modes can be calculated as a sum of the time coefficient in panel A and Δ time coefficients in panel B. Idem for the mode intercepts.
[b] Measured as land rent divided by the wage income, in %.

Table 4. Implied values of time (euro/hour)

Education	Low	middle	high
Car time	12	14	19
In-vehicle time train	4	5	6
Out-of-vehicle time train	12	14	19
In-vehicle time bus	9	10	14
Out-of-vehicle time bus	18	22	29

Table 4 details the values of time implied by these parameters. The figures are reasonably close to the values of time specified in the Dutch government's official guideline for cost-benefit analysis (Significance et al., 2013). The in-vehicle time value is higher for the car mode than for public transport; this reflects the higher effort car driving involves. The out-of-vehicle (waiting) time is perceived more negatively for the bus than for the train mode; this reflects the more comfortable waiting environment a train station offers, as compared to a bus/tram stop. The intercepts (mode-specific constants) differ according to mode and the travelers' education levels; for example, highly educated travelers have a relatively strong preference for trains and bicycles, while low-educated travelers prefer these modes the least.

The utility function for trips with a car and with bus-tram-metro has a part that relates to the urban density of the home and job locations. For cars, land prices at home and at job locations enter utility, in order to account for parking costs.[11] The coefficients are negative and highly significant. For bus-tram-metro, the utility includes a variable indicating the degree of urbanization (scale 1 to 5). Statistics Netherlands provided this variable, which is based on the construction density of a given postal code. We include the degree of urbanization to account for the fact that public transit is of better quality in places with higher population and construction density. This better quality is not wholly reflected in shorter travel times. It also includes such factors as e.g. variety of modes (tram-metro is only available in denser urban areas),[12] reliability, etc. The urbanization variables have positive and highly significant coefficients.

The parameters of the home location choice model (Table 5) represent the utility weights of the home locations' various attributes; these coefficients determine the attractivity of different locations and consequently the distribution of the population across locations. As the table illustrates, the weights differ between education levels. Low-educated are most sensitive to land rents, and much less to the supply of urban amenities in a home location. Highly educated, on the opposite, strongly value amenities such as culture, restaurants, nature, and are relatively less sensitive to the level of land prices.

Table 5. Parameters home location choice

Education level	Low [a]		Middle		High [a]	
Variable	coef	t-val	coef	t-val	Coef	t-val
(transport) accessibility of jobs[b]	0.63	(10.6)	0.44	(7.4)	0.42	(6.7)
(transformed) land rent	9.77		6.80	(21.4)	4.37	
# monuments 1km/1000	0.26		0.40	(9.2)	0.32	
# monuments 1-5km/1000	0.07		0.09	(7.7)	0.11	
share nature within 5km	0.07		-0.02	(0.6)	0.32	
dum. university in 10km	-0.07		-0.07	(3.3)	0.07	
# restaurants 1km/100	0.09		0.44	(7.4)	0.54	
# restaurants 1-5km/100)	0.11		0.05	(5.2)	0.03	

[a] The parameters reported without a t-value have been computed using the two-step approach as in Bayer et al. (2007), see Teulings et al. (2018) for the details.
[b] This variable is defined in equation (6); it contains the transport logsum (4), computed using the coefficients from Table 3.

4. Simulation design

LUCA was developed specifically to analyze the effects of transportation developments on population distribution and land prices in the Netherlands. We use the model to quantify the automation scenarios described in Table 1. In LUCA, changes due to automation technology directly affect the variables c_{shjm}

[11] By including land prices, we account for both parking fees and the scarcity of parking spaces. Locations with a scarcity of land command higher land prices. These locations also tend to have both higher parking fees and fewer parking spots.
[12] See Hensher and Mulley (2015) and the references therein.

(equation (3) and (4)). The full set of $\{c_{shjm}\}$ is an origin-destination matrix describing the trip characteristics of all possible combinations of home location *h*, job location *j* and transportation mode *m*, see Table 3 for the list of trip characteristics. In this paper, car automation and public transit automation are modelled by adjusting respectively the parameters of the car transportation mode and the bus-tram-metro mode reported in Table 3. We do not adjust the number of available modes (four) in the model, the main reason for which is that changing the number of alternatives in a choice set strongly affects welfare (Ben-Akiva and Lerman, 1985). To keep the welfare analysis transparent, we want to disregard welfare changes that are not connected to adjustments in the trip characteristics $\{c_{shjm}\}$. Table 6 below describes how automation scenarios are implemented in LUCA and shows which parameters are adjusted.

Table 6. Parameters scenarios in LUCA

	High automation	Full automation, mobility as a service
Public transit automation	**PT-1**	**PT-2**
In-vehicle travel time bus/tram/metro[13]	unchanged	set to 1.2 times the current travel time of the car
Out-of-vehicle travel time bus/tram/metro	reduced by 20%	set to 0
Access / egress 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, for trips longer than 5 km
which reduces the perceived cost of time in a car (VOT in a car) by	5%, for trips longer than 15 km	20%, for trips longer than 5 km
COMBI	**COMBI-1 = PT-1 + CAR-1**	**COMBI-2 = PT-2 + CAR-2**

High automation

Various studies argue that in a fully autonomous car, the value of time (VOT) may be 20% lower than its current value (see e.g. Kouwenhoven and De Jong, 2017 and the references therein). In the high automation scenario however, the driver must remain in the driver's seat, ready to take control when exiting the highway or when the automated system falters. Our simulation accounts for this by using one-quarter of the full automation VOT reduction (5%). Moreover, in the high automation scenario, the enhanced car travel experience applies to extra-urban roads only, which is approximated in the model by reducing the cost of driving time only for trips longer than 15 kilometers (see CAR-1 in Table 6).

To model a shift to faster and more frequent public transit, the out-of-vehicle (waiting) time of the bus-tram-metro mode is reduced by 20%. The same percentage reduction is applied to the access and egress coefficients for trains, because in LUCA travel time reductions in feeding modes do not automatically translate into a reduction of train access and egress times (see PT-1 in Table 6). To keep the simulations

[13] The adjustments in the bus/tram/metro travel times apply to all trips and not only the first/last mile.

transparent, we assume that the modes' out-of-pocket (monetary) costs do not change in the automation scenarios. All adjustments occur via the travel time variables.

Full automation

In full automation, cars and bus-tram-metro both meld into autonomous vehicles. Our simulation assumes that cars will be replaced by PAVs. Bus-tram-metro will be replaced by automated transit: mostly SAVs, and on links with very dense flows by automated rail-bound services (metro or light rail).[14] For PAV, we assume that the value of driving time (VOT car) decreases by 20% for trips longer than 5 kilometers (see CAR2 in Table 6). Reason to use a threshold of 5 kilometers is that, for very short trips, it is unlikely that passengers will benefit much from the ability to engage in various activities during the trip. To model a shift to SAV, the bus-tram-metro mode's in-vehicle travel time is set as equal to the car travel time, plus a 20% detour/waiting time; the out-of-vehicle time is set to zero.[15] The SAV total travel time in full automation therefore equals 1.2 times the current car travel time. By linking the SAV travel time to the car travel time, we aim at modelling the door-to-door demand-responsive mobility services SAVs provide in the full automation scenario. On few very dense trajectories automated metro and light rail services remain. We assume that people optimally make a choice between these rail-bound services and SAV; trips made with rail-bound services are therefore assigned a travel time equal to 1.2 times the car travel time as well.[16] Finally, the access and egress coefficients for train trips are set to half their current value, other train parameters remain unchanged. See PT-2 in Table 6. In Section 6.1 we run a sensitivity analysis to the above parameters, in which VOT- and time gains in full automation are assumed to be smaller.

LUCA's other parameters remain unchanged in the simulations, including the parameters relating to the urban density of home and job locations (see Section 3.4). This feature of the model deserves additional discussion, as it implies that, in more densely populated areas, the quality of SAV provision is higher, and the cost of using a PAV higher, *ceteris paribus*. Reasons for this may include city policies aimed at reducing traffic and the scale economies of shared transportation (see Litman, 2018, and Section 2 of this paper). In other words, keeping the travel time equal, a shared transportation mode is therefore assumed to be relatively more attractive in urbanized regions than a private transportation mode, in the same way that this holds for conventional cars and public transit. There may of course be other ways to model this characteristic of the transportation system; however, given the large uncertainty about future automation developments, the simulation was based on the most transparent and computationally easy approach.

[14] Hence, our assumptions imply that door-to-door automated transit replaces conventional urban transit, except for a few metro/ light rail lines. Note that in the Netherlands a major part of high density public transport takes place by train between the large cities in the Randstad (see the map in Figure 2 Section 5).

[15] Using SAVs will imply some waiting time between ordering the service and boarding it. Under a reasonable assumption that this time is valued equally to driving time, we do not model it separately. In the ITF/OECD (2015) Lisbon ride sharing simulations, detours increase the number of kilometers travelled by 6%. Waiting time for ride shared services amounts to 3.7 minutes. ITF capped the total allowable increase in door-to-door trip time, including waiting, at 20%. Our assumptions are in line with these simulation results.

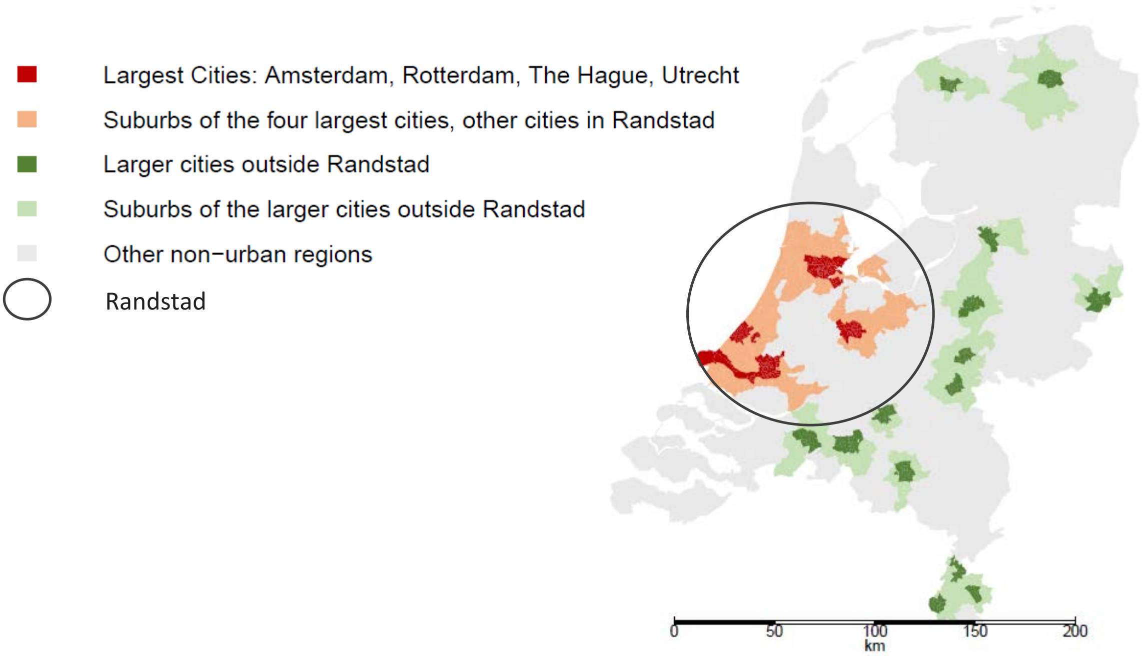
[16] Those for whom the travel time with the metro is longer will take an SAV.

5 Results

In LUCA, automation affects the behavior of economic agents through several channels (see also Section 3). First, agents enjoy more comfortable and quicker trips. Second, the attractiveness of different residential locations may change due to an increased transport accessibility. As discussed above, due to the private car automation component, suburbs and non-urbanized locations become relatively more attractive. Cities become relatively more attractive due to the public transit automation component. Consequently, in the new equilibrium with automation, both the modal split and population distribution across the country differ from that in the reference scenario. Section 5.1 discusses the results for modal split; Section 5.2 examines population relocation and land prices; and Section 5.3 provides insights into the welfare effects of these changes. The effects of automation are reported in comparison to the reference scenario (see Section 3.4).

In reporting the outcomes, we distinguish a number of non-contiguous regions, ordered by their degree of urbanization according to Statistics Netherlands' classification (see Figure 2). These are: (i) the 4 largest cities: Amsterdam, Rotterdam, The Hague and Utrecht – plotted in dark red; (ii) the suburbs of these four cities, as well as other larger cities in the urbanized western region of the country, called the Randstad – in light red; (iii) larger cities outside the Randstad – in dark green; (iv) suburbs of the larger cities outside the Randstad – in light green; and (v) other non-urban regions - in grey.

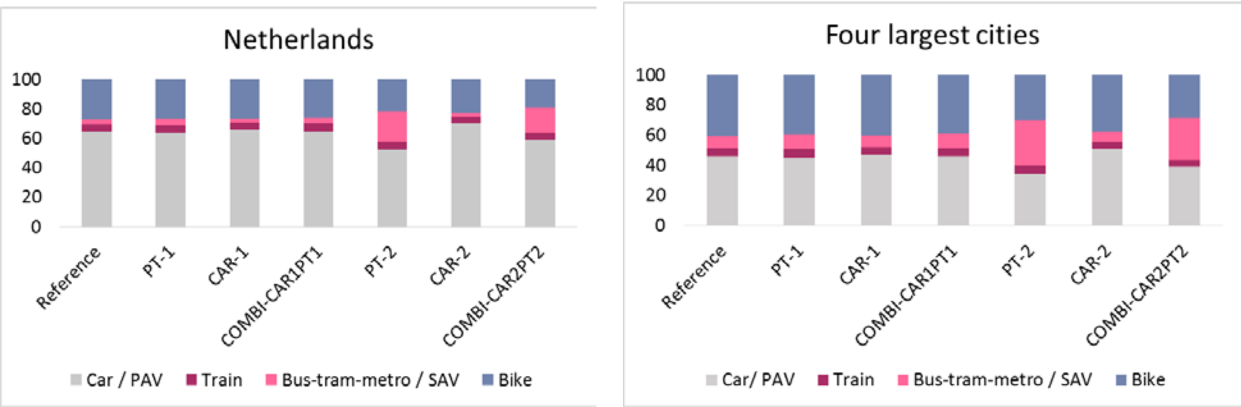
Figure 2. Regional division of the Netherlands



5.1 Effects of automation on modal split

Figure 3 presents the modal shift in the six scenarios presented in Table 6, for the Netherlands and the four largest cities. Zooming in on the largest cities is informative, as they differ considerably in the reference scenario's modal split, having relatively large shares of bicycles and public transit as compared to the country's average.

FIGURE 3. MODAL SPLIT BY SCENARIO, NETHERLANDS AND FOUR LARGEST CITIES



In high automation, the modal split does not change much, reflecting the relatively modest adjustments in the characteristics of the modes. PAV has approximately the same share as the conventional car, while SAV has a similar share to conventional public transit. In full automation, however, there are considerable shifts. Consider the COMBI2 scenario. Most prominently, SAV's share[17] increases compared to conventional public transit, while PAV's share is lower compared to the conventional car. SAV's increased share comes partly at the expense of the PAV and partly at the expense of bicycles, which is a popular mode in the Netherlands, especially in cities.[18]

Note that the reported changes in the modal split result from the two mechanisms described at the start of this section: (i) changes in the travel characteristics and (ii) relocation of people to other home locations. In the next section we will closely examine where people relocate to. Table 7 below illustrates that relocation results in a longer average distance between the home and job locations. This distance increases by around 5% in high automation and more than 25% in full automation. This occurs because vehicle automation lowers the generalized costs of transport, thereby inducing people to choose more remote home and job locations. In high automation, longer commutes largely result from the PAV component. In full automation, both PAV and SAV contribute to longer trips.[19] Longer commutes partly explain why the bicycles' share decreased in the modal split (Figure 3).

[17] This share includes the few metro/light transit lines.

[18] The resulting share of SAV in full automation (17% country average respectively 28% in cities) is in line with the results by Chen and Kockelman (2016) who predict a share of SAV between 14% and 39%.

[19] Note that shared automated vehicles (PT-2) make living in cities more attractive, yet at the same time raise commuting distances because within larger urban areas people live further away from their job locations.

Table 7. Percentage change in home-job distance.

High automation			Full automation		
PT-1	CAR-1	COMBI-1	PT-2	CAR-2	COMBI-2
0.7%	4.2%	4.8%	15.1%	16.8%	27.1%

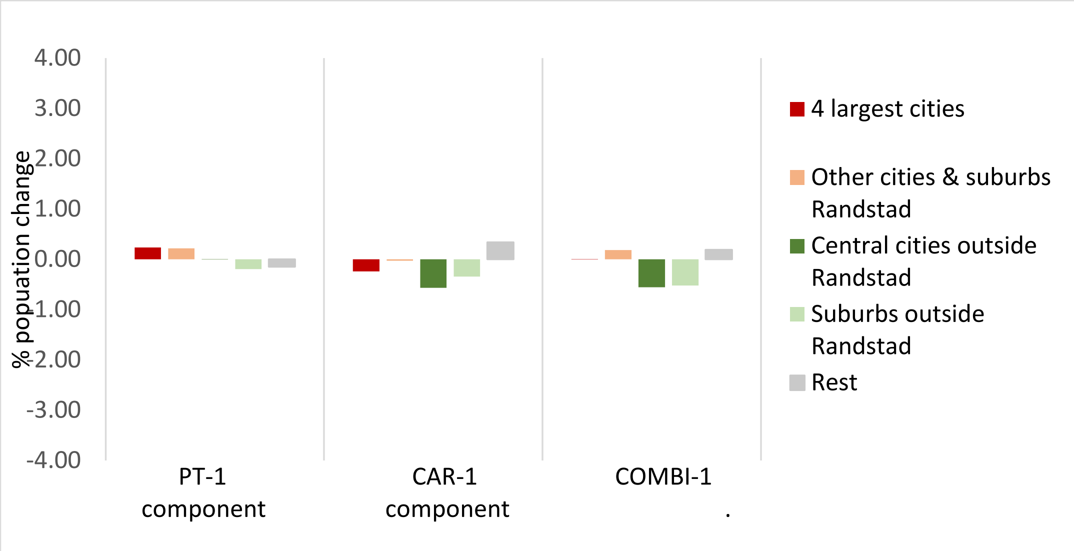
5.2 Effects of automation on population distribution

The figures below detail the population relocation effects in the high and full automation scenarios, aggregated for each of the five regions distinguished above. Let us first consider high automation (Figure 4 upper panel). The public transit and car automation components have opposite effects. Public transit automation (PT-1) attracts population to urbanized areas, especially to Randstad. This happens because of the cheap and fast automated transit that is feasible in higher density areas. The suburbs of the cities outside the Randstad, as well as the non-urban regions experience population loss. Private vehicle automation leads to suburbanization (CAR-1): cities lose population to suburbs and non-urban areas. This occurs because longer commutes become more acceptable. Smaller isolated cities outside the Randstad and their suburbs experience the largest population loss. The reason is that they are surrounded by extended and attractive non-urban areas, and that the urban amenities they offer are relatively limited. The combination of the car and public transit automation components (COMBI-1) results in a concentration of population in the cities and suburbs of the highly urbanized Randstad. Isolated cities and their suburbs lose population.

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 (Figure 4 lower panel). 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.

To put these effects into perspective, we compare the above results with the regional development scenarios for the Netherlands (CPB /PBL, 2015), which are widely used as input for national policy analysis and debate. In our calculation, the regional effects of full automation are between -3 and 3%. In the regional development scenarios, regional growth from 2012-2050 is between -10% and +30%, depending on the region and the assumptions made about economic growth and regional concentration or dispersion. Cities are expected to grow the most, and non-urban areas the least. When compared to those developments, population shifts due to automation could make a difference; for instance, they might increase the challenges the four largest cities and their suburbs face in accommodating population growth, and alleviate or eliminate such challenges for the cities outside the Randstad.

Figure 4. Population changes by region.
High automation



Full automation

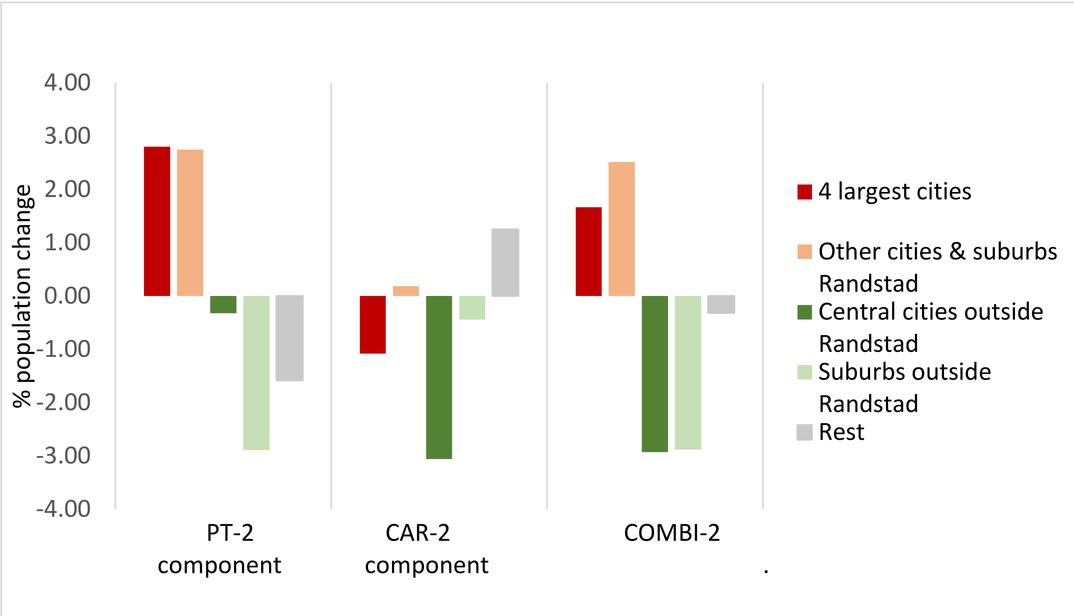
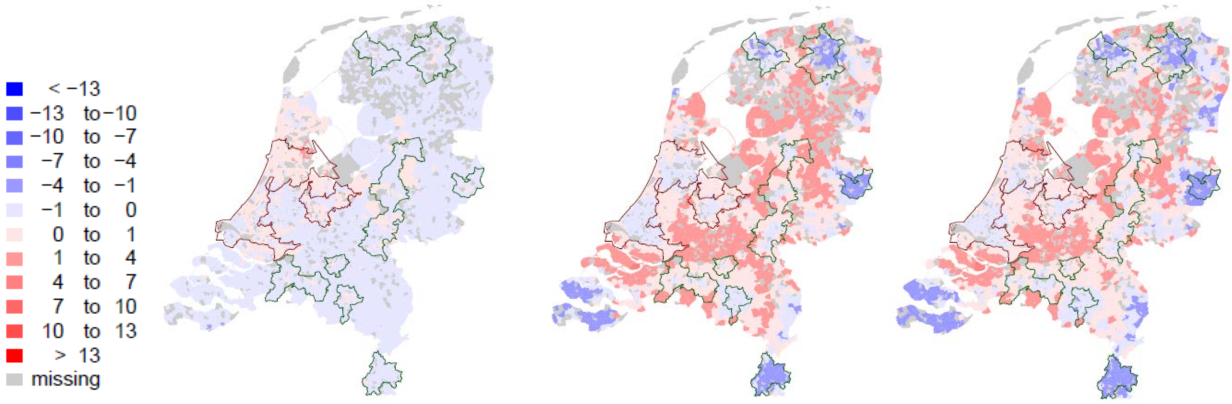


Figure 5. Population changes by zip code (in %).

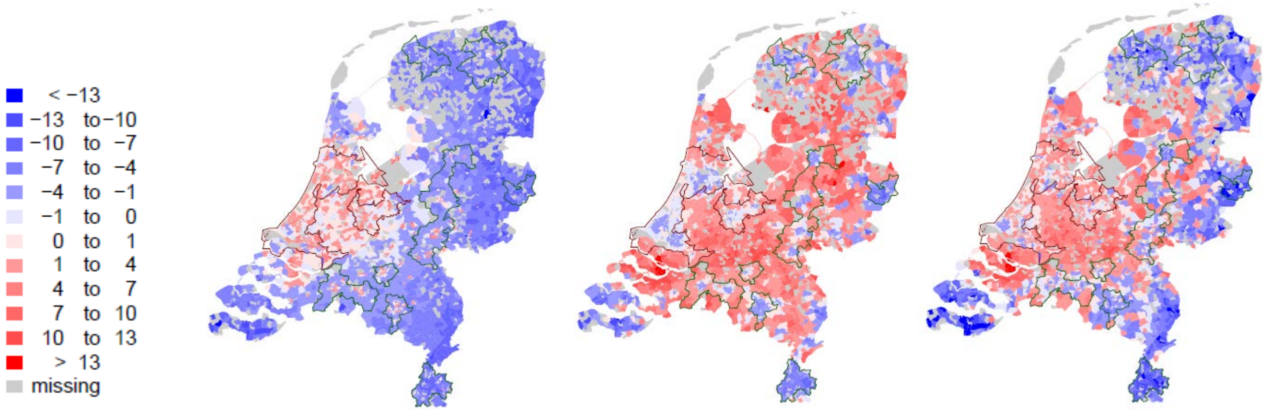
High automation

PT-1 CAR-1 COMBI-1



Full automation

PT-2 CAR-2 COMBI-2



The setup of LUCA allows for zooming in on the population relocation effects at the more detailed spatial level of a four-digit postal code (see Figure 5). This figure depicts the borders of the aggregated regions discussed above: red for cities and suburbs in the Randstad, and green for cities and suburbs outside the Randstad. Naturally, Figure 5 yields similar insights to Figure 4, while concurrently allowing for a more detailed study of the differentiated relocation effects in the less urban region (Rest). Here the area surrounding the urbanized Randstad stands out: in CAR and COMBI this area experiences considerable population growth, while in PT it experiences relatively small population decline. Conversely, the edges of the country are hit relatively harder by population decline, in PT as well as in COMBI.

The shifts in residential demand discussed above have implications for the housing and land markets. In the Netherlands – as in various other countries – cities have grown faster in recent decades than the rest of the country, which has led to an increasing divergence in housing prices between cities and less urban regions (see e.g. Gyourko et al., 2013). There is concern that such divergence could lead to a growing segregation between cities and non-urban regions. The CAR component offers a counterforce, which may somewhat relax the tight land markets in cities. The PT component however further increases the divergence.

5.3 Welfare effects

Table 8 details the welfare benefits, expressed in terms of yearly flows (see Section 3 for a discussion of how these benefits are defined). We distinguish the effects of (i) an enhanced travel experience and modal shift, due to faster and more comfortable trips with PAV and SAV; and (ii) relocation of population to other home and job locations and the consecutive change in land use. Part (ii) is a second order effect of PAV and SAV. Owing to the enhanced travel experience in a PAV, individuals can move to the attractive non-urban areas they always wanted to live in but could not do so because of the prohibitive costs of commuting to job clusters. This increases their utility. They can also switch jobs, choosing a job at a more distant but more productive location that yields a higher pay and a higher satisfaction. Owing to fast and frequent SAV services, commuting within urban regions becomes relatively much faster than in less urbanized locations, which increases both the absolute and relative utility of residing and working in a city. Residential relocations foster land redevelopment, allowing the land use to optimally adjust to the new situation and yielding additional benefits (see Teulings et al., 2018 and also Laird and Venables, 2017). Job relocations increase labour supply at most productive locations allowing the existing productivity and agglomeration benefits to be used more efficiently.

In the full automation scenario (COMBI-2), the total benefits amount to some 5 billion euro per year, or 0.7% of the Netherlands' GDP, while 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 greater travel comfort. Benefits due to relocation to other home and job locations equal 3% of the total welfare benefits in the high automation scenario and 10% in the full automation scenario. The major transportation improvements in full automation render it possible to achieve larger welfare gains by changing home or job locations.

TABLE 8. WELFARE EFFECTS
in bln euro, yearly effects

	High automation			Full automation		
	PT-1	CAR-1	COMBI-1	PT-2	CAR-2	COMBI-2
Transport benefits (i)	0.25	0.50	0.74	3.02	2.70	5.14
Relocation benefits (ii)	0.01	0.01	0.02	0.33	0.22	0.61
Total benefits: (i) + (ii)	0.26	0.51	0.76	3.35	2.92	5.75

6 Discussion

6.1 Sensitivity analysis

The scenarios described in the previous section rely on a considerable number of assumptions about future developments in vehicle automation. Because such developments are highly uncertain, it is important to test the robustness of the findings to the choice of assumptions.

This section contains two robustness checks, focusing on the COMBI-2 scenario:
(i) Travelling with autonomous public transit may not be as fast as assumed in COMBI2. To account for this, in this variant the trip duration with SAV equals 1.5 times the car trip duration, instead of 1.2 times the car trip duration in COMBI2.
(ii) Not all people may equally enjoy the enhanced travel experience in the autonomous car. For example, using a car as a workplace is less likely for people whose professions require face-to-face contact with other people, such as e.g. nurses or shop assistants.[20] We model this by assuming that highly skilled people experience a larger decrease of value of time in cars than people with other skill levels.

Table 9 summarizes these assumptions. Figure 6 reports the outcomes of the robustness checks, in a similar manner to Figure 4. For reference, the COMBI2 outcomes are also included in the figure.

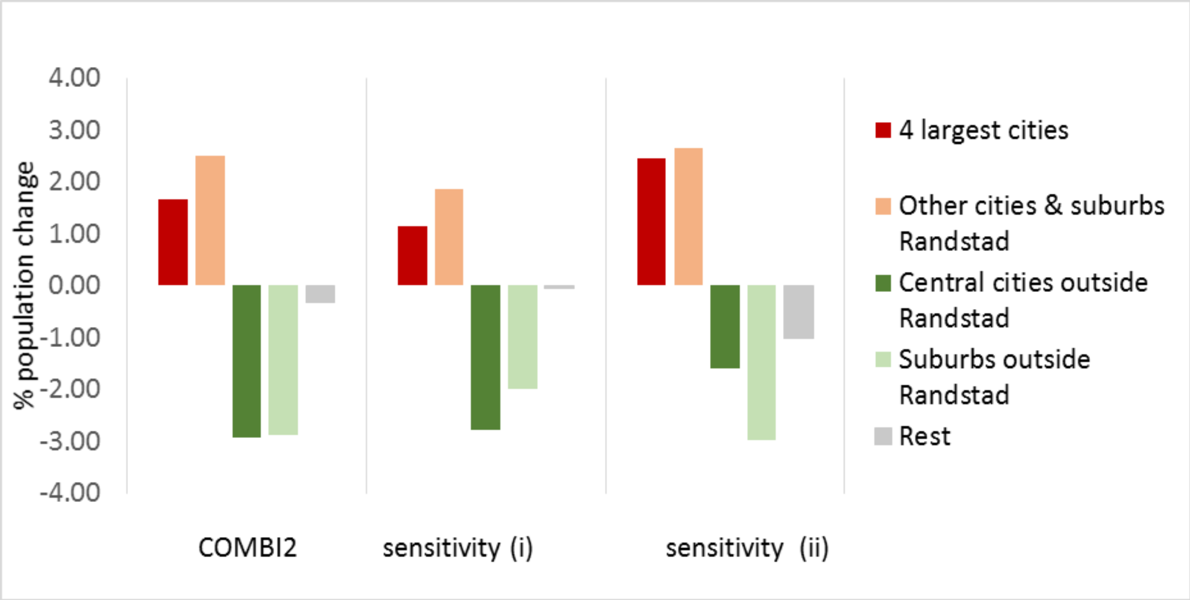
The robustness checks yield intuitive results. In scenario (i), with its smaller improvement in travel time due to SAV, the urbanization effect is smaller than in COMBI2, as is the population loss in less urbanized areas. In scenario (ii), with its differentiated enhancement of the travel experience in PAV, the urbanization effect is larger. In both robustness checks however, cities and suburbs in the Randstad gain population, while the isolated cities outside the Randstad lose population, as compared to the baseline. Hence, in light of these conducted robustness checks, the analysis' main conclusions are deemed to be robust.

Table 9. Parameters used in the sensitivity checks

	Sensitivity check (i)	Sensitivity check (ii)
Public transit automation	**PT-2a**	**PT-2**
In-vehicle travel time bus/tram/metro	set to 1.5 times car travel time	set to 1.2 times car travel time
Out-of-vehicle travel time bus/tram/metro	set to 0	set to 0
Access / egress train	reduced by 50%	reduced by 50%
Car transport automation	**CAR-2**	**CAR-2a**
Coefficient on travel time of the car	set to 0.8 times the current coefficient, for trips longer than 5km	For highly skilled set to 0.8 times the current coefficient; for other skill levels set to 0.9 times the current coefficient. For all skill levels VOT reduction for trips longer than 5km

[20] People may also face restrictions on travel time. E.g. if at the home location children must be brought to and picked up at a day care centre, longer travel times may be less feasible.

FIGURE 6. POPULATION CHANGES BY REGION. SENSITIVITY ANALYSIS. FULL AUTOMATION



6.2 Limitations

A general equilibrium model like LUCA provides a transparent and tractable analysis of the consequences that automated and autonomous driving may have for population distribution and land use; further, it allows for computing the associated welfare effects. Concurrently, the methodology entails a number of limitations and simplifications, including those pertaining to the workings of the transport market.

First, the analysis abstracts from feedback effects of automation on congestion and travel times. Meyer et al. (2017) argue that automation-induced increases in road capacity may vary between 80% and 270%. Even after accounting for the counteracting growth in travel demand, Meyer et al. find large net increases in accessibility, especially in rural regions, which implies that the analysis in Section 5 may underestimate the *suburbanization* effect. Concurrently, ITF/OECD (2015) Lisbon simulations reveal that ride sharing in multi-person automated vehicles reduces the fleet of vehicles in the city. In these simulations, all current trips made by cars and buses in the city can be replaced by a fleet of shared automated vehicles equal to some 10% of the current number of vehicles, while the number of kilometers traveled increases moderately with 6%.[21] Although these SAVs are used much more intensively than the current fleet, Martinez and Viegas (2017) show that accessibility of jobs within the Lisbon area improves considerably. Consequently, congestion in the city may decrease due to ride sharing automation, which would imply that the results of Section 5 underestimate the *urbanization* effect.

Second, the simulations above do not take into account that automation may free up parking spaces in city centers (Anderson et al., 2014, Zakharenko, 2016). Transforming existing parking places into residential

[21] Similar results were obtained for Helsinki and Auckland (ITF/OECD, 2017a and 2017b).

areas or green areas could make city life more agreeable. In the longer term, redesigning inner city districts without having to include parking facilities could ease residential land scarcity. Both mechanisms would attract more people to cities, strengthening the concentration effects in the LUCA scenarios.

Third, this paper focusses on the *use* of automated vehicles (private ride or shared ride); it disregards ownership issues. Privately owned vehicles will most likely be shared with relatives or close friends only. Compared to PAVs owned by fleet companies, privately owned PAVs could make more or longer trips empty of passengers and be used less intensively. Hence, a larger share of privately owned versus fleet-owned vehicles may increase traffic intensity within cities, thereby reducing the cities' attractiveness. It is however extremely difficult to predict to what extent vehicle ownership may change due to automation; this issue is one of the fundamental uncertainties in the KiM (2015, 2017) scenarios and transition paths.

Fourth, a number of simplifications may lead to underestimating the welfare effects of automation. The impact of automation on traffic safety is a major case in point. Automation will likely make both inner city and long distance traffic safer, this having among other things an impact on commuting and residential choice. Although it is difficult to state whether enhanced traffic safety will stimulate population dispersion or concentration, it will unambiguously yield additional welfare benefits. Further, LUCA's current version focusses on commuting trips only. However, trips with other purposes will also benefit from faster SAVs and the enhanced travel experience in PAVs, especially as automation will likely increase travel opportunities for children, the elderly and disabled, which will yield additional welfare benefits. Finally, it is likely that the *ceteris paribus* preference (as reflected in mode specific constants) for the PAV and SAV will be higher than for the conventional car respectively public transport. The reason is that both modes yield a higher comfort as compared to their conventional counterparts. This will also lead to higher welfare benefits of automation.

In summary, relaxing the limitations and simplifications of this paper's analysis would have various implications for population distribution and land use, and would certainly impact the size of the effects presented. Yet, the paper's main insights might be less affected, because the effects of relaxing the limitations on concentration and dispersion would be (partly) offsetting. It is however important to bear in mind that this paper's findings provide a first impression of a very complex phenomenon, and that vehicle automation raises many questions that remain open for future research.

6.3 Implications

This paper suggests that automated driving may lead to both population dispersion and population concentration. These effects become substantial when the technology reaches the level of full automation (SAE level 5). This result was obtained using a model calibrated for the Netherlands' spatial and transport structure. To what extent will our research findings apply to other countries?

The Dutch situation has some specific features, two of which stand out. First, the population size and density in the four Dutch cities comprising the Randstad, the county's polycentric urban region, have much smaller and less dense populations than other large metropolitan areas, such as Paris or London.[22] The insights derived from our research might not be directly applicable to metropoles with very high population density, because in such metropoles inner city congestion could restrict the use of automated vehicles, whereby the metro system will remain essential for inner-city travel. The size and population density of Dutch cities is however largely comparable to that of many other medium-sized European cities, and for those cities this paper's insights will likely be relevant.

A second distinct feature of Dutch cities concerns the widespread use of bicycles as a means of inner-city transport; for example, bicycles' share in home-to-work commutes in Amsterdam was 48% in 2016 (KiM, 2018). Consequently, a mode shift from cycling to automated transport could be much more pronounced in the Netherlands than in other countries where the modal share of the bicycle is smaller. The AV-induced reduction in bicycle use might still be of high importance for other countries though. At the moment, various European Union members carry out dedicated policies to promote cycling, and the European Commission works on integrating cycling into the multimodal transport policy (ECF, 2015; EC, 2018). The policies aim at an increase in the modal share of bicycle, and at related improvements in health, environment and urban quality of life. Our results suggest that realization of such policy goals may become more challenging in a world with automated vehicles. Furthermore, in many cities abroad the lower bicycle's smaller modal share is compensated by a larger share for public transit. From that perspective also, our findings pertaining to the impact of public transit automation on population concentration could be very relevant for medium-sized, non-bicycle oriented cities outside of the Netherlands.

The transition to automated driving poses many challenges to policy, concerning such diverse topics as regulation, safety, infrastructure investment, space for experimentation (see e.g. KiM, 2017, Bahamonde-Birke et al., 2017). The results of our paper are particularly interesting in light of the ongoing policy discussions about the growth of cities. In many developed countries, attractive cities have recently experienced higher growth rates than areas in the rest of the country (see e.g. Duranton and Puga, 2014, Gyourko et al., 2013), and this tendency towards urban concentration is expected to continue in the coming decades (CPB/PBL, 2015). Our simulations reveal that automation cannot be viewed as an unambiguous counterforce to this trend, as was thought up to now (see e.g. Litman, 2018). Rather, public transit automation may in fact intensify this concentration trend. Hence, policy challenges relating to the growth of cities will remain of vital concern, ranging from urban sprawl and investment in housing to an increasing segregation between those who can afford to reside in attractive, expensive cities and those who cannot. Automated driving in cities will also create new challenges, including for example those related to inner city congestion, regulation of automated vehicle flows, regulation of the market of fleet-owners, or the

[22] The four largest Dutch cities (Amsterdam, Rotterdam, Utrecht and The Hague) have a combined 2.4 million inhabitants, which is comparable to the 2.2 million inhabitants of inner Paris. However, the four Dutch cities' population density (4,000 inhabitants per square kilometre on average) is less than 20% of the density of inner Paris (21,000 people/km2). Analogously, the total population of the Dutch Randstad (7.1 million) is comparable to the population of the Grand Paris Metropolis, yet the population density of the Randstad (850 p/km2) is only 10% of the Grand Paris density (8700 p/km2). (Statistics Netherlands, 2017 and OECD, 2017).

transformation of redundant parking spaces into other uses. Policy makers may have to prepare for a shift away from conventional public transit (except on dense metro-train lines), and for discussions pertaining to the changing complexion and feel of cities.

The transition to fully autonomous driving may take many years. In the KiM (2017) transition paths, a fully self-driving city is not expected to emerge until around 2070 or beyond. The available transition time can therefore be used for experimentation and learning. Moreover, certain policy measures might require years or even decades to design and implement, with the redesign, planning and execution of infrastructural investments being primary examples. A further example is public transit concessions, which often span one or more decades. All told, automation developments may confront policy makers with a dilemma. On the one hand, given the large uncertainty and gradual transition to new technologies, monitoring and waiting might be the best policy response. On the other, the long periods of time needed for designing and implementing policy stress the need for promptly initiating the necessary policy adjustments.

7 Conclusions

This paper has studied the possible effects of automated and autonomous driving on population concentration and dispersion in the Netherlands, using as instrument the Dutch spatial general equilibrium model LUCA. Two possible automation developments were accounted for: *car* automation, whereby technology enhances the travel experience in cars; and *public transit* automation, whereby new technology leads to fast and comfortable door-to-door shared transit. We have considered scenarios in which the automation technology is at different levels of development.

The analysis suggests that car automation results in population flight from cities. Public transit automation has the opposite effect: it leads to population clustering in urban areas. A combination of these two components results in a concentration of the population in the largest, most attractive cities, at the expense of smaller cities. The effects are substantial in case of full automation (level 5 SAE), where regional changes in population amount to some 3% in absolute value. In high automation (level 4 SAE), the effects are much smaller.

Automation has a positive effect on welfare, amounting to yearly benefits up to 5 billion euro in full automation. In the first place, the welfare benefits arise from a reduction in generalized transportation costs and changes in modal split. A second part of the benefits is due to relocation. Following a change in generalized transportation costs, people move to other home and job locations that yield them higher utility. Land use and land prices adjust consecutively, generating additional welfare effects. In our simulations, these (wider) effects of automation amount to up to 10% of the total benefits. Land redevelopment is a necessary condition to realize these benefits, see also Teulings et al. (2018).

The quantitative effects are based on simulations and therefore cannot provide a precise picture of a remote and highly uncertain future. Nonetheless, given that the LUCA model was calibrated according to current empirical data for the Netherlands, it does provide a quantitative impression of two possible consequences of automation, both of which are highly relevant for spatial and transport policy. Policy focused solely on the impact of car automation would erroneously direct policy at population dispersion, without taking into account the offsetting impact that automated public transit has on population concentration.

This paper's findings are particularly interesting in 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 highways – led to the suburbanization of population and jobs (see Baum-Snow, 2007, 2010 and later studies). Vehicle automation may well be the next major transportation technology jump, and our simulations suggest that it could lead to further population concentration in already highly urbanized areas. In many developed countries this might pose additional challenges for policy makers on the local and national levels, because attractive cities already grow at (much) higher rates than other areas (see e.g. Duranton and Puga, 2014, Gyourko et al., 2013).

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Appendix A. Main notation

Table A1. Main notation

Population	
i, $i=1..N$	Individual workers
N	Total number of workers
$s=\{low, middle, high\}$	Education level
N_s	Total number of workers of education level s
$x=\{k,j,m\}$	Three discrete choices of the workers
Residential location choice	
$h \in H$	Residential location
$k \in K_h \times H$	House, at each h there are K_h houses
A_h	Residential land supply at location h
R_h	Land price at location h
$v(R_h)$	A function of land price at location h
L_{ih}	Land lot consumption of individual i at location h
L_h	Average land lot at location h
a_h and z_h	Observed respectively unobserved home location amenities (parks, restaurants, culture, etc.)
Choice of job location and commuting mode	
$j \in H$	Job location
y_{sj}	Job location amenities (e.g. availability of cafes or supermarkets near the office)
W_i	Take home pay of individual i
$m \in M$	Mode of transportation
c_{shjm}	Attributes of a trip between h and j with m (time, cost, etc.)
Parameters	
α, γ	Parameters indicating the utility weight of home amenities, respectively commuting variables
$\mu_{Ks}, \mu_{Js}, \mu_{Ms}$	Parameters connected to the nested logit structure of the model
ε_{ikjm}	Gumbel distributed error term that supports the nested logit structure