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The opportunity of shared autonomous vehicles to improve spatial equity in accessibility and socio-economic developments in European urban areas

Norman Eppenberger[1*] and Maximilian Alexander Richter[2]

Abstract

Background: This paper provides insight into the opportunity offered by shared autonomous vehicles (SAVs) to improve urban populations' spatial equity in accessibility. It provides a concrete implementation model for SAVs set to improve equity in accessibility and highlights the need of regulation in order for SAVs to help overcome identified spatial mismatches.

Methodology: Through the formulation of linear regression models, the relationship between land-use and transportation accessibility (by car and public transport) and socio-economic well-being indicators is tested on district-level in four European cities: Paris, Berlin, London and Vienna. Accessibility data is used to analyse access to points of interest within given timespans by both car and public transport. To measure equity in socio-economic well-being, three district-level proxies are introduced: yearly income, unemployment rate and educational attainment.

Results: In the cities of Paris, London and Vienna, as well as partially in Berlin, positive effects of educational attainment on accessibility are evidenced. Further, positive effects on accessibility by yearly income are found in Paris and London. Additionally, negative effects of an increased unemployment rate on accessibility are observed in Paris and Vienna. Through the comparison between accessibility by car and public transportation in the districts of the four cities, the potential for SAVs is evidenced. Lastly, on the basis of the findings a 'SAV identification matrix' is created, visualizing the underserved districts in each of the four cities and the need of equity enhancing policy for the introduction of SAVs is emphasized.

Keywords: Autonomous vehicles, Smart transportation, Accessibility, Spatial mismatch, Equity, Regulation

1 Introduction

The European perspective is optimistic and pushes policy to facilitate the research, testing and introduction of autonomous vehicles (AVs) [24]. But what role are AVs to play? Are they mostly set out to be present in long-haul trips, to improve freight or can they have a role in urban areas as well? And, if so, what role are they supposed to play?

* Correspondence: n.eppenberger@me.com
[1]Zurich, Switzerland
Full list of author information is available at the end of the article

No matter if people live in urban, suburban or rural areas, the means of transportation available to them and the commute time to their workplace, local schools or hospitals can be essential for a person's socio-economic wellbeing. The latter is a multi-dimensional concept as defined by the European Commission and the Human Development Index covering indicators on amongst others education, employment, income and health ([29], pp. 8, 42 [54];). In general, urban areas show a higher density of locations of interest or opportunities including workplaces, shops, schools as well as health centres and hospitals [46]. This paper focuses on four functional urban areas (FUA), as defined by the EU and the OECD and their political cores [11, 21]. While it is generally recognised that FUAs are associated with greater economic growth and development than rural areas, it is not clear whether all inhabitants share the same opportunities offered by the denser infrastructure of FUAs.

Nowadays most countries "*transport policies generally aim to improve accessibility and reduce the negative impacts of motorised transport*" ([27], p. 474). Thus, accessibility has become a central concept in spatial and transportation planning ([15], p. 3). Geurs & van Wee, [16] «*define accessibility as the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)*» (p. 128). The authors also identify four components of accessibility in the literature: (1) land-use, (2) transportation, (3) temporal and (4) individual [16]. Every component of accessibility can be distributed inequitably, and in turn, transportation and spatial planning policy affect equity in accessibility and cause socio-economic developments.

Here, it is noteworthy to say that there are various understandings of the concept of equity, different types of equity, various indicators and criteria to measure it and to categorize people into classes [25, 49, 57]. For example Ramjerdi [43] evaluated an equity objective for road pricing schemes in Norway. His research highlights the difficulty to assess equity on single measures yielding contradictory results and shows the sensitivity of these measures to the geographical level of analysis.

Further, there are multiple analysis on accessibility measures in European transport appraisals: Geurs, Boon, & Wee [14] developed a theoretical framework to describe the relationship between determinants of social impacts of transport, compare UK and Dutch UK transport appraisal guidelines and come to the conclusion that social impacts of transport appraisals are still far from being as complete as economic and ecological assessments. Lucas [26] and Halden [18] argue that due to the great flexibility in UK policy to assess accessibility, most local authorities struggle to find the right range and choice of calculation and that their mapping tools downplay the complexity and barriers causing social exclusion (cit. in [15]). Consequently, Pitarch-Garrido [37] for example, suggests the concept of spatial equity as indicator for social sustainability in transportation policy and uses time-distance to measure socio-spatial equity in Valencia.

More globally, Portnov et al. [38] were able to showcase that accessibility plays an important role in development when comparing accessibility in Swiss municipalities over the second half of the twenty-first century. Along those lines the ITF [21], was able to show "*a correlation between income and accessibility by public transport*" in the Paris FUA on a 500 m^2 grid-level analysis (p. 64), highlighting inequity in accessibility along social and spatial lines.

Of recent, research has begun to analyse the effects of shared mobility as well as autonomous vehicles in regards to their effects on accessibility and equity: Clark & Curl [5], as well as Boldrini et al. [3] analysed travel data of car- and bike sharing-data in Glasgow and in other 10 European cities, respectively. While they outline the potential of shared transportation in overcoming barriers of access such as upfront cost or maintenance, they showcase that only a small percentage of the population is making use of these services. These are mostly highly educated, middle to high income individuals who use shared mobility as a substitute for other means of transport. Pritchard, et al. [39] came to similar results in their assessments of bike-sharing in Sao Paolo, Brazil and its potential to alleviate spatiotemporal inequality in job accessibility, as measured by Gini coefficients. These findings highlight that car-hailing users increasingly substitute public transportation trips, wherein the current most well-off users put "*convenience over cost*" ([6, 12], p. 5) and therefore, bear the question on whether the introduction of Shared Autonomous Vehicles (SAVs) will reinforce similar trends.

Level 4 and 5 AVs are already being tested on public roads in several countries including the US, Singapore and many European countries and bring many benefits to accessibility [47]: AVs promise to improve road safety, by reducing crashes and by optimising traffic at large, improving reliability, which in turn reduces congestion and travel time [55, 56]. Their deployment has the potential to reduce pollution rates in urban areas as they are primarily electric vehicles and if the infrastructure is well connected, AVs offer an opportunity to decrease energy consumption [8]. Lastly, AVs are expected to strongly lower the cost of travel. On the one hand the cost per kilometre is reduced as the cost of a driver and most of the operating cost of vehicles are eliminated, especially if implemented in shared schemes [4]. On the other hand, AVs offer the opportunity to use the time of travel productively and have a 24-h service. Therefore, Pendleton et al. [35] argue that AVs, as part of shared mobility, make access to mobility more affordable and could strongly benefit neighbourhoods with lower accessibility.

However, there is a range of risks concerning shared mobility and AVs: Due to the lower cost of travel, they bear the risk of accelerating the urban sprawl [12]. In addition, the spatial extension of SAVs

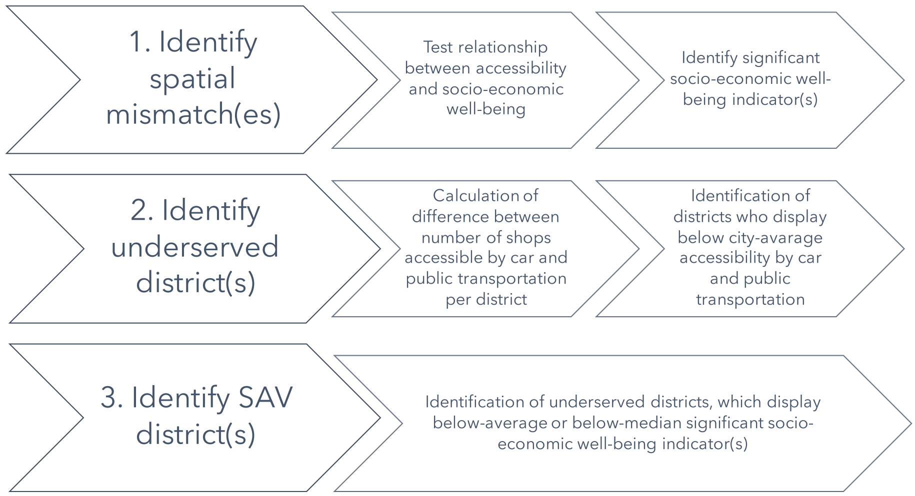


Fig. 1 Three-step process to identify SAV districts

will be limited, given the market imperative that lies at the core of these on-demand systems [5]. Also, SAVs bear the risk of technical unemployment in the mobility and transportation industry, industries that mostly offer low-skill jobs and are mainly held by marginalised communities, will be displaced by high-skilled tech jobs [36, 53, 59]. Lastly, SAVs also bring barriers of access best described by the STEPS[1] model created by Shaheen et al. [45] and adapted to include the usage of AVs by Fleming [12]. Overall, these findings raise the question:

1.1 Can shared autonomous vehicles improve equity in accessibility of European urban populations?

This paper proposes a three-step model for the introduction of SAVs which helps to address equity in accessibility and showcases concrete case-studies on accessibility in the European cities of Berlin, Paris, London and Vienna. Through the analysis of accessibility to shops within 30 min by car and public transportation and relating it to district-level socio-economic well-being indicators, it builds and tests the findings by the ITF [21], as well as Portnov et al. [38] and Pitarch-Garrido [37] and spatial mismatches are identified. Furthermore, it offers a tool to visualize city districts in which SAVs can aid to overcome identified spatial mismatches and contributes to the discussion of possible socio-economic developments caused by the introduction of SAVs and how these should be addressed.

[1]The STEPS model identifies (s)patial, (t)emporal, (e)conomic, (p)hysiological and (s)ocial barriers and offers possible solutions to overcome them.

2 Methodology and data

This analysis builds on four main underlying assumptions: Firstly, accessibility for low-income populations is improved through more affordable car travel [23]. Secondly, SAVs are expected to make car-travel more affordable [4]. Thirdly, SAVs offer an opportunity to improve equity in accessibility. And lastly, SAV travel needs to be regulated in order to improve equity in accessibility and bear socio-economic benefits [7, 12]. According to this logic, SAVs have the greatest opportunity to improve city populations' socio-economic well-being if deployed in underserved, low-income areas. In order to identify such areas, the authors propose a three-step model (see Fig. 1).

Step 1. entails showing that a relationship between accessibility and socio-economic well-being exists, by applying the four OLS regression models explained in Section 2.1. These relationships lay the ground for data-driven policy decisions. Step 2 ensures that accessibility is improved in city districts that will benefit the most from the deployment of SAVs: If the number of shops accessible within 30 min is greater in a district by car travel than by public transportation, AVs and SAVs offer room for improving the inhabitants' accessibility. Lastly, Step 3. adds the significant socio-economic well-being indicator(s) to the equation, in order for SAVs to yield economic, societal and environmental benefit to the cities' populations. Steps 2 and 3 are summarized by the 'SAV identification matrix' explained in Section 2.2, whilst the third section provides an overview of the data used.

2.1 OLS regression models for accessibility and socio-economic well-being

Based on the literature above, the authors of this paper test whether better accessibility by private car and public transport is present where yearly income is higher (H1), unemployment rates are lower (H2) and where educational attainment levels are higher (H3) in European cities.

Therefore, the linear relationship between accessibility rates and the defined socio-economic well-being variables are established as follows:

$$\mathrm{Y}_d^{C,PT} = \beta_0 + \beta_1^{C,PT}\,\mathrm{INC}_d + \mu_d \tag{1}$$

$$\mathrm{Y}_d^{C,PT} = \beta_0 + \beta_2^{C,PT}\,\mathrm{UEM}_d + \mu_d \tag{2}$$

$$\mathrm{Y}_d^{C,PT} = \beta_0 + \beta_3^{C,PT}\,\mathrm{EDU_d} + \mu_d \tag{3}$$

The regression is formulated for $\mathrm{Y}_d^{C,PT}$, the accessibility in a specific city district (*d*) by the two modes of transportation: car (*C*) and public transportation (*PT*). More precisely, $\mathrm{Y}_d^{C,PT}$ is the average number of shops accessible in any given *d* within 30 min by the two selected means of transportation. This point of interest and time are selected as they are very representative of overall accessibility (see Section 2.3 and Appendix 3). The district-level independent variables are the following: in Model (I), INC_d is the indicator for mean or median yearly income[2] in Euros (€) or British Pounds (£) in any given *d*; in Model (II) UEM_d is the unemployment rate in any given *d*, as a percentage of the labour force[3]; and in Model (III) EDU_d is the calculated weighted average educational attainment index on a scale from one to three in every *d*. The educational attainment index EDU_d is based on the percentage of the population with low (ISCED 2011 levels[4] 01–2), medium (ISCED 2011 levels 3–4) and high (ISCED 2011 levels 5–8) educational attainment. The authors attributed the values 1 to low; 2 to medium and 3 to high educational attainment. The weighted average was calculated based on the percentages of the population attributed to these three categories for every *d*. Finally, μ_d represents the error of the OLS regression models for any *d*.

Building on the literature above, the authors expect a positive linear effect of yearly income (INC_d), and a negative linear effect of increasing unemployment rates (UEM_d) on accessibility by public transportation (Y_d^{PT}). Since highly educated adults make use of shared mobility in Europe and because these services are mostly provided in core city areas, the authors expect a positive linear correlation between average educational attainment (EDU_d) and accessibility. The comparison to accessibility by car (Y_d^{C}) gives insights on the success of the European focus on *PT* in spatial and transportation planning. Furthermore, it offers the opportunity to learn about *d* where *C* and potential transportation by SAVs could bring greater benefits (see Section 2.2 for more details). Therefore, bivariate Models (I), (II) and (III) are tested for accessibility by car (Y_d^{C}), as well as public transportation (Y_d^{PT}).

However, all three independent variables are also known to be interrelated: Firstly, yearly income and unemployment are connected by definition, as the latter is a description of a state in which a person in working age is without work [20]. Naturally, an increasing unemployment rate, will negatively affect yearly income in a specific area. Secondly, income and income inequality are connected to educational attainment and inequality thereof, since a certain wealth and income is necessary to complete higher educational levels and higher educational attainment is associated with better paid jobs ([44, 50], pp. 389–390).

Given these interrelations between the independent variables, it is likely that there are cumulative effects on accessibility. To test this relationship and discuss potential multicollinearity, multiple linear regression Model (IV) is added to the analysis:

$$\begin{aligned}\mathrm{Y}_d^{C,PT} = \beta_0 &+ \beta_1^{C,PT}\,\mathrm{INC}_d + \beta_2^{C,PT}\,\mathrm{UEM}_d \\ &+ \beta_3^{C,PT}\,\mathrm{EDU}_d + \mu_d\end{aligned} \tag{4}$$

Together these four Models, enable the authors (1) to test whether there are spatial mismatches in terms of accessibility and socio-economic well-being in European cities and (2) how accessibility by car (Y_d^{C}) and public transportation (Y_d^{PT}) compare. The four Models are applied to district-level datasets of Paris, Berlin, London and Vienna.

2.2 SAV district identification matrix

Figure 2 exemplifies how SAV districts can be identified graphically. The y-axis showcases the difference (Δ) between the number of shops accessible within 30 min by public transportation (*PT*) and the number accessible within the same timeframe by car travel (*C*). The green arrow indicates that Δ between Y_d^{C} and Y_d^{PT} equals zero. If the number is positive, for a

[2]Statistical offices in the multiple cities, regions and countries use different indicators to track inhabitants' yearly incomes. This paper made use of both median and mean yearly income dependent on availability and timeliness of data (see Section 2.3 for details).

[3]Active population is calculated differently by various statistical offices, depending on included age-range, inclusion and definition of long-term unemployed, as well as inclusion of students ([20], pp. 1–2).

[4]International Standard Classification of Education (ISCED) as defined by the UNESCO Institute for Statistics in 2011 ([52], pp. 30–63). This classification is used to make statistical data collected by various statistical offices comparable between cities and calculate average educational attainment.

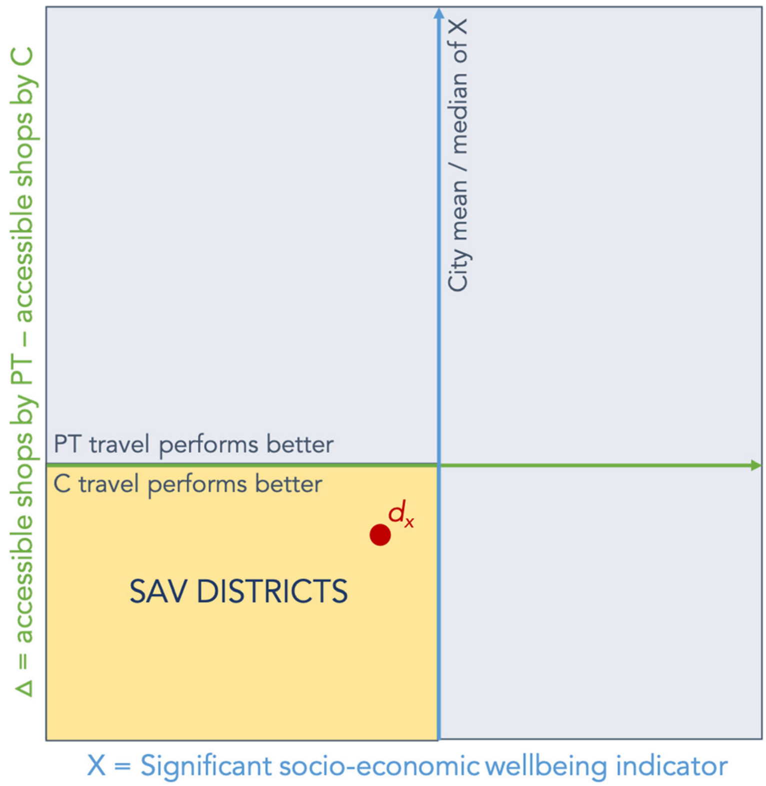


Fig. 2 SAV district identification matrix

particular district (d), PT performs better, and d finds itself in the upper half of the matrix. If C performs better in a d it finds itself in the bottom half of the matrix. This is the case for example district d_x (see red dot). In this paper Δ is normalised (only positive numbers) if one means of transport performs better than the other in every d of a city.

The x-axis showcases the previously identified significant mean or median socio-economic well-being indicator for each d, as well as the city mean or median (blue arrow). The mean is applied to the UEM_d, as well as the index for EDU_d, while the median is used for INC_d. In the case of district d_x in Fig. 2, its socio-economic well-being indicator value lies below the city average or mean. In result, example district d_x is identified as a SAV district.

2.3 Accessibility and socio-economic well-being data

The accessibility data[5] for the two dependent variables Y_d^C and Y_d^{PT} is obtained from the ITF and is based on TomTom navigation calculations ([21], p. 22). The socio-economic well-being data, for the three independent variables yearly income (INC_d), unemployment rate (UEM_d) and educational attainment (EDU_d) is publicly accessible and stems from corresponding city statistics offices. See Appendix 1 for a description table of the data and Appendix 3 for overview plots for each city.

2.3.1 Accessibility data

The FUA grid map data is obtained in a combined Shapefile for all cities. It is first imported, separated and combined with the corresponding FUA accessibility datasets in QGIS.[6]The estimated number of points of interest accessible within a specific timeframe were previously established by the ITF [21] on the basis of TomTom calculations for road travel and schedule data for public transportation. For road travel the estimations also include two city-specific coefficients to include congestion, depending on the capacity of the roads and commuting zones for every grid field.

Given the focus of this paper on SAVs, the datasets are limited to car travel (C) and public transportation

[5]The accessibility data used by the ITF for its city benchmarking is soon to be publicly accessible online and was received before publication and upon request for this paper.

[6]QGIS is a free opensource software for geographic information systems (GIS) [41]. This paper made use of version QGIS 3.8 Zanzibar.

(*PT*), and the number of shops accessible within 30 min. The number of accessible shops per districts within 30 min shows some of the greatest differences between districts in the four cities and is representative also of accessibility by *PT* to hospitals and schools (see Appendix 3).

To compare the selected accessibility data to district-level indicators, publicly accessible district maps of the four cities in Shapefile-format are added in QGIS and the *union vector geoprocessing tool* is applied. Data preparation and selection are performed in R.[7] The data cleaning procedure reduces the number of observations (500m^2 grid fields) from $n = 50'159$ to $n = 20'424$ for the Paris FUA dataset; from $n = 73'428$ to $n = 20'723$ for the Berlin FUA dataset; from $n = 28'579$ to $n = 17'570$ for the London dataset and; from $n = 38'381$ to $n = 2'012$ for the Vienna dataset.[8]

On the basis of these cleaned FUA accessibility datasets, the mean number of stores accessible by *C* or *PT* from every city-district are calculated, apt to be merged with the socio-economic well-being data set explained below.

2.3.2 Socio-economic well-being data

The socio-economic well-being indicators are compiled in a search effort at the various statistics offices, their publicly available databases and publications (see Appendix 2 for city-district socio-economic well-being data).

For the city of Paris, the *Institut national de la statistique et des études économiques* (Insee) provides the following district-level indicators for the year 2016: median yearly disposable household income, the unemployment rate for 15–64-year olds, and percentages of the population 15 and above who have completed five different schooling levels[9] [19].

The Berlin socio-economic well-being data is available at the *Amt für Statistik Berlin-Brandenburg*. Yearly mean income data stems from the 2014 handbook, while the unemployment rate and the percentage of the population who has attained a high, medium or low level of education according to ISCE D 2014, are based micro-census database established in 2017 [1, 2].

For London the data is provided by the Office for National Statistics (ONS). The yearly median income in 2016–7 by borough is presented before taxes and deductions [33]. The unemployment rate is calculated for the population of 16 years of age and above for the year 2017 and qualifications of the working population ages 16–64 in 2018 are subdivided into six categories[10] [28, 34].

Lastly, the datapoints for the socio-economic well-being variables for Vienna are: median yearly income after taxes and deductions for the year 2014, the unemployed population per district in 2013, as well as percentages of district populations' highest attained degrees[11] [48].

3 Results

In the first subsection, the OLS regressions are performed and the correlations in each city explained. The second subsection displays the districts (*d*) for every city, which are most promising for the deployment of SAVs.

3.1 Relating accessibility and socio-economic well-being in European cities

Tables 1 and 2 showcase the regression results and coefficient estimates of the four linear OLS regression models explained in Section 2.1. Table 2 displays the obtained results on the dependent variable accessibility by public transportation (*PT*), Y_d^{PT}, while Table 2 shows the relationship of the omitted variables on accessibility by car travel (*C*), Y_d^{C}. See Appendix 4 for detailed regression tables for each city.

The predictors vary in format amongst each other within and between the cities. However, in sight of the result Tables 1 and 2, it becomes obvious that the estimates $\beta_1^{C,PT}$ for yearly income (INC_d) are by far the smallest (between 10^0 and 10^1), while estimates $\beta_2^{C,PT}$ for the unemployment rate (UEM_d) range between 10^2 and 10^5 and estimates $\beta_3^{C,PT}$ for educational attainment (EDU_d) range between 10^4 and 10^5. In case of a significant correlation, a small change in EDU_d (values between 1 and 3) will increase $Y_d^{C,PT}$ greatly, while a similar change in INC_d will only have a limited effect. The two tables also describe minimum, maximum and

[7] Statistics are done using R version 3.6.1 [42], the *dplyr* [58], the *data.table* [10] and the *car* [13] packages.

[8] The ITF accessibility dataset for the Vienna FUA entails a very limited amount of datapoints for public transportation *PT*. Therefore, a separate dataset with $n = 12'708$ for *C* is created in order to have a stronger basis for the calculations of average Y_d^{C}.

[9] The completed levels of schooling are attributed as follows: high educational attainment for '*diplôme de l'enseignement supérieur*'; medium educational attainment for '*CAP ou d'un BEP*' as well as '*baccalauréat (général, technologique, professionnel)*'; and low educational attainment for '*d'aucun diplôme ou au plus d'un BEPC, brevet des collèges ou DNB*'

[10] Percentage of working population with no educational level as well as population with National Vocational Qualification (NVQ) level 1 are summed under low educational attainment; Medium educational attainment comprises the percentage of the population with NVQ2 only plus percentage with Trade Apprenticeships; and high educational attainment covers the percentages of the population with NVQ3 and NVQ4.

[11] The six degrees were attributed as follows: '*Pflichtschule*' and '*Lehre*' were attributed to low; '*BMS*' and '*AHS*' to medium; and '*BHS*', '*Hochschule*', and '*Kolleg*' to high educational attainment.

Table 1 Summary of city regression tables for four models on PT.

PT		Paris	Berlin	London	Vienna
Sample *d* size (n)		20	12	33	15
Min. Y_d^{PT}		155,448	8989	13,414	10,194
Max. Y_d^{PT}		453,727	65,107	453,143	70,992
Median Y_d^{PT}		356,265	21,600	78,586	61,674
Model (I)	INC_d	4.16	−1.89	12.44 ***	1.77
Model (II)	UEM_d	−13,868.54	2129.13	2239.50	− 3241.15 *
Model (III)	EDU_d	210,897.12 *	55,925.87	356,023.77 ***	45,523.07 *
Model (IV)	INC_d	1.85	−1.73	13.98 **	−1.44
	UEM_d	1885.38	7298.54 *	4010.04	− 1363.94
	EDU_d	181,189.35	170,604.36 **	− 33,498.52	49,461.60

*** $p < .001$, ** $p < .01$, * $p < .05$

median $Y_d^{C,PT}$, in order to gain a relative understanding between the cities. In the following the results of the bivariate and the multiple linear regression models are outlined separately.

3.1.1 Simple linear regression model

Model (I) only shows a significant effect between Y_d^{PT} and INC_d in London with estimate β_1^{PT} of 12.44 at $p < .001$ (see Table 2). This relationship is positive and strong (R^2 of .62 for 33 boroughs d). Nevertheless, the simple linear regression Model (I) performed on Y_d^C, displays positive, significant relationships with INC_d (see Table 2) both for London (β_1^C = 3.01, $p < .001$) and Paris (β_1^C = 3.89, $p < .01$). INC_d predicts Y_d^C better in London ($R^2 = .56$) than in Paris ($R^2 = 0.32$). In summary, H1 (see Section 2.1) is confirmed for London's political centre and is shown for Y_d^C for the city of Paris.

In comparison, Model (II) showed negative effect ($p < .05$) between UEM_d and Y_d^{PT} in Vienna (β_2^{PT} = − 3′241) and between UEM_d and Y_d^C in Paris (β_2^C = − 11′488). In both cases, the negative relationship confirms H2, although the validity of Model (II) is lower than in Model (I) with $R^2 = .27$ in Vienna and $R^2 = .25$ in Paris. No relationship between UEM_d and $Y_d^{C,PT}$ is identified for Berlin and London.

Across the cities, EDU_d shows positive significant relationships with $Y_d^{C,PT}$ in all cities but Berlin, strongly supporting H3. In Paris, the values of β_3^{PT} are 210′897 ($p < .05$) and β_3^C is of 142′660 ($p < .05$) with R^2 of .28 and .2 respectively. In London as well, EDU_d is a better predictor for Y_d^{PT} ($R^2 = .44$) than Y_d^C ($R^2 = .32$) with corre-

Table 2 Summary of city regression tables for four models on C

C		Paris	Berlin	London	Vienna
Sample *d* size (n)		20	12	33	23
Min. Y_d^C		382,199	20,310	24,925	28,564
Max. Y_d^C		554,045	75,630	124,658	83,350
Median Y_d^C		454,565	38,757	41,107	66,758
Model (I)	INC_d	3.89 **	−1.23	3.01 ***	0.31
Model (II)	UEM_d	−11,488.06 *	1746.96	213.45	468.03
Model (III)	EDU_d	142,659.47 *	64,150.32	81,138.96 ***	34,469.41 *
Model (IV)	INC_d	3.37	−1.20	4.60 ***	−1.82
	UEM_d	3232.48	7310.22 **	355.72	1783.30
	EDU_d	87,008.62	175,006.70 **	− 34,509.71	67,652.12 **

*** $p < .001$, ** $p < .01$, * $p < .05$

sponding estimates β_3^{PT} of 356′024 ($p < .001$) and β_3^{C} equalling 81′139 ($p < .001$). Lastly, in Vienna β_3^{PT} is of 45′523 ($p < .05$, $R^2 = .38$) and β_3^{C} amounts to 34′469 ($p < .05$, $R^2 = .2$).

When taking a within city perspective on these three univariate models it becomes clear that the only determinant showing a relationship with both accessibility by C and PT, $Y_d^{C,PT}$, in Paris, as well as London and Vienna, is EDU_d. However, in Paris changes in INC_d explain a greater change of Y_d^{C}, than EDU_d. Similarly, in London, both INC_d and EDU_d show significant effects with $Y_d^{C,PT}$, but INC_d explains a greater share of the change of $Y_d^{C,PT}$ than EDU_d. Finally, none of the univariate models show any relationship between $Y_d^{C,PT}$ and the three determinants in Berlin.

3.1.2 Multiple linear regression models

For Paris, the additive Model (IV) does not identify any significant relationship neither for PT nor for C. Meanwhile, the Berlin dataset shows significant correlations between both dependent variables and EDU_d, as well as UEM_d in the additive Model (IV). While the positive relationship between $Y_d^{C,PT}$ and EDU_d (β_3^{PT} = 170′604 and β_3^{C} = 175′007 at $p < .01$) exhibited by Model (IV) confirms H3, the relationship between $Y_d^{C,PT}$ and UEM_d (β_2^{PT} = 7′299, $p < .05$ and β_2^{C} = 7′310, $p < .01$) is also positive, defeating H2. In London, the multiple linear regression model showcases that the effect of EDU_d on $Y_d^{C,PT}$ is absorbed by INC_d, confirming H1 with estimates β_1^{PT} = 13.98 ($p < .01$) and β_1^{C} = 4.60 ($p < .001$). Nonetheless, like in Paris, the single linear regression models perform better than Model (IV). Finally, in Vienna, the significant effects of EDU_d and UEM_d on Y_d^{PT} is not found in Model (IV), but the significant coefficient measured in the single linear regression model between Y_d^{C} and EDU_d becomes stronger (β_3^{C} = 67, 652, $p < .01$).

3.2 Identifying SAV city-districts in European cities

As explained in Section 2, the selection of the relevant socio-economic well-being indicator is first explained for every city, before the performance of car travel (C) and public transportation (PT) are compared and the 'SAV identification matrix' is applied (see Fig. 3).

3.2.1 Paris

In Paris, EDU_d has an effect on both $Y_d^{C,}$ and Y_d^{PT}. However, INC_d explains a greater share of the change in Y_d^{C}, and as SAVs offer a great opportunity for low-income households to gain improved Y_d^{C}, both INC_d and EDU_d are included in the identification process. Furthermore, Paris offers greater accessibility by car in every district (d), thus creating a vast opportunity for the deployment of SAVs.

Figure 3 shows the two identification matrixes for Paris' political core. Applying INC_d in the identification matrix highlights how strongly accessibility $Y_d^{C,PT}$ could be improved in districts d_{12}, d_{13}, d_{14}, d_{17}, d_{18}, d_{19} and d_{20}, increasing $Y_d^{C,PT}$ by more than 100′000 shops within 30 min. Also, d_{10} and d_{11} would potentially improve their $Y_d^{C,PT}$ by 50′000 to 100′000 shops. Similarly, EDU_d spotlights the same d, except of d_{14} which performs better in terms of socio-economic well-being and d_{17} which performs clearly below average here.

3.2.2 Berlin

In Berlin, the selection of a significant socio-economic well-being variable is more difficult, as the three single linear regression models do not show any relationship between $Y_d^{C,PT}$ and the socio-economic well-being indicators. However, since EDU_d is positive and significant in the multiple linear regression models, confirming H3 for both dependent variables, it is selected. d_5, d_9, d_{10} and d_{12} have the lowest accessibility rates both by PT and C. The latter promises larger improvements in Berlin with possible improvements within 30 min between 10′000 and 20′000. However, in order to improve Berlins urban populations' socio-economic well-being, policymakers should focus on districts d_1, d_5, d_8, d_{10} and d_{12}, where the educational index scores below average (see Fig. 3).

3.2.3 London

As displayed in Section 3.1 there is a significant effect of both INC_d and EDU_d on $Y_d^{C,PT}$ in London, confirming H1 and H3. Therefore, both these socio-economic well-being indicators are included in the second part of analysis.

Since London is the only city where Y_d^{C} does not outperform Y_d^{PT} in every district, the identification matrixes in Fig. 3 show four fields, as described in Section 2.2. The benefits of improving $Y_d^{C,PT}$ by C are limited to a maximum of 20′000 more shops within 30 min. On the contrary, the difference Δ between Y_d^{PT} and Y_d^{C} can reach up to more than 330′000 shops (see d_1). When applying either socio-economic well-being variable (INC_d or EDU_d), the identified SAV districts in the bottom left

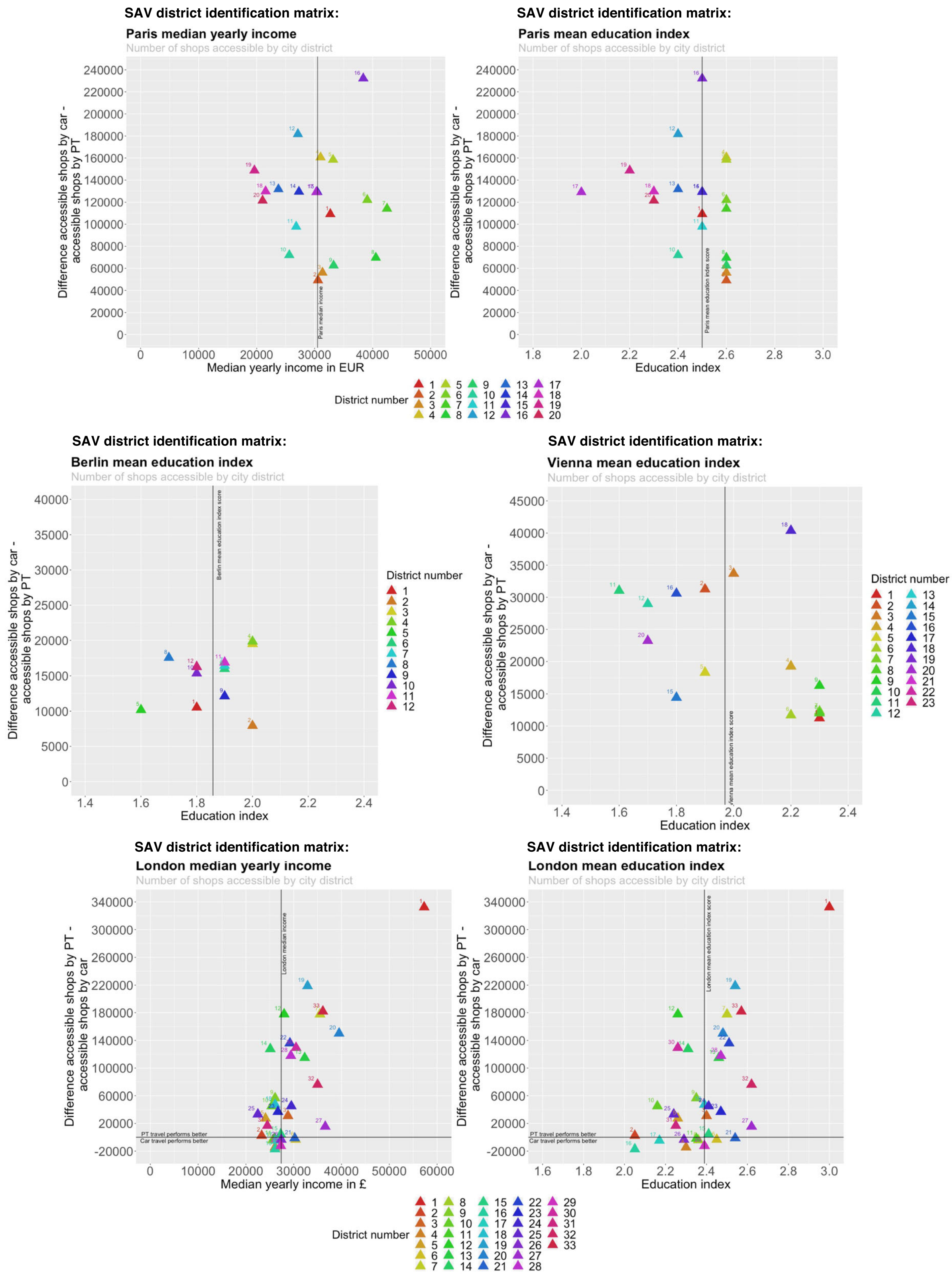


Fig. 3 SAV district identification matrixes per city

corner are: d_4, d_8, d_{11}, d_{16}, d_{17}, d_{26} and d_{29}. The Sutton borough (d_{29}) performs slightly below average in terms of INC_d, while its EDU_d equals the city average. The borough of Havering (d_{16}) has the highest potential of improvement.

3.2.4 Vienna

H2 and therefore, an effect of EDU_d on $\mathrm{Y}_d^{C,PT}$ is confirmed in Section 3.1. Therefore, this predictor is selected for the identification of SAV districts in Vienna.

In terms of accessibility $\mathrm{Y}_d^{C,PT}$, C performs better than PT in all 15 districts where data for both means of transportation is available. The city mean educational attainment index score is of 1.97. In result, d_2, d_5, d_{11}, d_{12}, d_{15}, d_{16} and d_{20} all find themselves below the mean and could potentially benefit from the deployment of SAVs (see Fig. 3). Especially, d_{11} offers a great potential, as it has by far the lowest EDU_d of all districts d and it could increase its $\mathrm{Y}_d^{C,PT}$ by over 30′000 shops within 30 min, almost quadrupling its current Y_d^{PT}.

4 Discussion and policy recommendations

AVs and especially shared AVs (SAVs) are expected to bring many benefits to its users, including, amongst others, improved security as well as the time and comfort gained for its users during travel. However, the expected reduced costs of car travel (C) through SAVs are likely to expand the urban sprawl, increase congestion within urban centres and cause a loss of employment opportunities in the transportation industry [4, 30, 31]. These negative externalities can be mitigated by policies aimed at ensuring the complementarity of SAVs to public transportation (PT) and their focused introduction so to improve social equity. As showcased by the ITF and confirmed in this paper, C offers better accessibility, in terms of the number of accessible shops within 30 min, in most European cities [21]. Nevertheless, this is only possible, since PT systems carry the majority of passenger traffic, relieving much of the potential C. Therefore, the three-step model developed in this paper, aims to purposefully deploy and support SAVs in city districts in which accessibility should be improved in order to increase accessibility and socio-economic well-being.

The first step of analysis showcases that there is a relationship between accessibility and socio-economic well-being in the investigated European urban areas, as this relationship is evidenced in the cities of Paris, London as well as Vienna and partially shown in the city of Berlin. Overall, educational attainment (EDU_d) is the best-performing socio-economic well-being indicator for accessibility across the cities. It showcases significant positive effects on district-level accessibility to shops within 30 min by C and PT ($\mathrm{Y}_d^{C,PT}$) in the simple linear regression models for Paris, London and Vienna, as well as in the multiple linear regression models for Berlin and partially in Vienna, thereby providing strong evidence for H3 (see Section 3.1). This tendency can likely be explained by (1) the greater share of high-skill employment in urban centres ([9], pp. 27–32, 2) the greater number of higher education institutions in urban centres and (3) the stability of educational attainment over generations ([32], pp. 76–77).

However, given the reasoning above and the significant correlations between yearly income (INC_d) and EDU_d identified within all four cities analysed, the authors also expect a significant effect between INC_d and $\mathrm{Y}_d^{C,PT}$ confirming H1. The latter is only supported in Paris and London. On the one hand, this can be explained by the focus of the analysis on the political core and its districts, which creates a "small n" problem in all cities analysed, and especially in Berlin.[12] Hence, in future analysis, a neighbourhood-level analysis would be beneficial to resolve the "small n" problem and improve comparability between the observations.

On the other hand, urban planning policies (including centrally located social housing) in Berlin and Vienna, likely decelerated the urban sprawl and gentrification, rendering the effect of INC_d less significant in these two cities. Meanwhile, if INC_d has a significant effect on $\mathrm{Y}_d^{C,PT}$, it has greater predictive ability than EDU_d in relative city terms. Therefore, INC_d is included in the identification process of SAV districts in Paris and London (see Section 3.2).

H2 is only confirmed for the effect of the unemployment rate (UEM_d) on accessibility by C (Y_d^{C}) in Paris and on accessibility by PT (Y_d^{PT}) in Vienna. While UEM_d is one of the most often measured and used economic socio-economic well-being indicators, it is less stable over time than INC_d and EDU_d, due to its responsiveness to cyclical downturns. In result, this predictor is not applied in any cities' 'SAV district identification matrix'.

In general, the simple linear regression models perform better than the multiple linear regression models in Paris, London and Vienna for $\mathrm{Y}_d^{C,PT}$.

[12] This issue is addressed by the predicted models with 95% confidence intervals created to showcase the stability of the OLS regressions applied (see Appendix 5)

While this hints at multicollinearity the Variance Inflation Factor does not show any alarming rates. In future research, it would be interesting to include data on employment and unfilled positions to gain more direct needs-based insight and see whether the models behave similarly, as described by Silva and Larsson (cit. in [22]) and to include more complex accessibility measures as proposed by Geurs & van Wee [16], Geurs et al. [14] as well as by [40]). However, we tried to the best of our knowledge to fill this gap with literature on the potential benefits and risks of SAVs. By doing so, we follow the logic typically found in equity assessment of transportation policy as described in the recent literature review by Guo et al. [17] and their three identified main components: population measurement, cost-benefit measurement as well as equity measurement.

Throughout this paper we have highlighted the importance of regulation to include equity in accessibility assessment alongside the introduction of SAVs. The 'SAV district identification matrix' is the very result of this. In literature, there are mainly three policy areas which can help to yield the benefits of SAVs and help improve overcome social and spatial inequity of urban inhabitants' [12, 51]: (1) incentivise the usage of shared mobility including SAVs by overcoming technical and economic barriers in underserved low-income areas and (2) incentivise the usage of public transport, shared vehicles and other means of transport in well-served areas and (3) offer a platform to share data between service providers both public and private to coordinate and optimise service provision and accessibility.

In the realm of policies (1) and (2), this paper offers a data-driven three-step model identifying districts where the deployment and focused support of SAVs may prove helpful in overcoming the spatial barrier described in the STEPS model by Fleming [12] and Shaheen et al. [45]. In order to be successful, the policies must be adapted to the various business models for the introduction of SAVs in European cities: The desired focused and complementary deployment of SAVs to *PT* is achieved easiest if all means of transportation are organised by the same entity, allowing for a simplified data-generation and analysis. If SAVs are privately owned, regulation is necessary to oblige companies and the corresponding sharing systems to focus their services on the identified districts and overcome part of the market incentive at the core of their services. The latter is strongly connected to the policies necessary to defeat the economic barriers discussed in the STEPS model as subsidies should be included for low-income urban populations. This can be offered through a monthly or yearly budget to use the services in the SAV districts or through adapted pricings schemes according to a user's registered address or depending on a users' address of departure or destination. Overall, these policies must be adapted to spatial planning measures, as well as existing and potentially growing transportation needs in every city. Policy (3) is therefore detrimental to help monitor and evaluate policies and their impact. Economic policy measures to facilitate access to required technologies (smartphones, mobile data subscriptions and alternative payment systems) are relevant to either business models. These measures are also closely connected to policies directed at overcoming the social barriers, as the sharing economy mainly is used by younger, more affluent and well-educated adults. With EDU_d being the best indicator for accessibility in European cities, it becomes evident that the urban populations with the greatest opportunity to improve their accessibility and socio-economic well-being need to be integrated in the sharing economy. Facilitating eased access to the required technologies and organising events to raise awareness is prerequisite to a successful deployment of SAVs.

5 Conclusion

In summary, this paper provides new evidence for spatial mismatches in European urban areas and offers insights on how SAVs can improve equity in accessibility and socio-economic well-being in the four European capitals analysed. Nevertheless, how SAVs will be deployed, which business models will prevail, how car-ownership will be affected and ultimately, who the largest beneficiaries of SAVs will be, remains to be seen. Certainly, policies must be introduced alongside and in preparation to the deployment of SAVs, in order to ensure their complementarity to *PT*, asses their effect on equity in accessibility and forego possible negative externalities. Therefore, policies must be implemented that are (1) data-driven, requiring the deployment and support of SAVs in areas with lower accessibility and socio-economic well-being, and (2) raise awareness among low-education as well as low-income populations and provide technologies and support to facilitate their access to SAVs. These policies will need to be continuously adapted, as to respond to user needs and market developments. Further research on a neighbourhood level and the application of broader accessibility measures, especially to include job-market data, are important as to secure the data-driven and well-directed approach described. The three-step model proposed in this paper can aid policymakers to maintain overview and aim at improving accessibility for European urban populations.

6 Appendix 1 - Data description and sources

Data title	City	Description	Downloaded from
ITF ACCE SSIBILITY DATA	Berlin, London, Madrid, Vienna	Csv-files with accessibility data by bike, car, public transport and walking to hospitals, schools, health, recreational zones, shops, food shops, restaurant and a number of population for 500 m2 grid fields of functional urban areas with increasing time (5 min–60 min) or distance (1-20 km); data calculated in 2018–9, but based on INSPIRE grid, and population data generated by the JRC of the European Commission (EC)	Received by e-mail by Dimitris Papaioannou, data analyst at the International Transport Forum (ITF) of the OECD in Paris, France
ITF MAPS OF FUNCTIONAL URBAN AREAS	Berlin, London, Paris, Vienna	Shapefile containing 500 m2 grid maps of the six corresponding urban areas. Best read with the application QGIS to visualize accessibility data	Received by e-mail by Dimitris Papaioannou, data analyst at the International Transport Forum (ITF) of the OECD in Paris, France
District map	Berlin	Mapname: "Ortsteile von Berlin"; coordination system: EPSG:25833; last updated in 2018	https://fbinter.stadt-berlin.de/fb/index.jsp
	Paris	Mapname: "Arrondissments"; last updated in 2016	https://opendata.paris.fr/explore/dataset/arrondissements/information/
	Vienna	Mapname: "Bezirksgrenzen Wien"; last updated in 2015	https://www.data.gv.at/katalog/dataset/stadt-wien_bezirksgrenzenwien/resource/f1540ea4-edd4-42f5-9b39-2cbba97fea36
	London	Mapname: "statistical-gis-boundaries-london.zip: London_Borough_Excluding_MHW.shp"; last updated in 2014	https://data.london.gov.uk/dataset/statistical-gis-boundary-files-london
Population size	Berlin	Population size per district; Micro Census of 2017	https://www.statistik-berlin-brandenburg.de/webapi/jsf/tableView/tableView.xhtml
	Paris	Population size per district; year 2016	One webpage per district: https://www.insee.fr/fr/statistiques/1405599?geo=COM-75101
	Vienna	Population size per district; year 2013	https://www.wien.gv.at/statistik/bevoelkerung/tabellen/bevoelkerung-bez-zr.html
	London	Population size per district; year 2018	https://data.london.gov.uk/london-area-profiles/
Yearly income	Berlin	Monthly mean income per district; year 2014.	https://www.statistik-berlin-brandenburg.de/produkte/kleinestatistik/AP_KleineStatistik_EN_2015_BE.pdf
	Paris	Median yearly disposable household income in Euro; year 2016	One webpage per district: https://www.insee.fr/fr/statistiques/1405599?geo=COM-75101
	Vienna	Average yearly income after taxes and deductions per employee per district, in Euro; year 2014	https://www.wien.gv.at/statistik/bezirke/index.html

Appendix 1 - Data description and sources *(Continued)*

Data title	City	Description	Downloaded from
	London	Median yearly income of taxpayers per borough in £; years 2016 and 2017	https://data.london.gov.uk/dataset/average-income-tax-payers-borough
Activity rate	Berlin	Estimated number of employed people per district; Micro Census 2017:	https://www.statistik-berlin-brandenburg.de/webapi/jsf/tableView/tableView.xhtml
	Paris	Activity rate for 15–64-year-olds per district; year 2016	One webpage per district: https://www.insee.fr/fr/statistiques/1405599?geo=COM-75101
	Vienna	Active population; year 2013	https://www.wien.gv.at/statistik/bezirke/index.html
	London	Employment rate per borough for population aged 16+; year 2017	https://data.london.gov.uk/london-area-profiles/
Unemployment rate	Berlin	Estimate of number of unemployed people per district; Micro Census 2017	https://www.statistik-berlin-brandenburg.de/webapi/jsf/tableView/tableView.xhtml
	Paris	Unemployment rate for 15–64-year-olds per district; year 2016	One webpage per district: https://www.insee.fr/fr/statistiques/1405599?geo=COM-75101
	Vienna	Unemployed population; year 2013	https://www.wien.gv.at/statistik/bezirke/index.html
	London	Unemployment rate per borough for population aged 16+; year 2017	https://data.london.gov.uk/london-area-profiles/
Educational attainment	Berlin	Estimate of number of people of highest, middle and lowest educational attainment per district, calculated percentage of total population, Micro Census 2017	https://www.statistik-berlin-brandenburg.de/webapi/jsf/tableView/tableView.xhtml
	Paris	Attribution of percentages of population with educational attainment defined by six different school diplomas to three groups (high-medium-low) for population 15 and above; year 2016	One webpage per district: https://www.insee.fr/fr/statistiques/2011101?geo=COM-75113#chiffre-cle-6
	Vienna	Attribution of percentages of population with educational attainment defined by six different school diplomas to three groups (high-medium -low); year 2011	https://www.wien.gv.at/statistik/bezirke/index.html
	London	Percentage of population aged 16–64 (1) with no qualifications and with NVQ1, (2) NVQ2 only plus with Trade Apprenticeships, and (3) with NVQ3 only and with NVQ4+; 2018 data	https://data.london.gov.uk/dataset/qualifications-working-age-population-nvq-borough

7 Appendix 2 - City district-level socio-economic well-being indicators

7.1 Paris socio-economic well-being data

CITY DISTRICTS	DISTRICT _NUM	POP_ SIZE	UNEMP _RATE	MEDIAN _INC	LOW _EDU	MID _EDU	HIGH _EDU	EDU
Paris_City		2,190,327	11.4	30,298	15.5	22.9	61.6	2.5
1 Arrondissement	1	16,252	10.9	32,697	14.8	20.1	65.1	2.5
2 Arrondissement	2	20,260	10.8	30,567	13.2	17.3	69.5	2.6
3 Arrondissement	3	34,788	10.7	31,333	12.8	17.6	69.6	2.6
4 Arrondissement	4	27,487	10.6	31,007	11.3	19	69.7	2.6
5 Arrondissement	5	59,108	9.7	33,169	10.8	16.1	73.1	2.6
6 Arrondissement	6	40,916	10.1	39,063	10.8	15.9	73.3	2.6
7 Arrondissement	7	52,512	9.6	42,466	11.5	16.2	72.3	2.6
8 Arrondissement	8	36,453	9.1	40,540	12.7	18.4	68.9	2.6
9 Arrondissement	9	59,629	9.9	33,258	10.8	15.9	73.3	2.6
10 Arrondissement	10	91,932	12.1	25,618	18.2	19.5	62.3	2.4
11 Arrondissement	11	147,017	12	26,810	16.1	20.5	63.4	2.5
12 Arrondissement	12	141,494	10.7	27,110	17.9	23.1	59	2.4
13 Arrondissement	13	181,552	12.9	23,751	13.6	31.9	54.5	2.4
14 Arrondissement	14	137,105	11.8	27,288	16.9	21.2	61.9	2.5
15 Arrondissement	15	233,484	9.9	30,448	14.4	19.9	65.7	2.5
16 Arrondissement	16	165,446	10.2	38,378	14	19.4	66.6	2.5
17 Arrondissement	17	167,835	11.5	30,282	16.4	70.7	12.9	2.0
18 Arrondissement	18	195,060	13.3	21,542	22.1	23.2	54.7	2.3
19 Arrondissement	19	186,393	16.7	19,611	27.5	26.4	46.1	2.2
20 Arrondissement	20	195,604	15	21,017	23.5	26.2	50.3	2.3

7.1.1 Berlin socio-economic well-being data

CITY DISTRICTS	DISTRICT _NUM	POP _SIZE	UNEMP _RATE	MEAN _INC	LOW _EDU	MID _EDU	HIGH _EDU	EDU
Berlin_City		3,558,900	7.9	21,000	15.6	40.1	30.4	1.9
Mitte	1	365,300	12	19,200	20.4	32.8	33.0	1.8
Friedrichshain-Kreuzberg	2	275,200	7.4	20,100	12.8	30.7	43.0	2.0
Pankow	3	388,200	5.1	22,200	8.6	36.1	39.8	2.0
Charlottenburg-Wilmersdorf	4	313,300	6.5	21,600	13.4	38.5	35.5	2.0
Spandau	5	233,600	9.2	19,200	23.9	45.1	16.4	1.6
Steglitz-Zehlendorf	6	288,400	5.7	25,200	13.3	38.3	33.9	1.9
Tempelhof-Schoeneberg	7	339,500	7.5	23,100	16.5	40.1	30.1	1.9
Neukoeln	8	321,500	12.4	18,600	25.2	38.9	21.6	1.7
Treptow-Koepenick	9	252,600	5.5	21,900	11.5	43.7	31.2	1.9
Marzahn-Hellersdorf	10	255,400	7.8	20,400	13.1	48.0	23.7	1.8
Lichtenberg	11	274,200	6	19,200	11.5	46.7	28.2	1.9
Reinickendorf	12	251,700	10	22,200	18.3	48.7	20.4	1.8

7.1.2 London socio-economic well-being data

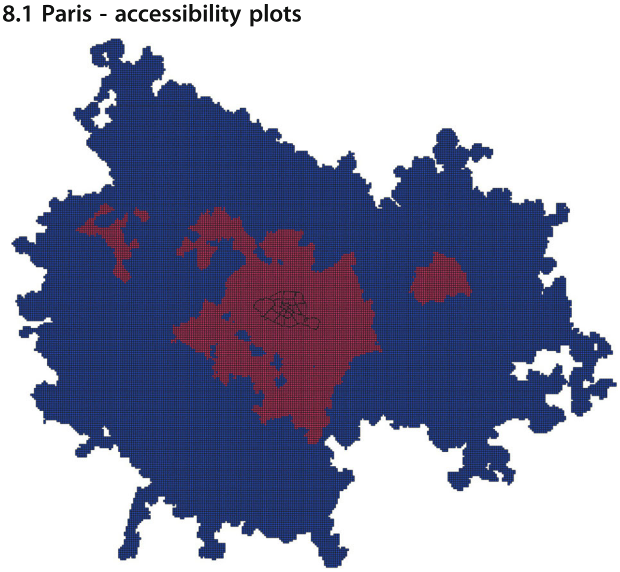
CITY DISTRICTS	DISTRICT _NUM	POP _SIZE	UNEMP _RATE	MEDIAN _INC	LOW _EDU	MID _EDU	HIGH _EDU	EDU
London_City		9,006,352	5.0	27,400	15.4	12.2	66.8	2.4
City of London	1	7681		57,300			100	3.0
Barking and Dagenham	2	212,773	10.4	23,300	25	20.3	46.6	2.1
Barnet	3	397,049	3.7	28,800	13.5	13.1	66.7	2.4
Bexley	4	249,999	3.3	26,100	17.6	21.7	56.2	2.3
Brent	5	336,859	7.4	24,100	16.7	21	55.7	2.3
Bromley	6	332,733	5.7	30,400	14	16.3	66.2	2.5
Camden	7	252,637	7.2	35,500	11.9	7.5	74.2	2.5
Croydon	8	391,296	7.5	25,600	14	16.6	62.9	2.4
Ealing	9	350,784	3.7	26,100	18	8.3	66.7	2.3
Enfield	10	337,697	6.1	25,400	21.2	11.2	57.3	2.2
Greenwich	11	286,322	5.7	26,000	15.7	14.5	63.5	2.4
Hackney	12	281,740	1.6	28,000	13.8	8.6	65.1	2.3
Hammersmith and Fulham	13	184,050	2.9	32,300	13.6	6.6	73.2	2.5
Haringey	14	284,288	7	25,100	17.2	9.6	64.7	2.3
Harrow	15	255,369	2.1	27,300	14.9	14.9	65.4	2.4
Havering	16	257,511	3.5	26,100	23.9	20.8	46.4	2.0
Hillingdon	17	309,926	5	26,200	21.2	12.9	56.5	2.2
Hounslow	18	278,264	7	26,100	15.7	10.2	67.5	2.4
Islington	19	238,267	4.7	32,900	8.6	8.2	76.3	2.5
Kensington and Chelsea	20	159,301	6.3	39,500	13.5	8.2	72.7	2.5
Kingston upon Thames	21	179,581	5.1	30,200	13.2	10.9	73.1	2.5
Lambeth	22	334,724	4.5	29,200	12.2	9.8	73.1	2.5
Lewisham	23	310,324	2.8	26,700	13.6	11.6	70	2.5
Merton	24	209,421		29,500	16.9	12.5	66.3	2.4
Newham	25	353,245	5.5	22,500	20.7	8.7	62.1	2.2
Redbridge	26	305,910	4.4	27,400	15.2	15.1	61.3	2.3
Richmond upon Thames	27	199,419	4.2	36,600	9.4	9.5	77.8	2.6
Southwark	28	322,302	4.9	29,400	13.9	7.5	72.8	2.5
Sutton	29	207,378	2.2	27,300	15.2	15.4	64.3	2.4
Tower Hamlets	30	317,203	9.1	30,500	17.7	10.9	62.3	2.3
Waltham Forest	31	283,524	3.1	24,500	18.6	11.3	61.1	2.2
Wandsworth	32	324,400	4.1	35,000	8.7	10.2	77.7	2.6
Westminster	33	254,375	4.4	36,100	7.6	6.7	78.6	2.6

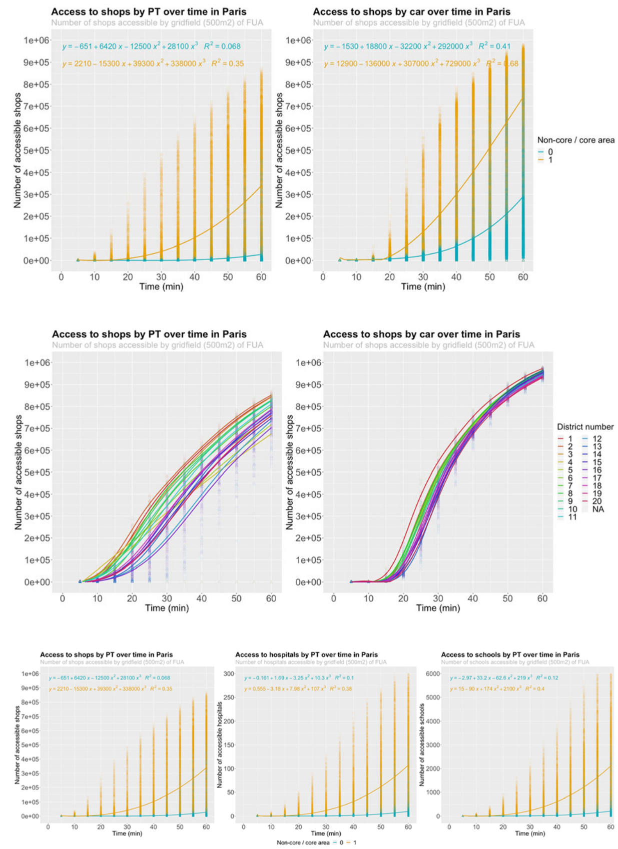
7.1.3 Vienna socio-economic well-being data

CITY DISTRICTS	DISTRICT _NUM	POP _SIZE	UNEMP _RATE	MEDIAN _INC	LOW _EDU	MID _EDU	HIGH _EDU	EDU
Vienna_City		1,741,246	11.4	20,956	41.3	20.7	38.0	2.0
1. Innere Stadt	1	16,268	4.6	32,852	22.2	22.9	54.9	2.3
2. Leopoldstadt	2	96,866	12.1	19,518	45.7	19.6	34.7	1.9
3. Landstraße	3	85,508	10.0	22,519	37.7	20.6	41.7	2.0
4. Wieden	4	30,989	7.8	24,208	27.7	21.1	51.2	2.2
5. Margareten	5	53,071	12.0	18,801	44	19.3	36.7	1.9
6. Mariahilf	6	30,117	9.4	22,133	29.8	21.6	48.6	2.2
7. Neubau	7	30,309	7.4	23,093	25.4	21.3	53.3	2.3
8. Josefstadt	8	23,930	6.4	23,336	24	21.8	54.2	2.3
9. Alsergrund	9	39,968	7.6	22,492	26.4	21.3	52.3	2.3
10. Favoriten	10	182,595	15.3	18,239	62.5	17.8	19.7	1.6
11. Simmering	11	92,274	13.7	19,369	61.4	19.6	19	1.6
12. Meidling	12	89,616	14.0	18,743	53.7	19.2	27.1	1.7
13. Hietzing	13	50,831	7.5	27,581	28.7	22.8	48.5	2.2
14. Penzing	14	86,248	10.6	20,227	43.5	21.8	34.7	1.9
15. Rudolfsheim-F.	15	73,527	13.8	16,766	53.1	18.3	28.6	1.8
16. Ottakring	16	97,565	12.6	18,701	51.4	19	29.6	1.8
17. Hernals	17	53,489	11.3	19,665	44.5	19.8	35.7	1.9
18. Währing	18	48,162	8.1	24,150	28.9	20.6	50.5	2.2
19. Döbling	19	68,892	9.0	25,588	32.4	22.4	45.2	2.1
20. Brigittenau	20	83,977	7.3	17,657	56.5	18	25.5	1.7
21. Floridsdorf	21	146,516	6.2	20,869	55.9	20.8	23.3	1.7
22. Donaustadt	22	165,265	4.8	22,515	49.7	23.1	27.2	1.8
23. Liesing	23	95,263	4.6	23,940	45.1	22.6	32.3	1.9

8 Appendix 3 - Plots of accessibility and socio-economic well-being data

8.1 Paris - accessibility plots

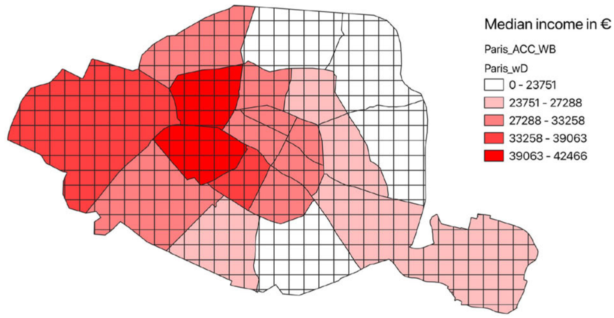


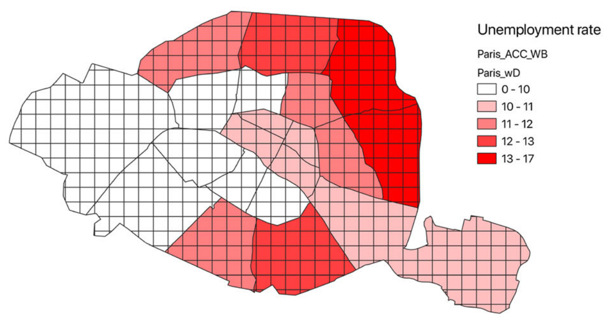


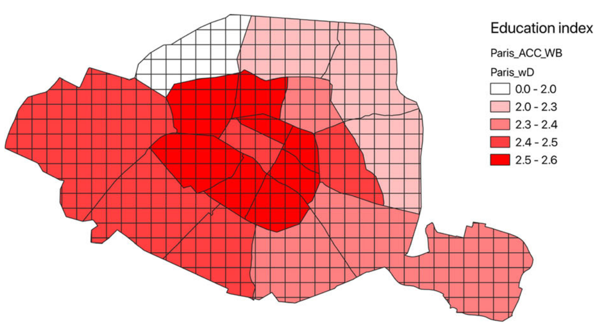
non-core	intersect	x	x^2	x^3	core	intersect	x	x^2	x^3
shops	−0.101	1	−1.947	4.377		−0.144	1	−2.569	−22.092
hospitals	− 0.095	1	− 1.923	6.095		−0.175	1	−2.509	−33.648
schools	−0.089	1	−1.886	6.596		−0.167	1	−1.933	−23.333

Regression functions for accessibility by PT to shops, hospitals and schools in core and non-core of Paris FUA, normalised by multiplier of x

8.1.1 Paris - socio-economic well-being plots

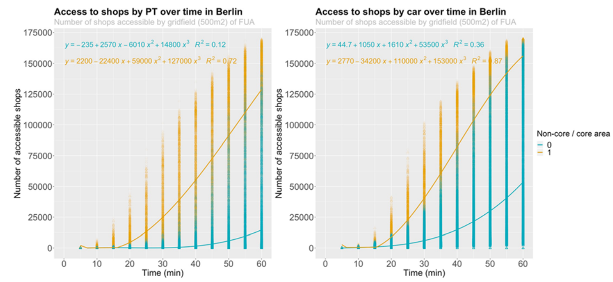


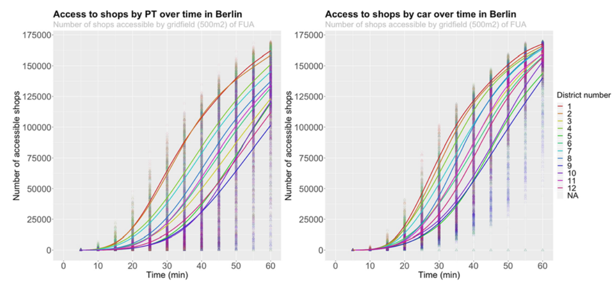


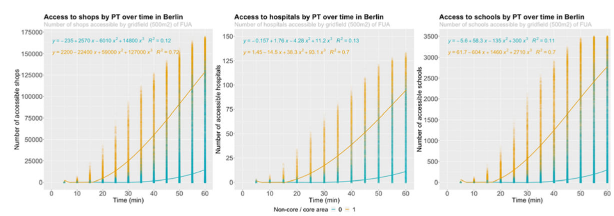


8.1.2 Berlin - accessibility plots

The Berlin FUA (blue) and its political core (red).



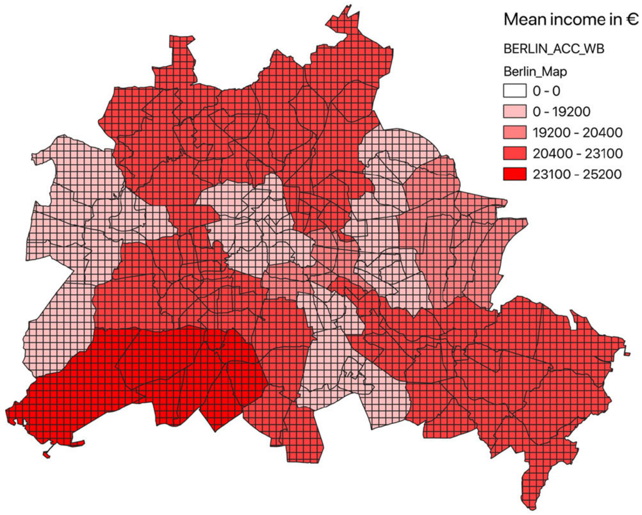


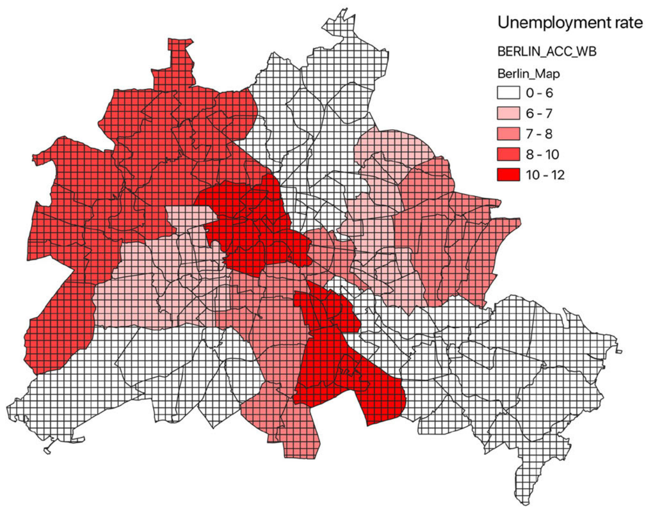


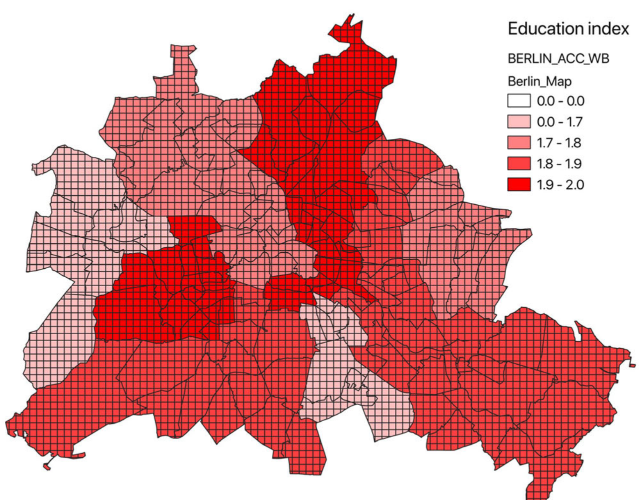
non-core	intersect	x	x^2	x^3	core	intersect	x	x^2	x^3
shops	−0.091	1	−2.339	5.759		−0.098	1	−2.634	−5.670
hospitals	−0.089	1	−2.432	6.36		−0.1	1	−2.641	−6.421
schools	−0.096	1	−2.315	5.146		−0.102	1	−2.417	−4.487

Regression functions for accessibility by PT to shops, hospitals and schools in core and non-core of Berlin FUA, normalized by multiplier of x

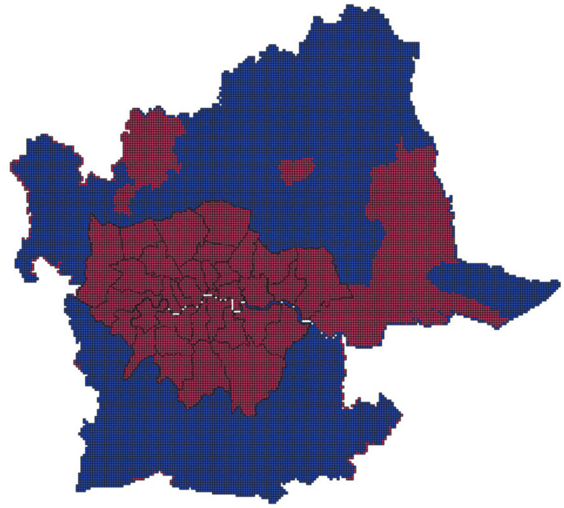
8.1.3 Berlin - socio-economic well-being plots

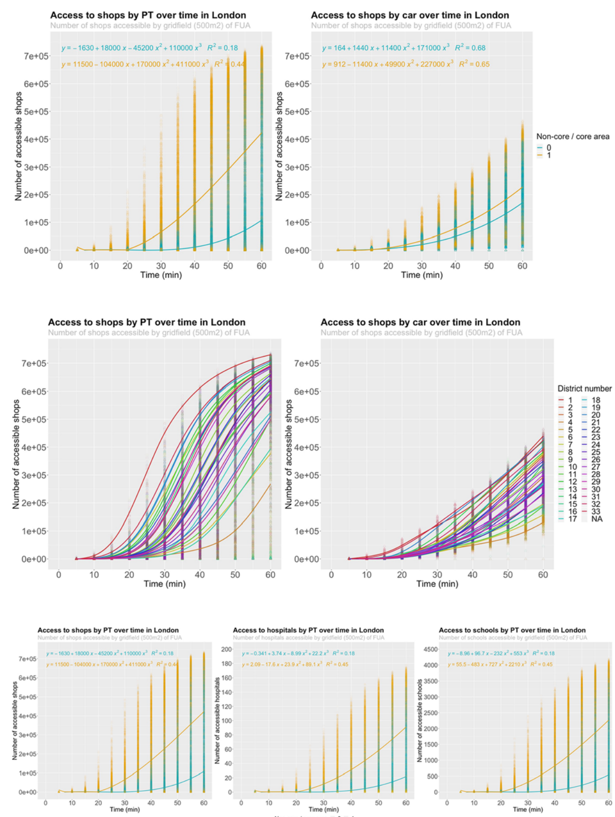






8.1.4 London - accessibility plots

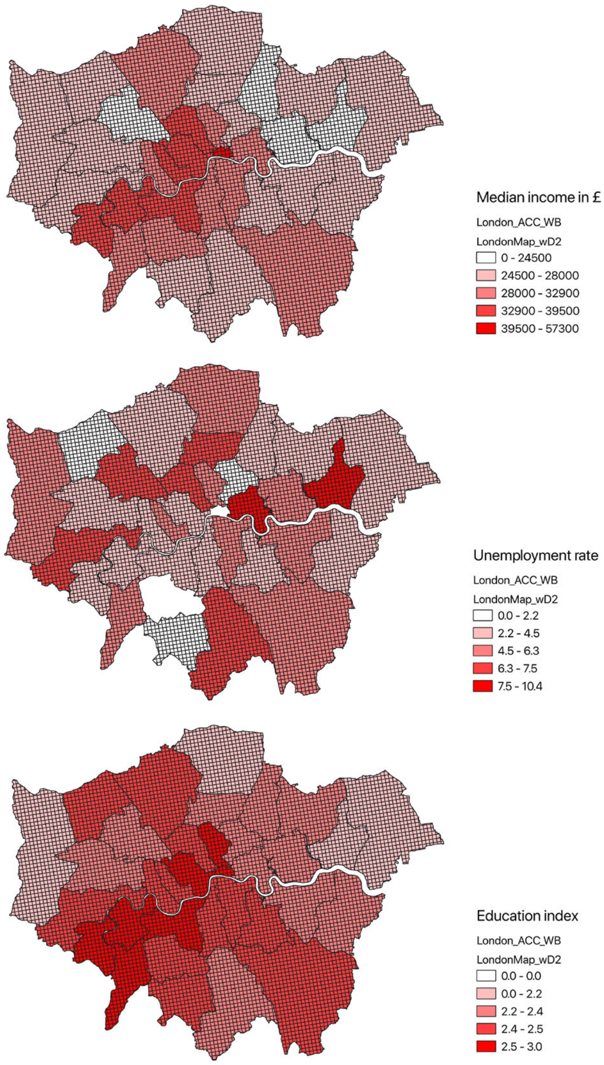




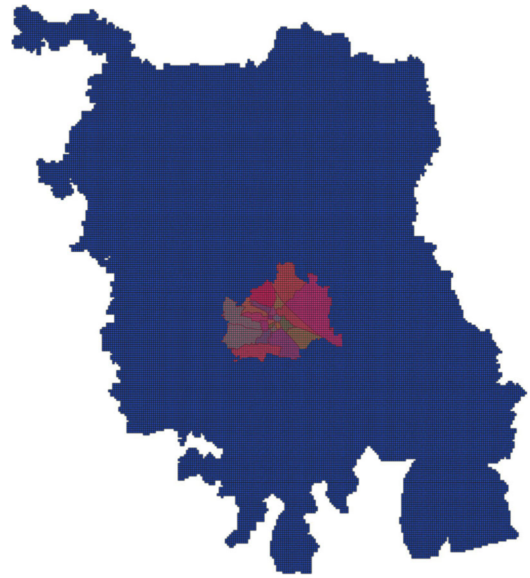
non-core	intersect	x	x^2	x^3	core	intersect	x	x^2	x^3
shops	−0.091	1	−2.511	6.111		−0.111	1	−1.635	−3.952
hospitals	−0.0912	1	−2.404	5.936		−0.119	1	−1.358	−5.063
schools	−0.093	1	−2.399	5.719		−0.115	1	−1.505	−4.576

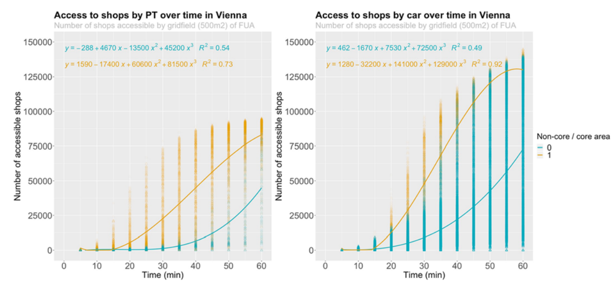
Regression functions for accessibility by PT to shops, hospitals and schools in core and non-core of London FUA, normalized by multiplier of x

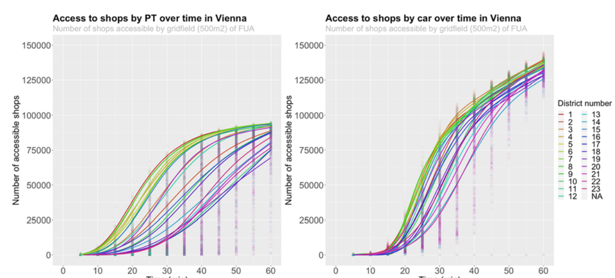
8.1.5 London - socio-economic well-being plots

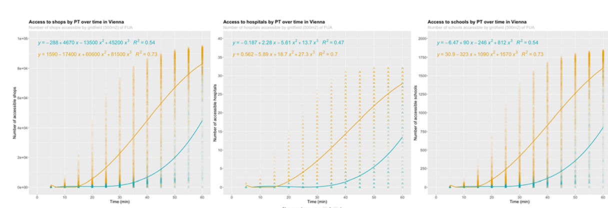


8.1.6 Vienna - accessibility plots





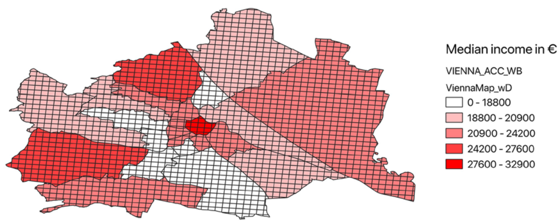


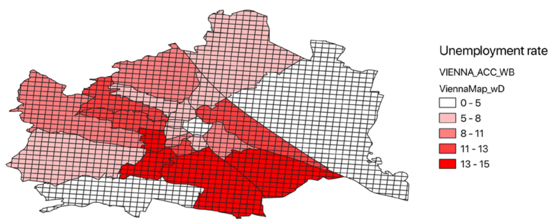


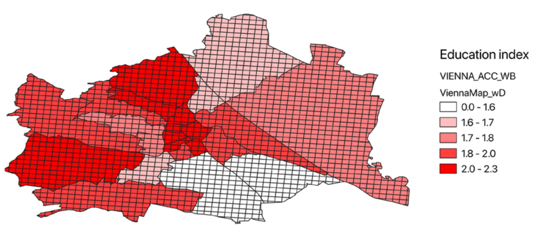
non-core	intersect	x	x^2	x^3	core	intersect	x	x^2	x^3
shops	−0.062	1	−2.891	9.679		−0.091	1	−3.483	−4.684
hospitals	−0.082	1	−2.461	6.009		−0.095	1	−3.175	−4.635
schools	−0.072	1	−2.733	9.022		−0.096	1	−3.375	−4.861

Regression functions for accessibility by PT to shops, hospitals and schools in core and non-core of Vienna FUA, normalized by multiplier of x

8.1.7 Vienna - socio-economic well-being plots







9 Appendix 4 - OLS regression models of accessibility and socio-economic well-being per city

9.1 Paris linear OLS regression models on access to shops within 30 min

```
================================================================
             Model 1      Model 2       Model 3      Model 4
----------------------------------------------------------------
(Intercept)  205864.89 *  489562.09 *** -188053.98   -192350.28
             (81228.68)   (102602.33)   (245015.68)  (532248.29)
MEDIAN_INC       4.16                                    1.85
                (2.62)                                  (5.07)
UNEMP_RATE                -13868.54                   1885.38
                           (8901.75)                 (18402.92)
EDU                                     210897.12 *  181189.35
                                        (99191.75)   (141830.52)
----------------------------------------------------------------
R^2              0.12         0.12          0.20         0.21
Adj. R^2         0.07         0.07          0.16         0.06
Num. obs.       20           20            20           20
RMSE         73903.77     74049.28      70523.87     74331.46
================================================================
*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1
```

```
==================================================================
             Model 1        Model 2        Model 3      Model 4
------------------------------------------------------------------
(Intercept)  334198.53 ***  582757.30 ***  100425.04    98747.46
             (40996.64)     (54560.80)     (133943.37)  (271164.18)
MEDIAN_INC       3.89 **                                    3.37
                (1.32)                                     (2.58)
UNEMP_RATE                  -11488.06 *                 3232.48
                             (4733.68)                 (9375.72)
EDU                                        142659.47 *  87008.62
                                           (54225.42)   (72258.30)
------------------------------------------------------------------
R^2              0.32           0.25           0.28         0.38
Adj. R^2         0.29           0.20           0.24         0.26
Num. obs.       20             20             20           20
RMSE         37299.71       39377.16       38553.47     37869.60
==================================================================
*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1
```

9.1.1 Berlin linear OLS regression models on access to shops within 30 min

```
==============================================================
             Model 1     Model 2     Model 3     Model 4
--------------------------------------------------------------
(Intercept)   67815.44    11211.09   -75844.49   -310324.83 *
             (65437.46)  (19943.19)  (87144.08)  (109514.14)
MEAN_INC        -1.89                                -1.73
                (3.09)                               (2.51)
UNEMP_RATE                 2129.13                 7298.54 *
                          (2410.72)               (2452.10)
EDU                                   55925.87   170604.36 **
                                     (46798.26)   (45728.33)
--------------------------------------------------------------
R^2              0.04        0.07        0.12         0.66
Adj. R^2        -0.06       -0.02        0.04         0.54
Num. obs.       12          12          12           12
RMSE         20204.67    19818.22    19248.06     13371.99
==============================================================
*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1
```

```
==============================================================
             Model 1     Model 2     Model 3     Model 4
--------------------------------------------------------------
(Intercept)   68908.33    29120.32   -76247.67   -314926.48 **
             (63060.24)  (19224.12)  (80475.90)   (92950.95)
MEAN_INC        -1.23                                -1.20
                (2.98)                               (2.13)
UNEMP_RATE                 1746.96                 7310.22 **
                          (2323.80)               (2081.24)
EDU                                   64150.32   175006.70 **
                                     (43217.30)   (38812.26)
--------------------------------------------------------------
R^2              0.02        0.05        0.18         0.73
Adj. R^2        -0.08       -0.04        0.10         0.63
Num. obs.       12          12          12           12
RMSE         19470.67    19103.65    17775.22     11349.58
==============================================================
*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1
```

9.1.2 London linear OLS regression models on access to shops within 30 min

```
=====================================================================
             Model 1         Model 2      Model 3         Model 4
---------------------------------------------------------------------
(Intercept)  -250125.00 ***  96719.60 *  -733066.38 ***  -234310.93
              (52713.04)    (41464.37)   (185727.14)     (236424.90)
MEDIAN_INC       12.44 ***                                   13.98 **
                 (1.74)                                      (4.37)
UNEMP_RATE                   2239.50                       4010.04
                            (7684.07)                     (6279.66)
EDU                                       356023.77 ***   -33498.52
                                          (77471.76)     (127922.38)
---------------------------------------------------------------------
R^2               0.62          0.00          0.41            0.44
Adj. R^2          0.61         -0.03          0.39            0.37
Num. obs.        33            31            33              31
RMSE          63751.64      86482.40      79987.03        67353.56
=====================================================================
*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1
```

```
=====================================================================
             Model 1       Model 2        Model 3         Model 4
---------------------------------------------------------------------
(Intercept)  -39021.20 *   46807.45 ***  -143773.65 **    -4314.62
             (14511.40)   (11466.63)     (50585.78)      (63023.16)
MEDIAN_INC       3.01 ***                                     4.60 ***
                (0.48)                                       (1.16)
UNEMP_RATE                    213.45                        355.72
                            (2124.97)                     (1673.95)
EDU                                       81138.96 ***   -34509.71
                                         (21100.68)      (34099.93)
---------------------------------------------------------------------
R^2              0.56          0.00           0.32            0.48
Adj. R^2         0.55         -0.03           0.30            0.42
Num. obs.       33            31             33              31
RMSE         17550.22      23915.99       21785.76        17954.26
=====================================================================
*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1
```

9.1.3 Vienna linear OLS regression models on access to shops within 30 min

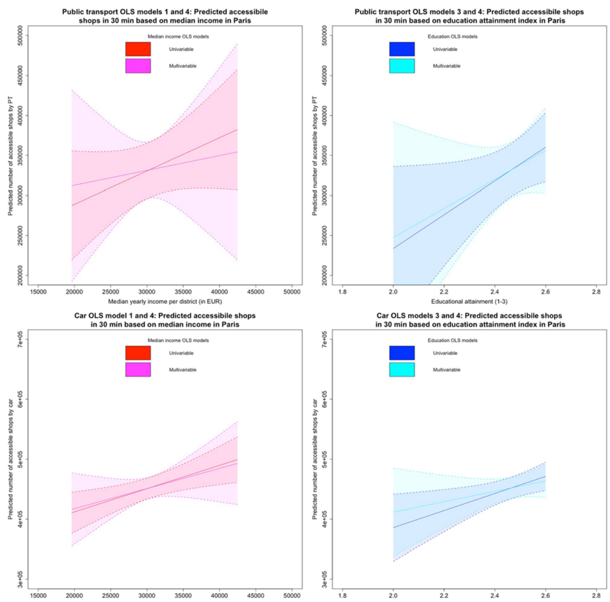
```
================================================================
             Model 1     Model 2         Model 3      Model 4
----------------------------------------------------------------
(Intercept)  12998.09    83027.79 ***  -40345.33    -3800.50
             (26816.66)  (14929.96)     (32430.75)  (80270.69)
MEDIAN_INC       1.77                                   -1.44
                (1.22)                                  (1.82)
UNEMP_RATE               -3241.15 *                 -1363.94
                         (1461.18)                  (2569.24)
EDU                                     45523.07 *   49461.60
                                       (15987.84)   (30006.35)
----------------------------------------------------------------
R^2              0.14        0.27           0.38         0.42
Adj. R^2         0.07        0.22           0.34         0.26
Num. obs.       15          15             15           15
RMSE         18101.48    16618.75       15312.75     16159.01
================================================================
*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1
```

```
=================================================================
             Model 1      Model 2         Model 3      Model 4
-----------------------------------------------------------------
(Intercept)  56196.41 *   58475.84 ***   -5016.45    -47245.89
             (24612.12)  (12428.53)     (30073.83)  (44055.41)
MEDIAN_INC       0.31                                   -1.82
                (1.11)                                  (1.54)
UNEMP_RATE                  468.03                    1783.30
                          (1253.78)                  (1436.06)
EDU                                     34469.41 *   67652.12 **
                                       (15161.86)   (20213.47)
-----------------------------------------------------------------
R^2              0.00         0.01          0.20         0.39
Adj. R^2        -0.04        -0.04          0.16         0.30
Num. obs.       23           23            23           23
RMSE         19029.65     19000.92      17077.77     15636.12
=================================================================
*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1
```

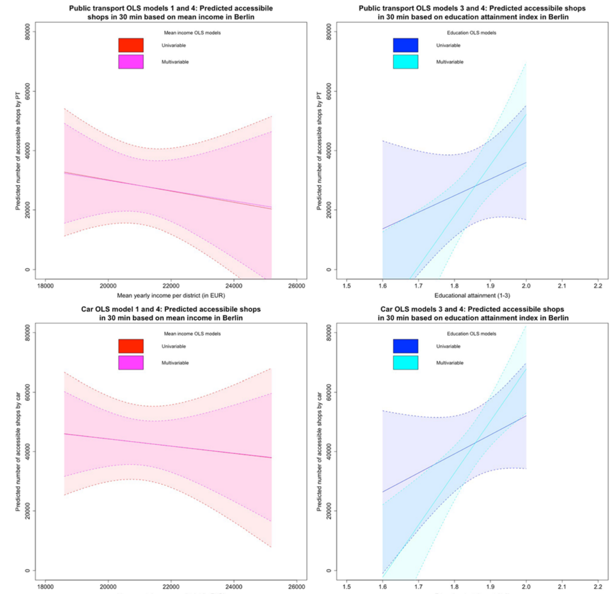
10 Appendix 5 - Plots of predicted accessibility by C and PT on basis of OLS regression models (I), (III) and (IV)

As the sample sizes are very small (number of districts between $n = 12$ and $n = 33$), the analysis also includes predicted models to test the validity of the four models. Here, one hundred predicted values for the two dependent variables Y_d^C and Y_d^{PT} are created, while changing independent variables INC_d and EDU_d from their minimum to their maximum respectively and keeping the remaining variables at their sample means.

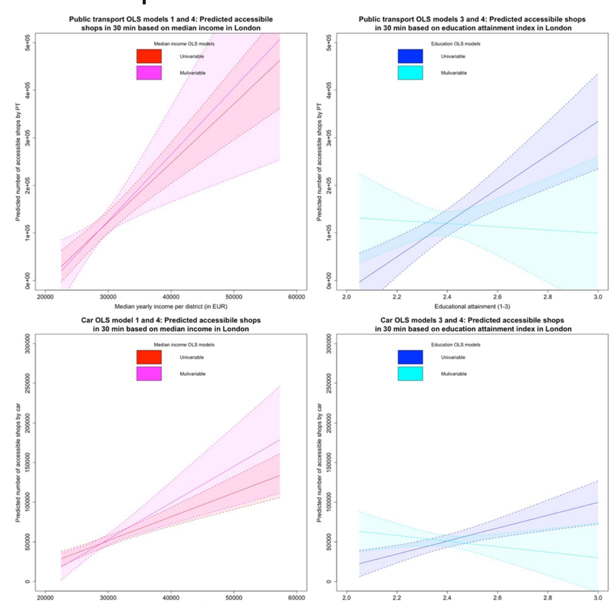
10.1 Paris plots



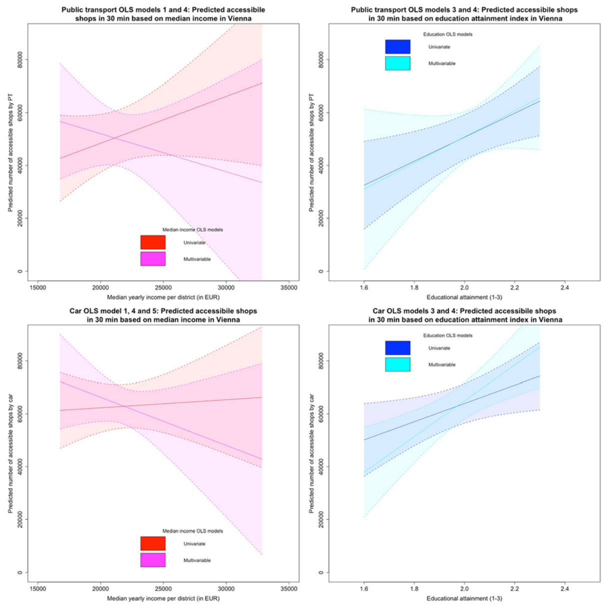
10.2 Berlin plots



10.3 London plots



10.4 Vienna plots



Abbreviations

C: Car travel; *d*: District, borough of a political city core; EDU_d: Educational attainment index per district; EU: European Union; FUA: Functional urban area; HDI: Human Development Index; INC_d: Mean or median yearly income per district; ITF: International Transport Forum; OECD: Organisation for Economic Co-operation and Development; OLS: Ordinary Least Squares; *PT*: Public transportation; SAVs: Shared autonomous vehicles; UNDP: United Nations Development Programme; UK: United Kingdom; US: United States; UEM_d: Unemployment rate per district; Y_d^C: Number of accessible shops per districts by car travel; Y_d^{PT}: Number of accessible shops per districts by public transportation

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Authors' contributions

NE carried out the literature and data research, performed statistical analysis and wrote the manuscript. MAR conceived the research project and participated in its design. Both authors read and approved the final manuscript.

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Not applicable

Availability of data and materials

The data sources are listed in Appendix 1 and are for the most part publicly available. The data that support the findings of this study are available on request from the corresponding author.

Declarations

Competing interests

Neither author has conflicts of interest to disclose regarding this manuscript.

Author details

[1]Zurich, Switzerland. [2]Center for Mobility, University of St. Gallen, St. Gallen, Switzerland.

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