Transportation Research Part D 103 (2022) 103171

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Modal accessibility disparities and transport poverty in the Oslo region

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ARTICLE INFO

Keywords:
Accessibility
Public transport competitiveness
Transport poverty
Transport related social exclusion

ABSTRACT

Sufficient accessibility to opportunities, with different transport modes, is an important factor in order to avoid transport-related social exclusion and transport poverty. This paper investigates the social and geographical disparities in accessibility and time competitiveness of public transport in the Oslo region. Both place-based access to employment opportunities and the working population's individual-specific commutes are measured. The study combines registry data with detailed accessibility metrics and uses descriptive maps and spatial regression models to study transport poverty. The results show that less affluent neighbourhoods suffer from low accessibility and poor time competitiveness of public transport, which is partly related to the suburbanization of poverty. This suggests that the transition to low emission mobility, with restrictions on car use, may be especially burdensome in less affluent neighbourhoods. The findings can help policy makers in securing an equitable transition from car to more sustainable transport modes.

1. Introduction

Inequality, justice and social exclusion are becoming increasingly important concepts in transport-related research (Banister, 2018; Lucas, 2012; Martens, 2016). A central topic is *transport poverty*, which occurs when people lack available transport options to reach daily activities, or when the available transport alternatives are disproportionately time consuming or costly (Lucas et al., 2016; Mattioli, 2021). Related to transport poverty is the concept of *car dependency*, which describes a process whereby "access to modes alternative to the car and/or their viability are diminished, such that car use becomes essential to access services, opportunities and social networks" (Mattioli, 2021, p. 3). In order to reduce climate gas emissions from the transport sector, a transition from car to more sustainable transport modes is necessary. Public transport (PT) plays a crucial role in reducing car dependency. Sufficient PT access, both in absolute terms and relative to the car, is important to avoid transport poverty and transport-related social exclusion, and to secure a just transition to low emission mobility. However, previous studies have found that transport services are often unevenly distributed both geographically and among social groups (see for example Cao and Hickman, 2018; Ermagun and Tilahun, 2020; Mattioli, 2021; Pereira et al., 2019), and that PT often competes poorly with the car in terms of accessibility and travel times (Golub and Martens, 2014; Salonen and Toivonen, 2013).

A common way to operationalize the distribution of transport wealth and poverty is by mapping the population's *accessibility* to services and opportunities, such as workplaces (Giannotti et al., 2021; Pereira, 2018; Smith et al., 2020). Securing sufficient access for all, including disadvantaged groups, is important to achieve distributive justice and avoid transport poverty (Pereira et al., 2017).

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https://doi.org/10.1016/j.trd.2022.103171

Available online 15 January 2022

However, this approach has been accused of being too theoretical and missing individual needs, as all workplaces are not equally relevant for all workers (Dixit and Sivakumar, 2020). For example, increasing PT access to workplaces in the finance sector is not a relevant measure to reduce car commuting among teachers. Different solutions to this problem have been applied, such as weighing the accessibility by education level (Pereira et al., 2019), and to measure access to low-income jobs specifically (Liu and Kwan, 2020). However, the issue still remains that this measure reflects theorised accessibility, and it is not clear to what extent this overlaps with the direct mobility needs of the population. As an alternative, using individual commute times as the unit of analysis is more related to the actual transport needs of the population. On the other hand, several authors argue that this approach suffers from sample selection bias, where the observed commute times of the working population cannot be generalised, neither to potential new employees nor to possible alternative job locations for current workers (Cooke and Ross, 1999; DeRango, 2001).

The current study asks the following research question: *How do general car and PT employment accessibility and individual commute times, in absolute and relative terms, vary geographically and among socioeconomic groups in the Oslo region?* Although the Oslo region is characterised by a comprehensive and efficient PT system (Grue et al., 2021), there are also clear signs of residential segregation and political protest against car restrictive measures (Christiansen, 2018; Wessel, 2015). This suggests that there may be distributional differences related to transport and accessibility.

To answer the research question, this paper studies both the modal accessibility disparities between PT and car, as well as the absolute accessibility levels with the two modes. The accessibility disparity is defined as the *time competitiveness of PT relative to the car for accessing jobs*.[1] This is measured as the ratio between car and PT accessibility (Kwok and Yeh, 2004). PT time competitiveness is closely linked to mode choice, where more travellers tend to travel by PT when its competitiveness increases (Cui et al., 2020; Kwok and Yeh, 2004; Lunke et al., 2021). While modal competitiveness is an important factor in terms of sustainable transport and the transition to low-emission mobility, the absolute accessibility levels are more important in explaining social exclusion and transport poverty. A complete understanding of transport and environmental justice should therefore include both relative and absolute accessibility measures, which is the case in this paper.

This paper makes several contributions. First, both general access to employment and individual commute times of the population in the Oslo region are measured, and the correlation between the two concepts is investigated. Second, the paper uses a weighted measure of employment accessibility, which takes into account that different workplaces are not equally attractive to all workers. Third, this study uses highly representative data encompassing the entire population, which enhances data quality and reduces selection bias. Fourth, a combination of spatial and non-spatial multivariate models represents an improvement over simpler approaches, which tend to dominate research on equity and PT accessibility (see assessments by Golub and Martens, 2014; Pereira et al., 2017; Smith et al., 2020). Lastly, as mentioned above, this paper studies both absolute levels of car and PT access and the time competitiveness of PT. This has seldom been the case in previous studies.

The next section presents relevant literature on the theme of the paper. The data sources and methodology are presented in Section 3, and the results in Section 4. The paper ends with a discussion and conclusions in Section 5.

2. Literature review

According to Lucas et al. (2016), the concept of transport poverty consists of the following sub-concepts: mobility poverty, accessibility poverty, transport affordability and exposure to transport externalities. This study's combination of general accessibility and individual commute times is useful for studying the first three sub-concepts. Exposure to transport externalities is, however, beyond the scope of this paper. Accessibility is considered a highly important concept in order to reduce transport poverty and secure distributive justice in transport (Martens, 2016; Mattioli, 2021; Pereira et al., 2017). Pereira et al. (2017) argue that equity in transport policies is achieved when access to key destinations such as employment, healthcare and education services is secured for all, including disadvantaged groups, such as the disabled, elderly and low-income people. Drawing on theories of distributive justice from John Rawls and Amartya Sen, Pereira et al. (2017) argue that "accessibility […] should be the primary focus of transport researchers and policy makers addressing questions over distributive justice and transport disadvantage" (p. 184). In the literature, PT access is often given more attention than car access for several reasons. First, low-income groups are often more dependent on PT as they do not have access to a private car, and the distances of daily trips are often so far that walking or bicycling are not an option. Second, environmentally friendly transport modes central in the transition to low-emission mobility. Following the 2016 Paris agreement (United Nations, 2016), a reduction of transport-related climate gas emissions is high on the political agenda. Measures taken to reduce the use of private cars can only be considered just if they secure that accessibility to PT is satisfactory for the whole population (Schwanen, 2020). Third, there is a clear connection between PT accessibility and employment in the research literature (Bastiaanssen et al., 2020). Accessibility calculations are usually conducted for specific transport modes. In the evaluation of environmental justice and the transition to low-carbon mobility, it is however relevant to also study PT time competitiveness, which can be defined as the gap in accessibility between PT and car.

Access to employment opportunities is affected by several factors, such as the transport system, the housing market and the spatial distribution of jobs. An early example is the spatial mismatch hypothesis (Kain, 1968), which states that discrimination in the housing market and limited access to private cars led to increased unemployment among African-Americans in inner areas of American cities. In recent years, the opposite phenomenon has become more common: As inner-city areas have been gentrified, the increasing pressure

[1] The shorter term *PT time competitiveness* is used in the rest of the paper.

on central housing has led to a *suburbanization of poverty*, where low-income groups have relocated to the urban peripheries (Allen and Farber, 2021; Ehrenhalt, 2012; Hochstenbach and Musterd, 2018; van Ham et al., 2020). Since accessibility, especially with PT, is usually better closer to urban centres, this process tends to lead to a suburbanization of *transport* poverty (Allen and Farber, 2021). Lucas et al. (2018) show that residential location within a city is an important factor behind transport poverty. In a study from Merseyside, England, low-income households in central locations, where the access to PT is better, were found to undertake more daily trips than their suburban counterparts. Suburbanization of poverty thus has clear implications for transport justice, accessibility and the ability to choose environmentally friendly transport modes (Cao and Hickman, 2018; Mattioli, 2021; Sterzer, 2017). Several studies have considered distributive justice in access to opportunities. In American cities, accessibility advantages for low-income groups in the inner city have been identified (Grengs, 2010; Shen, 1998). However, the opposite is more often the case. In cities such as London (Smith et al., 2020), Madrid (Cadena et al., 2016), Paris (Korsu and Wenglenski, 2010) and Chicago (Ermagun and Tilahun, 2020), lower accessibility has been identified among low-income groups. Among different ethnic groups, the picture is more unclear. In Chicago, African-Americans, Hispanics and Asians were found to experience lower accessibility than other ethnic groups (Ermagun and Tilahun, 2020). On the other hand, higher accessibility among immigrants than the native population has been documented in Europe (Bartzokas-Tsiompras and Photis, 2019) as well as Australia and Canada (Allen et al., 2021).

Low levels of employment accessibility will intuitively lead to longer commutes. This can in turn lead to increased time poverty, as the long time spent commuting can lead people to miss out on other activities (Mattioli, 2021). The social differences in commute times are, however, more unclear. In the US, low-skilled and low-wage workers tend to experience long commutes (Cooke and Shumway, 1991), while in Europe, it is often found that people with high income and higher education levels commute longer than others (Joly and Vincent-Geslin, 2016; Rüger et al., 2011). Simultaneously, in Madrid, higher commuting times were found among immigrants than the native population (Blázquez et al., 2010).

Although the distributive and equity aspects of accessibility and commute time have been studied elsewhere, research in a Norwegian context is quite scarce. However, there is much evidence on the residential location patterns of different groups in the Oslo region, which can give some ground for hypotheses regarding this study's research question. First, there is reason to believe that suburbanization of poverty is happening in the region, as there is considerable pressure on housing prices in Oslo, especially in the inner city (Lindquist and Vatne, 2019). Those who are not able to pay a premium for housing may be forced to trade away a central, PT-accessible location against a need for space or other dwelling qualities (Barlindhaug et al., 2019). This is especially the case for families with children. The preference for single-family housing is high among parents, who often trade a central location for a larger dwelling in the suburbs outside of the municipality of Oslo (Barlindhaug et al., 2019; Wessel and Lunke, 2021). Secondly, the residential mobility of the native population differs from that of immigrants. Immigrants, especially those of non-Western origin, are overrepresented in the central, eastern and southern parts of the Oslo municipality (Turner and Wessel, 2013; Wessel et al., 2018). The native population tends to avoid these areas (Wessel and Nordvik, 2018), and are instead overrepresented in the western parts of Oslo, as well as in the neighbouring municipalities. The current study supplements the existing research on residential mobility and seeks to unveil how these patterns relate to transport poverty. Based on the existing literature, distributive differences can be expected in transport access and commuting among different income groups, ethnic groups and households with children.

3. Data sources and methodology

Census tracts form the unit of analysis in this paper. Data on socioeconomic status and residential and work locations were gathered from different population registers provided by Statistics Norway and the Norwegian Directorate of Taxes. These individual-level data cover the entire population in the Oslo region in 2017, in total 983,448 individuals distributed on 1,798 census tracts.

This study utilizes several dependent variables: the ratio between PT and car on both general accessibility and commute times, as well as absolute levels of PT and car accessibility and average PT and car commute times. In the multivariate models, the dependent variables are used directly or with logarithmic transformations. In the scatterplots, rank transformations (percentiles) are used to measure the correlation between the dependent variables. In these plots, *commute time efficiency* is used instead of actual commute times, in order to make the two scales (accessibility and commute times) comparable. High percentiles indicate high accessibility and short commute times (higher *commute time efficiency*), respectively. All the dependent variables are based on travel times between building-weighted centroids of census tracts, calculated with GTFS timetable data and road network data,[2] using R statistical software and the r5r package (Pereira et al., 2021). Access to employment is measured by a weighted cumulative opportunity approach where all reachable destinations are weighted by travel time (Handy and Niemeier, 1997; Kwan, 1998, p. 199; Levinson and King, 2020). This approach provides more realistic metrics of accessibility than unweighted calculations, especially for PT accessibility (McCahill et al., 2020). Travel times are measured with departure time at 08:00 am. To account for the sensitivity to departure times for PT (Pereira, 2019), travel time with PT is measured as the median travel time of several departures within a time window.[3] PT travel time also includes walking to, from and between stops,[4] It is rarely possible to park the vehicle at the point of interest, and often drivers have to spend time searching for a parking space. Therefore, a random number of minutes between 5 and 10 is added to the travel time with car

[2] This paper uses publicly available data from Entur (www.entur.no) and Open Street Map (www.openstreetmap.org).

[3] The median of 60 departure times is used, calculated for each minute within a one-hour time window, stretching from 07:30 am to 08:30 am.

[4] A maximum walking distance of 800 m is used, as was recommended and used in previous studies (see for example Liao et al. 2020). This means that opportunities within 800 m of the residential location are accessible either by walking alone or in combination with PT. In addition, up to 800 m' walking distance to, from and between PT stops is accepted.

to account for time spent searching for parking, parking the vehicle, and walking from the vehicle to the destination (International Transport Forum, 2019; Liao et al., 2020).

Employment accessibility is measured by calculating the weighted number of workplaces that can be accessed from each census tract via car and PT. Accessibility, $A_{o,t}$, for residents in census tract o is measured as follows:

$$A_{o,T} = \sum_{d} O_d df(t_{od}) \tag{1}$$

where O_d is the number of opportunities (workplaces) in location d. $df(t_{od})$ is the distance decay function, reducing the weight of accessible opportunities at location d based on the travel time (t_{od}) between population weighted centroids of origin o and destination d. In this case, a negative exponential function is used to weight opportunities, as recommended in the literature (Handy and Niemeier, 1997; Kwan, 1998).

$$df(t_{od}) = e^{\beta t_{od}} \tag{2}$$

The distance decay function ($\beta = -0.03$) was found by investigating the distribution of commute trip durations in the study region with data from the Norwegian National Travel Survey (Grue et al., 2021).

As all employment opportunities are not equally relevant for all employees, workplaces and workers are divided into four groups, based on employment sector and typical level of education (Stambøl, 2005; Wessel, 2013): Knowledge intensive business sector (KIBS); public sector jobs requiring higher education; consumption services in the private sector; and industry and manufacturing,[5] Accessibility to jobs in each of these groups is calculated, and the accessibility level is weighted based on the group distribution of the workers in each census tract.

For each census tract, access with car and PT is calculated: $A_{o,t\ Car}$ and $A_{o,t\ PT}$. The PT time competitiveness is calculated by:

$$A_{ratio} = \frac{A_{PT}}{A_{car}} \tag{3}$$

The value of A_{ratio} is 1 when the accessibility levels of car and PT are equal, and it goes towards 0 when PT accessibility is relatively lower than car, and increases towards infinity when car access is lower than that of PT. A higher A_{ratio} thus means that the level of PT access is higher than that of car.

The average commute time of each census tract is found by calculating the travel time (CT_{car} and CT_{PT}) between the residential location and work location of all workers. Second, the average commute time gap is based on the ratio for all workers:

$$CT_{ratio} = \frac{CT_{car}}{CT_{PT}} \tag{4}$$

Notice that the numerator and denominator has been exchanged for commute time, in order to get similar measures of the ratio: Higher values of CT_{ratio} indicate better PT time competitiveness (travel time is lower with PT).

This paper uses independent variables on sociodemographic and urban form characteristics of the census tracts. The sociodemographic variables are based on registry data from the entire population of the study area. As this study uses census tracts, the data are aggregated to tract level averages. The average income level of each census tract is measured by ranks (percentiles). Rank transformation is used both to control for non-linearity and to ensure that observations with zero or negative values are included. Income is measured after tax and includes labour incomes, capital incomes and public transfers. A variable that captures "cultural capital" is included, measured by the share of workers in creative, artistic and scientific industries.[6] The background for this choice is twofold. First, gentrification in Oslo has primarily been explained as a cultural phenomenon, and not as a rent-gap phenomenon (Hjorthol and Bjørnskau, 2005). Second, accessibility tends to vary for different workplaces, especially highly skilled workplaces, which tend to be located closer to PT stations (Gundersen et al., 2017). As mentioned, residential mobility patterns in the Oslo region vary both between natives and immigrants and between families with children and others. To control for ethnicity, the share of native Norwegian inhabitants is measured. This share equals all inhabitants who are neither first nor second-generation immigrants. Lastly, a variable measuring the share of households with children in each census tract is included.

There is a clear relation between the built environment and the other variables under study. First, PT accessibility and PT use tend to be higher in central and densely built areas. Second, there is a clear preference for a central residential location among the population in the Oslo region, as reflected by the housing costs. Those who are able to pay a premium for housing can therefore be expected to choose to settle in or close to the inner city. Three measures of the built environment are especially important in explaining travel

[5] The groups consist of the following sectors, based on Statistical Classification of Economic Activities in the European Community (NACE rev.2) codes. KIBS: 58.11–58.29, 62.01–62.02, 63.11–68.1, 68.31–71.2, 73.1–73.2 | Public sector: 72.11–72.2, 75, 84.11–84.21, 84.23–85.42, 85.6–88.99, 91.01–91.04 | Consumption services: 47.11–47.89, 55.1–56.3 | Industry and manufacturing: 1.11–46.9, 47.911–53.2, 59.11–61.9, 62.06–62.09, 68.2, 74.2–74.9, 77–82, 84.22, 85.5, 90, 92–99.

[6] NACE rev.2 codes within the cultural capital group are: 58.1|58.110|58.11|58.119|58.130|58.140|58.190|58.29|59.1|59.11|59.110|59.12| 59.120|59.2| 59.20|59.200|59.13|59.14|60.1|60.10|60.100|60.2|60.20|60.200|63.910|71.1|71.11|71.111| 71.112|71.113|72.2|72.20|72.200| 73.11|73.110|73.12|73.120|73.200|74.1|74.10|74.101| 74.102|74.103|74.2|74.20|74.200|74.3|74.30|74.300|85.3|85.31|85.310|85.4|85.41| 85.42|85.421|85.422|85.423|85.429|85.51|85.510|85.52|85.521|85.522|85.529|90|90.0|90.011|90.012|90.019|90.03|90.031|90.032|90.033| 90.034|90.039|90.04|91|91.01|91.011|91.012|91.013|91.02|91.021|91.022| 91.023|91.029|91.03|91.030

Table 1
Descriptive statistics of all census tracts, weighted by population (N = 1,798).

	Mean	Std.dev.	Min.	Max.
Dependent variables				
Emp. accessibility ratio (PT/car)	0.45	0.14	0.00	0.87
Emp. accessibility car	88 694	19 879	25 235	134 857
Emp. accessibility PT	41 532	18 496	1	79 315
Avg. commute time ratio (car/PT)	0.57	0.09	0.01	1.11
Avg. commute time car	28.59	5.38	17.60	55.90
Avg. commute time PT	52.11	17.32	24.63	188.63
Independent variables				
Avg. income (1000 NOK)	359.95	86.46	102.93	1 031.39
Cultural capital	0.08	0.05	0.00	0.35
Native Norwegians (share)	0.74	0.15	0.00	1.00
Children in hh (share)	0.32	0.11	0.00	0.81
Population density (people per km^2)	6 807.76	8 193.71	1.02	44 800.00
Building diversity (Shannon index)	0.42	0.26	0.00	1.55
Travel time to Oslo centre (car, minutes)	30.51	12.93	11.00	84.00

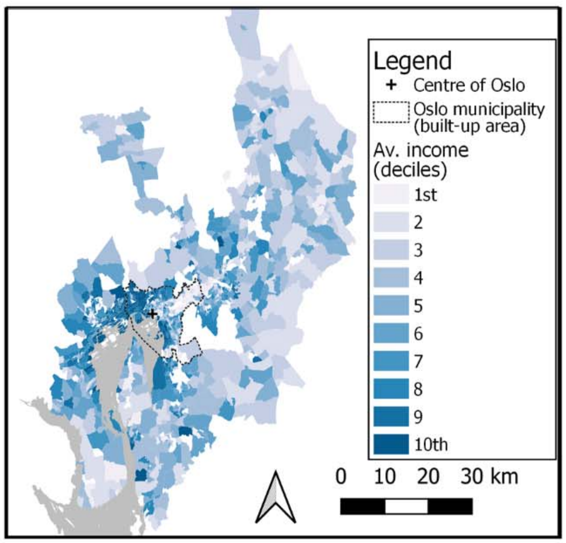

Fig. 1. Study area. Average income level (1,000 NOK in deciles) in census tracts.

behaviour: density, diversity and design (Cervero and Kockelman, 1997). In this study, the first two measures are included to control for urban form: population density and building diversity. Both factors are intuitively related to accessibility, as they lead to closer proximity to a variety of services and opportunities. Population density is measured by the number of residents per km^2. Building diversity is based on the Shannon index of diversity, $H = -\sum_{i=1}^{s} p_i log p_i$, where s are all existing building types (residences, industry, offices, transport buildings, hotels and restaurants, cultural institutions, health- and emergency buildings and prisons), and p_i represents the proportion of building types relative to the total number of building types (Shannon, 1948). The design measure of Cervero and Kockelman is not included, as this is better suited for studies of walking and bicycling than car and PT (Chevalier et al., 2019). Instead, a variable on centrality is added, measured by the distance to the centre of Oslo.[7] This variable has been linked to transport mode choice in the Oslo region (Engebretsen et al., 2018), and as mentioned to residential location preferences. Both population density and distance to Oslo are log transformed in the regression models, in order to control for non-linear relations. Table 1 shows the descriptive statistics of all variables under study.

The study area is defined as Oslo municipality plus all neighbouring municipalities where at least 20 percent of the work force commutes to Oslo.[8] This delineation represents a functional region, which is argued to be more suited in studies of social phenomena than administrative regions (Gundersen et al., 2019). The region is characterised by rapid population growth, gentrification and

[7] Measured by the travel time by car (in minutes) from the census tracts centre to the centre of Oslo. The centre of Oslo is defined by the location of the city hall.

[8] The study area includes the following municipalities: Oslo, Vestby, Nordre Follo, Ås, Frogn, Nesodden, Bærum, Asker, Lørenskog, Lillestrøm, Rælingen, Enebakk, Ullensaker, Nes, Eidsvoll, Nittedal, Gjerdrum, Lunner.

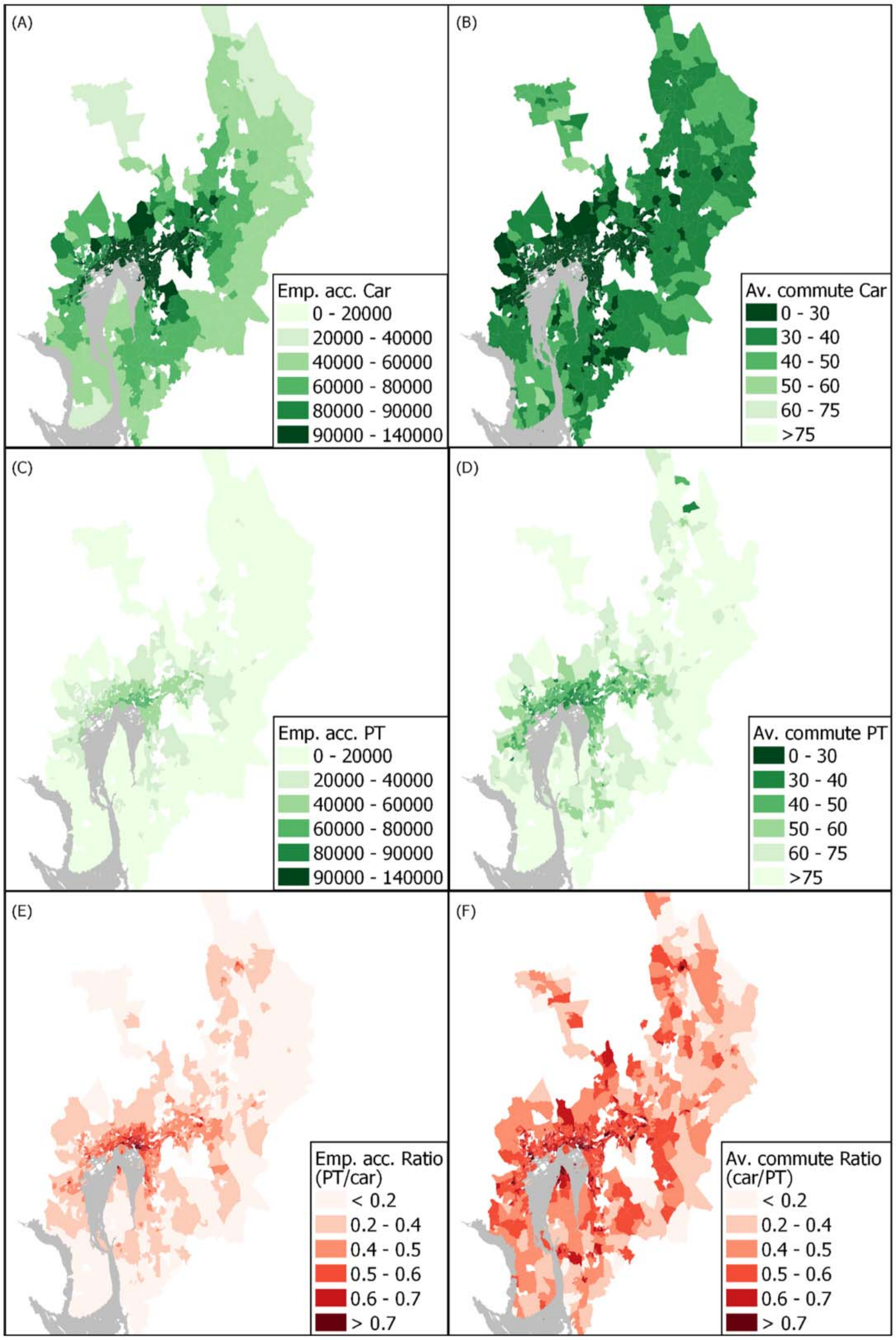

Fig. 2. Employment accessibility (A) and average commute time (B) with car, employment accessibility (C) and average commute time (D) with PT, employment accessibility ratio (E) and commute time ratio (F) in study area.

increasing housing prices (Hjorthol and Bjørnskau, 2005; Lindquist and Vatne, 2019). Moreover, the municipal and regional authorities are actively promoting a shift away from private car use through toll roads, parking fees, investments in bicycle and pedestrian infrastructure and compact city developments around PT hubs. At the same time, restrictions on car use, such as toll roads

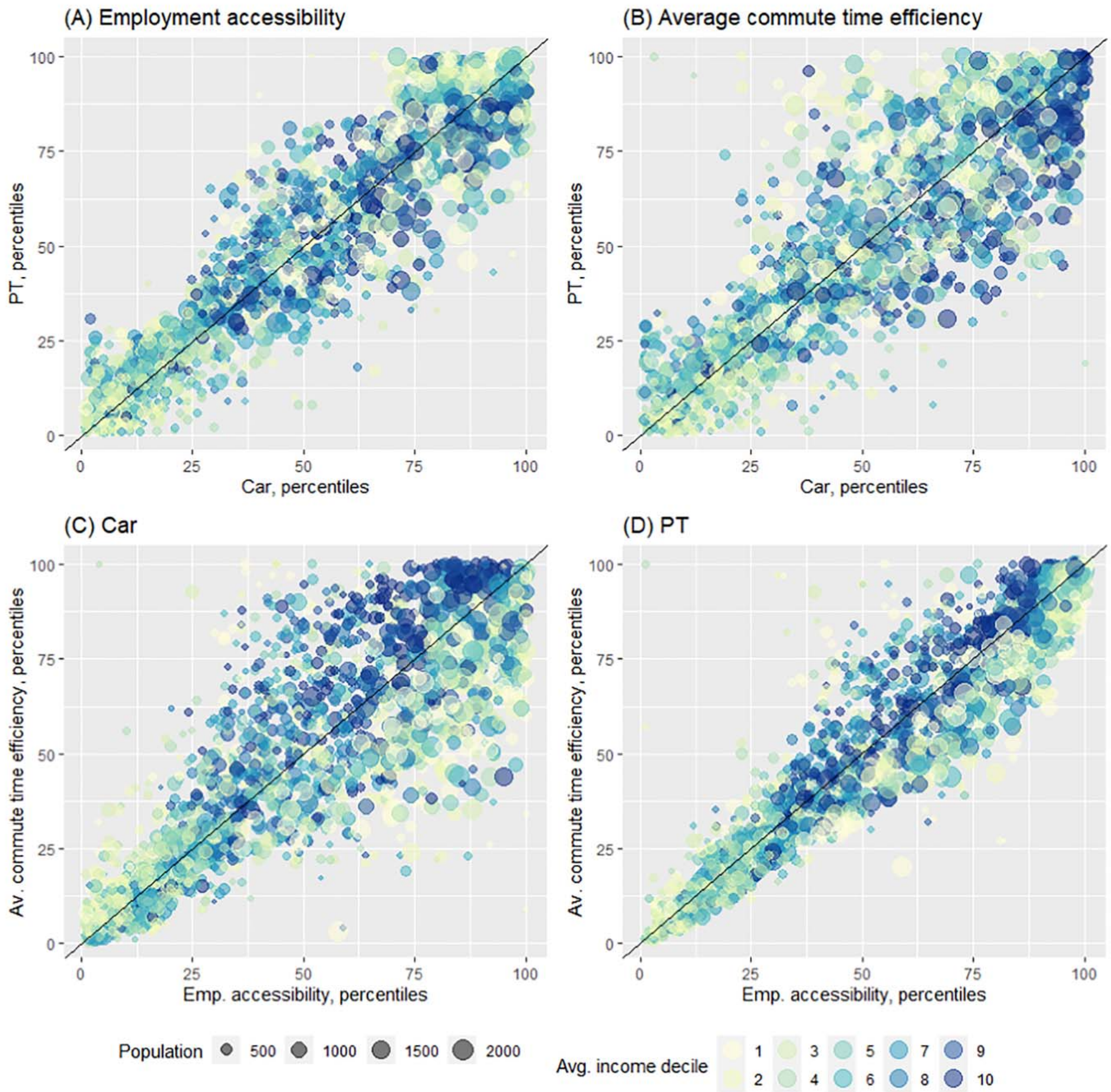

Fig. 3. Correlation between car and PT in employment accessibility (A) and average commute time efficiency (B), and between employment accessibility and average commute time efficiency with car (C) and PT (D).

and parking fees, have led to widespread political protests. In the 2019 municipal election, the anti-toll party (FNB) received 5.8 percent of the votes and became the sixth largest party in Oslo.[9]

Fig. 1 shows the study area with average income levels. The map clearly displays an east-west divide, especially within the municipality of Oslo, where the west is relatively more affluent than the outer east and outer south.

In the next section, maps and scatterplots are presented to show the comparison of accessibility and commute times. The scatterplots present the correlations between selected variables, as well as the relationship between area-based income and accessibility or commute times. Next, multivariate regression models are presented, which test the association between the independent variables and accessibility and commute times, respectively. The spatial models allow us to control for spatial autocorrelation in the data, which is necessary to avoid violating the assumption of uncorrelated variables in statistical analysis. In other words, spatial models control for characteristics in neighbouring census tracts. To find the appropriate model, the spatial dependence of the baseline model (a regular OLS) was first tested. This test showed a significant level of spatial autocorrelation in the residuals (Moran's I-value of 0.25–0.75, $p < 0.001$) suggesting spatial models are better suited than OLS models. Next, a Lagrange multiplier test was conducted to suggest that a

[9] www.valgresultat.no (accessed 15.9.2021).

spatial Durbin model (SDM) was the best fit to the data (Anselin, 2010; Elhorst, 2010; LeSage, 2008).The SDM is defined as follows:

$$Y = pWy + X\beta + WX\theta + \varepsilon \tag{5}$$

where Y is the vector of the dependent variables (accessibility and commute time ratio, with absolute accessibility and commute times for each mode in the appendix). $X\beta$ is the vector and coefficients of the independent variables. In addition, the SDM includes a spatial lag component to both the dependent (pWy) and the independent ($WX\theta$) variables. The use of the SDM is also intuitive, as one can expect spatial autocorrelation to happen both in the dependent variables, as well as in several of the independent variables, such as income, cultural capital and urban form. In other words, this study controls for the fact that both accessibility levels, urban form and sociodemographic characteristics of census tracts may be influenced by the characteristics in neighbouring census tracts (defined by queen's contiguity). Moreover, the spatial lag component of the independent variables ($WX\theta$) can be considered as a factor of other variables with spatial patterns, that are not included in the model. The Rho and AIC levels of the models confirmed that the spatial model was a better fit than the OLS model. The data was found to be within the suggested thresholds for collinearity and multicollinearity (Hair et al., 2009; Tabachnick et al., 2001).

4. Results

4.1. Geographic disparities and correlations between accessibility and commute times

Table 1 shows that employment accessibility with car is higher and average commute times are lower than with PT. This results in low ratio levels, indicating that, on average, car commuting is more efficient and accessible. The ratio of employment accessibility is lower than that of average commute times, which suggests that the difference between car and PT is greater for the former.

Fig. 2 maps the levels of employment accessibility and average commute times with car (A, B) and PT (C, D), as well as the ratio (E, F). Unlike the income distribution (Fig. 1), there is little or no east-west distinction in accessibility and commute times. Instead, there is a clear difference between central and less central areas, where areas close to the centre of Oslo are characterised by higher employment accessibility and lower average commute times. Furthermore, in central areas, the PT service competes well with car travel, which is shown in higher ratio levels (E, F). In other words, PT time competitiveness is higher closer to the centre of Oslo. Simultaneously, the average commute times (B, D, F) are more evenly distributed in the region compared with the general employment accessibility (A, C, E). In the mapping of ratios (E, F), high levels (over 0.6) of employment accessibility (E) are found in inner Oslo and in a few PT hubs around the city. Outside of central municipality, the ratio levels are rarely higher than 0.4. These ratio levels are comparable to the situation in San Francisco (Golub and Martens, 2014). With commute times, on the other hand, higher ratio levels are found in large parts of the region. This means that PT time competitiveness seems to be lower on actual commute trips than on general access to employment. This could indicate that workers have adapted, either by adjusting their residential or workplace location, to increase PT time competitiveness on their commutes.

Fig. 3 maps the correlation between car and PT, and employment accessibility and commute time efficiency, respectively. All variables are ranked by percentiles, as described in the previous section.. Fig. 3A and 3B compare the two transport modes (PT and car) for employment accessibility and commute time efficiency, and 3C and 3D compare accessibility with average commute time efficiency for PT and car. The figures also depict the size and income level of each census tract.

Fig. 3A shows that the two modes are clearly correlated, in that the points follow the diagonal line. Points over the diagonal line represent census tracts where PT access is relatively better than car access, and vice versa for points below the diagonal line. The correlation is visibly lower for average commute time efficiency (3B), where the points are more dispersed, than for accessibility (A). For commute time efficiency, there are more outliers, i.e. census tracts with a larger mismatch between PT and car travel times. There is also a visible distribution of poor and affluent census tracts in the figures. Among the lowest percentiles, there are more poor census tracts (yellow dots), while there are more affluent census tracts (blue dots) in the highest percentiles. In other words, more affluent census tracts are generally characterised by higher levels of employment accessibility and commute time efficiency.

Fig. 3C and 3D present the correlation between employment accessibility and average commute time efficiency. Here, there is a stronger correlation for PT (3D) than for car (3C). These figures also show some interesting patterns regarding income level: All in all, there are more blue dots above the diagonal line and more yellow dots below the line. This means that many affluent census tracts experience relatively high commute time efficiency compared to their level of general employment access, while the opposite is the case for many poor census tracts. A possible explanation can be found in the location patterns of workplaces, where highly skilled and high income workplaces often tend to be located centrally or in PT hubs, where PT access is relatively good (Gundersen et al., 2017).

4.2. Explanatory factors and their association with accessibility and commute times

In this section, the association between employment accessibility and commute times, and sociodemographic and urban form characteristics is presented. The models of the ratio variables, which measure PT time competitiveness, are presented in this section, while the separate models for PT and car are included in the appendix.[10] For each model, different variables are introduced step-wise:

[10] Please note that the dependent variables in the appendices vary in terms of direction. For general accessibility, higher values (more reachable workplaces) equal 'better' access. For commute time, the opposite direction is the case: lower values (shorter commute times) are more desirable.

Table 2
Employment accessibility ratio (PT/car).

	Step I—Sociodemographics		Step II—Urban form		Step III—Full model	
	OLS	Durbin	OLS	Durbin	OLS	Durbin
Average income (rank)	0.002***	0.003***			0.001***	0.001***
	(0.000)	(0.000)			(0.000)	(0.000)
Share cultural capital	1.311***	1.449***			0.209***	0.172
	(0.064)	(0.241)			(0.046)	(0.143)
Share native Norwegians	−0.694***	−0.931***			−0.137***	−0.195**
	(0.022)	(0.076)			(0.018)	(0.060)
Share of households with children	−0.332***	−0.462***			−0.107***	−0.128
	(0.026)	(0.091)			(0.019)	(0.071)
Population density (log)			0.039***	0.060***	0.037***	0.059***
			(0.001)	(0.004)	(0.001)	(0.004)
Diversity (Shannon index)			0.063***	0.089***	0.047***	0.096***
			(0.008)	(0.023)	(0.009)	(0.029)
Distance to Oslo centre (log)			−0.198***	−0.121***	−0.158***	−0.055*
			(0.006)	(0.019)	(0.008)	(0.027)
rho		0.819***		0.690***		0.681***
		(0.014)		(0.020)		(0.020)
R^2	0.527	0.862	0.802	0.890	0.810	0.892
Num. obs.	1798	1798	1798	1798	1798	1798
Parameters		11		9		17
Log Likelihood		2473.430		2671.135		2689.367
AIC	−3258.280	−4924.859	−4505.174	−5324.269	−4555.040	−5344.734
LR test: statistic		1668.579		821.095		791.694
LR test: p-value		0.000		0.000		0.000

Notes: AIC = Akaike information criterion; R^2 = Adjusted (OLS), Pseudo (Durbin); Standard errors are in parenthesis; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table 3
Commute time ratio (car/PT).

	Step I—Sociodemographics		Step II—Urban form		Step III—Full model	
	OLS	Durbin	OLS	Durbin	OLS	Durbin
Average income (rank)	0.001***	0.002***			0.001***	0.001***
	(0.000)	(0.000)			(0.000)	(0.000)
Share cultural capital	0.765***	0.885***			0.225***	0.298
	(0.054)	(0.157)			(0.051)	(0.164)
Share native Norwegians	−0.402***	−0.519***			−0.156***	−0.268***
	(0.018)	(0.048)			(0.020)	(0.071)
Share of households with children	−0.196***	−0.254***			−0.123***	−0.194**
	(0.022)	(0.074)			(0.021)	(0.073)
Population density (log)			0.034***	0.052***	0.032***	0.049***
			(0.001)	(0.004)	(0.001)	(0.004)
Diversity (Shannon index)			0.067***	0.088***	0.046***	0.072*
			(0.008)	(0.022)	(0.010)	(0.035)
Distance to Oslo centre (log)			−0.046***	0.024	−0.003	0.102***
			(0.007)	(0.019)	(0.009)	(0.026)
rho		0.689***		0.613***		0.590***
		(0.020)		(0.023)		(0.024)
R^2	0.342	0.623	0.515	0.664	0.536	0.672
Num. obs.	1798	1798	1798	1798	1798	1798
Parameters		11		9		17
Log Likelihood		2186.670		2289.974		2310.688
AIC	−3558.631	−4351.340	−4001.879	−4561.947	−4086.743	−4587.376
LR test: statistic		794.708		562.068		502.633
LR test: p-value		0.000		0.000		0.000

Notes: AIC = Akaike information criterion; R^2 = Adjusted (OLS), Pseudo (Durbin); Standard errors are in parenthesis; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Step I includes the sociodemographic variables, step II includes urban form variables, and the full models are presented in step III. Urban form has previously been found to be correlated with both accessibility and sociodemographic characteristics, and it is useful to include the full model (step III). However, in this study, most attention is given to how suburbanization of poverty may lead to distributional differences in accessibility. In the full model, the association with suburbanization is lost, as centrality is controlled for. Therefore, most emphasis is placed on the results in step I, where the distributional effect of suburbanization is more clearly measured. For each model step, both OLS and Durbin models are presented. In all cases, the model fit is improved in the spatial models, which shows that controlling for spatial dependence better explains the data. Table 2 presents the models of employment accessibility ratio, and Table 3 presents the models of average commute time ratio. For both dependent variables high values indicate better PT time competitiveness.

In step I in Table 2, there is a positive association with the area-based income level. In other words, affluent census tracts experience better PT time competitiveness in the general access to employment. Moreover, the share of cultural capital employees shows a substantial positive association with employment access ratio, while the share of native Norwegians is related to lower ratios. Lastly, families with children tend to reside in areas where PT time competitiveness is low. This reflects the findings in the literature on residential mobility, where native Norwegians who need residential space choose residential locations further from the centre of Oslo, while this is not always the case for immigrants. Step II models the association between accessibility and urban form. There is a clear association between urban form and accessibility ratio, which increases with density and diversity and decreases with distance to Oslo. In the final model (III), the correlation with the sociodemographic variables is weaker. However, income and the share of natives, as well as urban form, still show a highly significant association with accessibility.

There are similar associations with commute times (Table 3), as with employment accessibility (Table 2). Higher income and high shares of cultural capital workers in the area are associated with higher PT time competitiveness, while neighbourhoods with few immigrants and many families with children experience lower PT time competitiveness on individual commute trips. As for the urban form variables (step II), population density and building diversity show a significant (positive) association with the dependent variable. Finally, in the full model (step III), all variables, except cultural capital, show significant correlations. A comparison of the two models (Tables 2 and 3) shows that the correlations of all sociodemographic variables are stronger for employment accessibility than for commute times (in step I). This confirms the finding from the maps in Fig. 2 that PT time competitiveness is lower on actual commute trips than what should be expected from the levels of general access to employment opportunities. In the appendix, models are included for car and PT accessibility (appendix Tables A.1 and A.2) and car and PT commute times (appendix Tables A.3 and A.4). These models show similar results as Tables 2 and 3: High income is associated with higher accessibility and lower commute times. However, the association with income is stronger for PT than for car.

To sum up, our models document that there is a significant and somewhat substantial association between sociodemographic variables and PT time competitiveness. This is found both in the general access to employment opportunities and in the individual commute trips of the workers in the study area. Although several of the sociodemographic variables are correlated with urban form, it is still noteworthy that census tracts with lower income, fewer employees in cultural capital sectors, more native Norwegians, and more families with children suffer from lower PT time competitiveness. The reduced coefficients in the full models suggest that the social differences in accessibility and commuting are somewhat related to gentrification and suburbanization of poverty in the region.

4.3. *Robustness checks*

Several tests were conducted to ensure that our results were robust in relation to alternative specifications. First, accessibility measures without weights for employment type and with alternative distance decay functions were applied. Second, several alternative independent variables were tested: Work income was included instead of income after tax; separate variables for Western and non-Western immigrants were included, instead of the share of native Norwegians; and education level was included instead of cultural capital. Third, a separate model for only the municipality of Oslo was tested. These tests provided similar results to the ones reported in this paper, with no change in the direction of the effect of independent variables.

5. Discussion and conclusions

This study has documented substantial socio-spatial differences in both the absolute and relative levels of accessibility and commuting in the Oslo region. By considering the sub-concepts of transport poverty (Lucas et al., 2016), several conclusions can be drawn. First, low-income neighbourhoods suffer from higher mobility poverty in terms of higher commute burdens, as inhabitants from these areas experience longer commute times and lower PT time competitiveness on commute trips. Second, accessibility poverty is higher in poor areas as the general accessibility is lower. Third, poor neighbourhoods experience lower PT time competitiveness in access to jobs, both in general and individual terms. This means that if car use is to be reduced by increasing the cost of car driving, these neighbourhoods will likely suffer from higher transport unaffordability. Overall, the results suggest that the transition to low-emission mobility will not be without equitable and distributional challenges.

There is a significant association between income and accessibility, even when sociodemographic characteristics and urban form are controlled for. Although it is difficult to compare these results directly with other studies, the findings are in line with research from other parts of the world (Cooke and Shumway, 1991; Giannotti et al., 2021; Jang and Yi, 2020; Pereira, 2018). This study finds strong evidence that PT time competitiveness is low in most suburban and *peri*-urban parts of the study region, where the accessibility ratio is mostly below 0.5. This means that the level of car access is more than double that of PT. Moreover, census tracts with a high share of workers in cultural capital sectors experience higher PT time competitiveness. This suggests that these workers have a higher preference for (or means to obtain) a central residential location.

Neighbourhoods with many non-Western immigrants also experience better PT accessibility, which is in line with findings from Europe, Canada and Australia (Allen et al., 2021; Bartzokas-Tsiompras and Photis, 2019), but opposite of the findings from Chicago (Ermagun and Tilahun, 2020). A possible explanation to these variations can be the differences in the geographic scope of the study areas. The former studies, which find higher accessibility among immigrants, use functional labour market regions, similar to the current study. The latter article studies only the city of Chicago. In a regional context, immigrants tend to end up in the major city and not in the less accessible neighbouring suburbs. Within the city, however, there might be less variation between different ethnic groups in terms of centrality and accessibility. This is in line with the literature on ethnic segregation in Oslo: non-Western immigrants have traditionally clustered in the eastern and southern parts of the municipality of Oslo (Groruddalen and Søndre Nordstrand), and less so in the neighbouring municipalities. Native Norwegians, on the other hand, tend to avoid these areas, and rather settle in the suburbs outside of Oslo municipality, where accessibility is generally lower (Turner and Wessel, 2013; Wessel and Nordvik, 2018). Moreover, ethnic Norwegians have a higher preference for single-family housing after becoming parents than what is the case for immigrants (Wessel and Lunke, 2021). PT accessibility, therefore, emerges as the result of complex adjustments, some of which are socioeconomic in nature, some demographic and some cultural.

While a cumulative opportunities approach to accessibility is both easy to communicate and, with the use of open data, increasingly easy to implement, it does not necessarily reflect the actual situation for the individuals in a study area, as these results have shown. The combination of individual-level measurements of commute habits is thus a useful way to reduce this source of error. Previous studies have found clear relations between general employment access and commute times (Wang, 2000). This study identifies certain similarities but also interesting socio-spatial variations between the two concepts. The mapping of employment accessibility and average commute times shows that there are larger disparities in the former than in the latter. In other words, while the general accessibility (and PT time competitiveness) to employment is poor in many regions, this is less the case when looking at individual commute trips. These differences indicate that average commute times are more evenly distributed than general employment accessibility and point to some relevant topics for future studies: The variations identified here are most likely related to residential location preferences, as well as the characteristics of the housing market. Much research exists on the relationship between accessibility and housing affordability (Cao and Hickman, 2018; Sterzer, 2017), between accessibility and residential mobility (Saghapour and Moridpour, 2019) and the suburbanization of poverty (Allen and Farber, 2021; Hochstenbach and Musterd, 2018; van Ham et al., 2020). However, a more detailed understanding of the trade-offs that households make between different residential and dwelling characteristics when relocating, hereunder the importance of commuting distances and accessibility, should be further investigated.

Another topic for future research is the concept of competitiveness between car and PT. In this study, competitiveness is defined as the time competitiveness of PT relative to the car for accessing jobs. This definition can partly explain differences in car dependency, as defined by Mattioli (2021): with lower PT time competitiveness, people tend to rely more on the car to undertake daily activities. However, the degree to which this car dependency is *forced* may vary depending on PT competitiveness not only in relative, but also in absolute terms. Low or non-existent absolute levels of PT competitiveness may literally *force* people into car dependency. However, low levels of relative PT time competitiveness may also happen where job access by PT is sufficient, but that by car is even better. In this case, people are not strictly car dependent, but rather lured into more car oriented mobility patterns. When evaluating transport poverty and the equity of sustainable mobility transitions, it is therefore important to consider both absolute and relative levels of modal accessibility in tandem. In future research, competitive measures could be further developed to better investigate the equity aspect of accessibility. For example, competition could be defined by the dynamics between supply and demand (Morris et al., 1979), or based on generalized travel times (Tiznado-Aitken et al., 2021). Moreover, a complete definition of car dependency should include other variables besides the ones studied in this paper, such as revealed car use and ownership rates (Mattioli, 2021).

With an area-level unit of analysis, there are certain limitations to the study design that are important to consider. First, this study applies average levels of commute times and other characteristics of the census tracts, and considers neither characteristics at the individual level nor the internal variation within census tracts. Second, the geographic aggregation of data to census tracts may be sensitive to the modifiable areal unit problem (MAUP) (Pereira et al., 2019). However, as the Norwegian census tracts are designed to be as homogenous as possible, both in terms of building structure and communication (and hereunder transport),[11] the sensitivity to MAUP is arguably reduced. Thirdly, accessibility is measured from a single centroid of each census tract. For large tracts, there may be some internal variation in accessibility that is not accounted for. However, with the use of building-weighted centroids, the calculations reflect the most representative levels of each tract. A fourth limitation of this study lies in the timing of the data sources. While the accessibility and travel time data were gathered in 2020, the other variables are from 2017. However, the transport system and travel times have been quite stable during this period.

For policy makers working to reduce emissions in the transport sector and increase PT commuting, this research provides some interesting insights. While restrictions on car use, such as toll roads, increased fuel prices and removal of parking spaces, may be efficient measures to reduce car commuting, they may also be associated with negative distributional effects. The low levels of PT time

[11] https://www.ssb.no/en/klass/klassifikasjoner/1.

competitiveness in large parts of the region indicate that many commuters lack realistic alternatives to car use. This study documents that this risk is somewhat higher in poor areas and in the urban peripheries. With rising housing prices and suburbanization of poverty, the distributive differences in PT time competitiveness are likely to increase. These findings can be useful for policy makers to design car restrictive measures that are more socially acceptable in order to avoid protest and social friction. In a welfare state such as Norway, with clear goals of reducing social differences, the disparities in access and PT time competitiveness are important to take into account, especially when transitioning to low-emission mobility.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This paper is part of the "Transport, inequality and political opposition (TRIPOP)" project, funded by The Research Council of Norway, grant no. 302059. Data on loan from Statistics Norway have been essential. I am grateful to Terje Wessel and Lars Böcker for their invaluable supervision. I also wish to thank Askill H. Halse, Ismir Mulalic and two anonymous reviewers for their comments on earlier drafts of the paper.

Appendix A

See Tables A1–A4.

Table A1
Employment accessibility car (log access).

	Step I—Sociodemographics		Step II—Urban form		Step III—Full model	
	OLS	Durbin	OLS	Durbin	OLS	Durbin
Average income (rank)	0.005***	0.009***			−0.000	−0.001
	(0.000)	(0.001)			(0.000)	(0.001)
Share cultural capital	1.395***	1.174			−0.742***	−1.447***
	(0.126)	(0.630)			(0.082)	(0.368)
Share native Norwegians	−1.467***	−2.233***			−0.262***	−0.152
	(0.043)	(0.201)			(0.033)	(0.162)
Share of households with children	−0.303***	−0.227			0.214***	0.698***
	(0.051)	(0.295)			(0.034)	(0.168)
Population density (log)			−0.001	−0.003	−0.003	−0.002
			(0.002)	(0.012)	(0.002)	(0.026)
Diversity (Shannon index)			−0.148***	−0.325***	−0.163***	−0.239**
			(0.014)	(0.057)	(0.016)	(0.074)
Distance to Oslo centre (log)			−0.684***	−0.759***	−0.721***	−0.878***
			(0.012)	(0.051)	(0.014)	(0.058)
rho		0.921***		0.870***		0.827***
		(0.008)		(0.012)		(0.014)
R^2	0.464	0.935	0.790	0.948	0.826	0.951
Num. obs.	1798	1798	1798	1798	1798	1798
Parameters		11		9		17
Log Likelihood		2044.347		2246.820		2292.049
AIC	−869.122	−4066.694	−2138.035	−4475.639	−2761.962	−4550.098
LR test: statistic		3199.572		2339.604		1790.136
LR test: p-value		0.000		0.000		0.000

Notes: AIC = Akaike information criterion; R^2 = Adjusted (OLS), Pseudo (Durbin); Standard errors are in parenthesis; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Table A2
Employment accessibility PT (log access).

	Step I—Sociodemographics		Step II—Urban form		Step III—Full model	
	OLS	Durbin	OLS	Durbin	OLS	Durbin
Average income (rank)	0.017***	0.023***			0.004***	0.005*
	(0.001)	(0.003)			(0.001)	(0.002)
Share cultural capital	5.862***	6.963***			−1.193*	−1.184
	(0.533)	(1.495)			(0.476)	(1.039)
Share native Norwegians	−4.761***	−6.456***			−1.226***	−1.728***
	(0.183)	(0.473)			(0.190)	(0.473)
Share of households with children	−0.787***	−0.243			0.190	0.845
	(0.214)	(0.430)			(0.197)	(0.589)
Population density (log)			0.205***	0.260***	0.200***	0.257***
			(0.013)	(0.027)	(0.013)	(0.029)
Diversity (Shannon index)			−0.400***	−0.764***	−0.393***	−0.501*
			(0.077)	(0.153)	(0.093)	(0.210)
Distance to Oslo centre (log)			−1.394***	−1.216***	−1.273***	−1.007***
			(0.066)	(0.130)	(0.081)	(0.174)
rho		0.596***		0.432***		0.392***
		(0.024)		(0.029)		(0.030)
R^2	0.358	0.605	0.590	0.652	0.604	0.660
Num. obs.	1798	1798	1798	1798	1798	1798
Parameters		11		9		17
Log Likelihood		−2007.008		−1893.970		−1874.088
AIC	4576.277	4036.016	4020.828	3805.939	3947.428	3782.177
LR test: statistic		542.262		216.889		167.252
LR test: p-value		0.000		0.000		0.000

Notes: AIC = Akaike information criterion; R^2 = Adjusted (OLS), Pseudo (Durbin); Standard errors are in parenthesis; ***p < 0.001; **p < 0.01; *p < 0.05.

Table A3
Commute time car (log commute time).

	Step I—Sociodemographics		Step II—Urban form		Step III—Full model	
	OLS	Durbin	OLS	Durbin	OLS	Durbin
Average income (rank)	−0.003***	−0.005***			−0.000*	−0.000
	(0.000)	(0.000)			(0.000)	(0.000)
Share cultural capital	−0.834***	−0.777**			0.383***	0.770***
	(0.084)	(0.266)			(0.070)	(0.173)
Share native Norwegians	0.770***	1.172***			0.086**	0.069
	(0.029)	(0.076)			(0.028)	(0.060)
Share of households with children	0.192***	0.145			−0.117***	−0.320***
	(0.034)	(0.109)			(0.029)	(0.089)
Population density (log)			−0.001	−0.010*	−0.002	−0.015***
			(0.002)	(0.005)	(0.002)	(0.004)
Diversity (Shannon index)			0.085***	0.164***	0.059***	0.070*
			(0.011)	(0.025)	(0.014)	(0.033)
Distance to Oslo centre (log)			0.381***	0.362***	0.388***	0.389***
			(0.010)	(0.023)	(0.012)	(0.028)
rho		0.677***		0.518***		0.462***
		(0.020)		(0.026)		(0.028)
R^2	0.379	0.687	0.652	0.731	0.666	0.739
Num. obs.	1798	1798	1798	1798	1798	1798
Parameters		11		9		17
Log Likelihood		1483.772		1619.826		1649.372
AIC	−2127.850	−2945.545	−2869.945	−3221.652	−3009.044	−3264.743
LR test: statistic		819.695		353.707		257.699
LR test: p-value		0.000		0.000		0.000

Notes: AIC = Akaike information criterion; R^2 = Adjusted (OLS), Pseudo (Durbin); Standard errors are in parenthesis; ***p < 0.001; **p < 0.01; *p < 0.05

Table A4
Commute time PT (log commute time).

	Step I—Sociodemographics		Step II—Urban form		Step III—Full model	
	OLS	Durbin	OLS	Durbin	OLS	Durbin
Average income (rank)	−0.005***	−0.007***			−0.001***	−0.002***
	(0.000)	(0.001)			(0.000)	(0.001)
Share cultural capital	−2.306***	−2.384***			−0.151	0.094
	(0.131)	(0.452)			(0.101)	(0.276)
Share native Norwegians	1.379***	1.936***			0.294***	0.416***
	(0.045)	(0.137)			(0.040)	(0.099)
Share of households with children	0.505***	0.670***			0.068	0.054
	(0.052)	(0.189)			(0.042)	(0.158)
Population density (log)			−0.062***	−0.094***	−0.060***	−0.096***
			(0.003)	(0.007)	(0.003)	(0.008)
Diversity (Shannon index)			−0.022	0.033	−0.023	−0.022
			(0.016)	(0.038)	(0.020)	(0.052)
Distance to Oslo centre (log)			0.450***	0.344***	0.383***	0.241***
			(0.014)	(0.032)	(0.017)	(0.047)
rho		0.736***		0.547***		0.526***
		(0.018)		(0.025)		(0.026)
R^2	0.489	0.794	0.757	0.829	0.765	0.831
Num. obs.	1783	1783	1783	1783	1783	1783
Parameters		11		9		17
Log Likelihood		900.616		1063.572		1077.248
AIC	−657.118	−1779.232	−1685.171	−2109.143	−1740.031	−2120.496
LR test: statistic		1124.114		425.972		382.466
LR test: p-value		0.000		0.000		0.000

Notes: AIC = Akaike information criterion; R^2 = Adjusted (OLS), Pseudo (Durbin); Standard errors are in parenthesis; ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

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