Journal of Transport Geography 123 (2025) 104129

Contents lists available at ScienceDirect

Journal of Transport Geography

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

Does adolescent experience influence mobility later in life? A propensity score matching approach

Erik B. Lunke

Institute of Transport Economics (TØI), Gaustadalléen 21, 0349 Oslo, Norway.

ARTICLE INFO

Keywords:
Mobility socialisation
car ownership
Propensity score matching
Norway

ABSTRACT

While research shows that car restrictions and investments in sustainable transport infrastructure reduces car use, less is known about the influence of social norms and childhood experiences in shaping mobility behaviour. This study examines the impact of growing up in a car-owning household on car ownership later in life, utilizing Propensity Score Matching (PSM) and longitudinal registry data from Norway. The analysis reveals that experiences in the parental household at age 18 significantly influence car ownership in adulthood (at age 30), with a modest effect size of 4–5 %, after controlling for sociodemographic and neighbourhood factors. These findings suggest that traditional policy measures aimed at reducing car use may need to be complemented by public awareness campaigns to address deeply ingrained mobility behaviors shaped by early life experiences.

1. Introduction

Knowledge on how different factors influence travel behaviour is important for planners and policy makers working to reduce car use and its negative externalities in urban areas. From the past decades' work in transportation research, we have good empirical evidence that the density, diversity and design of urban settlements (Cervero and Kockelman, 1997; Kenworthy and Newman, 2015), as well as walkability, bicycle infrastructure and access to public transport (Cervero and Duncan, 2003; Ewing and Handy, 2009; Handy, 2020) are significantly associated with car ownership and use. At the same time, researchers have been debating whether these findings represent strong causal links between the various factors and individual travel behaviour, or if the documented associations are influenced by self-selection bias (Næss, 2009). For example, studies have found that observed impacts of urban form and transport investments on reduced car use were totally or partially explained by endogeneity, stemming from the fact that individuals with a preference for sustainable transport mode use (walking, bicycling and public transport) are selected into areas where access with such transport modes is high (Cao and Cao, 2014; Cao et al., 2009; Scheiner, 2018; Wolday et al., 2019). Individuals who prefer to use private cars, are on the other hand less likely to relocate to such areas. The literature on self-selection bias in transportation research draws on the work of Jon Elster, who discussed the relative role of instrumental rationality and social norms on social behaviour (Elster, 1989). Elster claimed that individual actions may be irrational in terms of expected outcomes, because individuals are also driven by social norms and expectations. To take an example from the mobility field, an individual may choose to drive her car to work, even though this is a more costly alternative than public transport because of high toll and parking fees and cheap public transport tickets, if driving a car represents a status symbol among her social circles. Such individuals, who display strong preferences for car driving despite increased costs, poses several challenges for policy makers working to reduce car use and encourage more sustainable mobility patterns. First, they will likely be less influenced by car restrictive policies, because of a willingness to take a relatively high cost to be able to use a car. Second, they may be more likely to reside in car-friendly neighbourhoods. In other words, developing compact urban environments that encourage less car use is simply not a relevant residential location for this group, and therefore, strategies and measures for more sustainable transport will be less effective. To sum up, based on Elster's theory, we can expect that certain people display relatively irrational transport behaviour. This irrationality can in part be explained by the preferences that have developed because of experiences earlier in life.

This delayed influence of life events and experiences is the central topic the *mobility socialisation theory* (Baslington, 2008; Döring et al., 2014). According to Baslington (2008), our preferences and attitudes toward transport modes are embedded in the childhood, through various agents of socialisation: the family, school, media, and peer groups. In other words, future travel behaviour is in part determined by the transmission of values and behavioural patterns during childhood, in

E-mail address: ebl@toi.no.

https://doi.org/10.1016/j.jtrangeo.2025.104129
Received 23 August 2024; Received in revised form 14 October 2024; Accepted 17 January 2025
Available online 22 January 2025

line with Elsters arguments. If this is the case, we can assume that policies to reduce car use by contextual adjustments – such as densification and improvement of public transport services, may be inefficient, if travel behaviour is also a result of childhood experiences and social norms.

The aim of this study is to investigate to what extent growing up in a car-owning household increases the likelihood of owning a car later in life. We ask the following research question: *to what extent does car ownership in the parental household of adolescent's influence car ownership later in life?*

The article is organised as follows. The next chapter describes previous research on socialisation effects and childhood experiences' effects on transport behaviour. Chapter 3 describes the data, variables and analytical technique used. Chapter 4 presents the study results as well as a review of the validity of the analyses. Concluding remarks are presented in the final chapter.

2. Previous research on mobility socioalisation

Even though the importance of experiences, socialisation and *life paths* were recognized as early as the 1970s (Hägerstrand et al., 1978), empirical studies on mobility socialisation have not emerged until recent years. This is partly explained by the lack of adequate data to study these relationships. More recently, various studies have attempted to empirically measure the influence of socialisation and childhood experiences on travel behaviour. Haustein et al. (2009) conducted a survey among German students. They found that socialisation during the childhood had an influence on mobility outcomes later in life, both in terms of social norms and on actual car use. Similar results were found by Döring et al. (2014), who documented that both travel related attitudes and residential location of the surveyed individuals was heavily influenced by the same characteristics of their parents. Other studies have documented the influence of childhood experiences on walking (Mjahed et al., 2015), cycling (Thigpen, 2019) and public transport use (Van Acker et al., 2019, 2020). These studies all use retrospective surveys to investigate travel socialisation. Individuals are asked to describe their current transport mode use and travel related attitudes, as well as their childhood experiences in terms of transport mode use, residential location characteristics and so on.

An important limitation with this approach is the difficulty for adults to remember and correctly state information from the time of childhood. To overcome this limitation, panel surveys with several registrations is an alternative, although they are difficult to conduct over long time periods. A notable exception is the US Panel Study of Income Dynamics, which has been utilized in several studies on this topic. Ralph (2022), for example, found that growing up in a carless household was associated with lower education and employment levels later in life. Moreover, Smart and Klein (2018) found that individuals who were exposed to public transport during young adulthood had higher preferences for a low car lifestyle later in life. Similarly, other studies have explored how various previous experiences influence mobility outcomes later in life, such as income (Dargay, 2001) and residential locations (Macfarlane et al., 2015).

The current study provides several contributions to the existing literature on socialisation and previous life experiences on car ownership. First, the study utilizes disaggregated registry data on the whole Norwegian population, with yearly observations about individuals and their parents from 2005 to 2019. This provides correct observations on car ownership, neighbourhood characteristics and sociodemographic traits over an extended period, which is more reliable and detailed than retrospective and panel surveys. Second, the current study uses Propensity Score Matching (PSM), which is a technique that seeks to mimic a controlled experiment with non-experimental data, in order to isolate the effect between a treatment and control variable (in this case, car ownership in the adolescent household and car ownership later in life) (Angrist and Pischke, 2009). An important weakness with the existing studies on travel socialisation is the lack of convincing causal links in the observed relationships. By using longitudinal registry data and PSM, the current study seeks to overcome some of the limitations of alternative techniques, to estimate the isolated effect of the treatment variable.

3. Data and methods

This study uses a longitudinal database containing annual observation on all Norwegian inhabitants over 18 years from 2005 to 2019, delivered by Statistics Norway. The analysis is split in two parts, one for the whole of Norway, and one for inhabitants in the Oslo region, the largest metropolitan area. This division is done to allow for different levels of detail in the contextual control variables, and to investigate heterogeneity in the level of mobility socialisation at different geographical scales. The sample used in this study consists of all inhabitants who fulfil the following criteria: they were 18 years old in 2007, they were present in the data in both 2007 and 2019, and they lived with one or both parents in 2007 (when they were 18 years old). This selection makes it possible to investigate whether car ownership status in 2019 (at age 30) is influenced by the car ownership status of their parents in 2007 (at 18 years old), while controlling for other relevant covariates.

3.1. Variables

The outcome variable is *car ownership in 2019* (at age 30), whereas the treatment variable is *car ownership in 2007* (at age 18). A car owner is defined by car ownership at the household level, regardless of whether the specific person is registered as a car owner. In other words, individuals may be defined as a car owner if their partner (in 2019) or parent (in 2007) were registered car owners.

Different control variables are included, to control for factors related to individual's residential location and their sociodemographic characteristics. For residential location characteristics, different variables are used for the national level analyses and the analyses of the Oslo region. At the national level, the *centrality index*, developed by Statistics Norway (Høydahl, 2020), is included. This index measures a census tract's centrality by the number of employment and other service opportunities that are reachable within 90 min travel time by car, with a distance decay function to weigh opportunities by travel time. Based on this calculation, all census tracts are divided in 6 levels of centrality, from the most central (level 6) to the least central (level 1) census tracts. As most of the Oslo region is defined as level 6 in the centrality index, the Oslo level analyses use more detailed variables on urban form. Following the recommendations of Cervero and Kockelman (1997), three variables on population density, building use diversity, and travel distance from Oslo centre are included.[1] These are variables that are well developed and adapted in previous research. Earlier studies have found clear associations between these factors and transport mode ownership and use, both in Norway and in other countries (Cervero, 2002; Engebretsen et al., 2018; Ewing and Cervero, 2010). The reason for using the centrality index on the National level analyses, and not the more detailed variables, is that the index is developed specifically for studies at this scale, and that they take better account of the heterogeneity between different urban areas in Norway, and between urban and rural areas.

In addition to the residential location characteristics in 2019 (at age

[1] Population density is measured as the number of 1000 residents per km2 in each census tract. Building use diversity is measured with Shannon's index of diversity, based on six building use typologies (residences, industry, offices, transport buildings, hotels and restaurants, cultural institutions, health- and emergency buildings, and prisons) (Shannon, 1948). Distance to Oslo is measured by the travel time with car from each census tract to the census tract where Oslo's city hall is located.

30), a similar variable is included for the residential characteristics of the parental household in 2007 (at age 18). The motivation is to include a control for previous experience in terms of residential location. For the parental residential characteristics (in 2007), the centrality index is used both for the national and Oslo region level analyses, since the parental residential location may be outside of the Oslo region.

Four sociodemographic variables are included to describe the status of the observed individuals in 2019. *Income* is measured as the total household income after taxes, weighted by the number of household members using OECD's square root scale.[2] To account for non-linearity, income is included as both a linear and a quadratic term in the analyses. *Education level* is measured by a four-level scale: 1) No education, 2) high school education, 3) higher education at bachelor level, and 4) higher education at master level or higher. *Gender* is a dichotomous variable, male or female. *Children in the household* is a dichotomous variable indicating whether the individuals lived in a household with children (under 18 years old). All four variables have previously been found to influence car ownership both internationally (Clark et al., 2016; Haque et al., 2019; Oakil et al., 2014, 2016) and in Norway (Grue et al., 2021; Hjorthol et al., 2014).

Finally, a variable on *commute distance* is included which measures the distance (scaled to 10 km by car) from the individuals' residential location to their workplace. The motivation for including this variable is the documented relationship between commute distance and car use (Beige and Axhausen, 2012; Prillwitz et al., 2007).

Table 1
Descriptive statistics (means) of individuals growing up in car owning and car free households. Norway as a whole and the Oslo region.

	Norway		Oslo region	
	Car owner (2007)	Car free (2007)	Car owner (2007)	Car free (2007)
N	44,503	4112	14,834	1769
Car owner (in 2019)	0.69	0.56	0.52	0.42
Centrality index (2007)	3.75	4.41	4.61	5.20
Centrality index (2019)	4.35	4.68	–	–
Population density	–	–	9.94	9.85
Building use diversity	–	–	0.53	0.53
Distance to Oslo centre	–	–	31.06	29.83
Household income (1000 NOK)	420.31	364.70	445.05	371.71
No education	0.15	0.30	0.11	0.28
High school	0.27	0.25	0.17	0.19
Higher education (bachelor)	0.39	0.31	0.43	0.35
Higher education (master)	0.19	0.13	0.29	0.18
Gender (female)	0.50	0.52	0.49	0.53
Couple	0.65	0.57	0.59	0.54
Children in household	0.39	0.36	0.25	0.28
Commute distance (10 km)	4.86	4.27	3.03	2.28

Table 1 shows the descriptive statistics of the treatment and control group (living in car owning and car free households at age 18, respectively), at the national and Oslo region level. We see, first, that growing up in a car owning household is much more common than growing up in a car free household. There is also a clear association between car ownership as an adolescent and car ownership at the age of thirty: among those growing up with a car, 69 % owned a car at age 30, while the share was 56 % for those growing up without a car in Norway as a whole (in the Oslo region, the numbers are 52 and 42 %). Car ownership is also related to residential location characteristics. Those growing up without a car tend to live in more central areas (higher centrality index). For the other background variables, we see that those living in car owning households at age 18 generally achieve higher incomes and higher education later in life, and there is a slightly higher share living in couple households and living with children among those growing up with a car.

3.2. Analytical approach: Propensity score matching

A common goal of quantitative social science is to estimate the effect of one or more independent variables (a *treatment*) on a dependent variable (an *outcome*). However, an important weakness of conventional statistical methods is the lack of ability to uncover causal inference, because they do not readily control for selection biases. In other words, traditional statistical (regression) models can document an *association* between independent and dependent variables, but they can often not answer whether one influences the other, whether the relationship is explained by unobserved characteristics, or whether the causal direction goes the other way (that the dependent variable is influencing the independent variable). The ideal method for measuring treatment effects and establishing convincing causal links is the Randomized Control Trial (RCT), where individuals are randomly assigned to either a treatment or a control group *before* the former undergoes treatment. This approach secures that the two groups are equal on all relevant characteristics, except for the treatment of interest, avoiding that certain people are selected into either group because of underlying characteristics (Angrist and Pischke, 2009; D'Agostino, 2007).

In the social sciences, however, it is rarely possible to conduct controlled experiments to study social phenomena. For example, we cannot assign individuals to growing up in either car owning or car free households. In this context, the estimated effects of car ownership in the parental household on car ownership later in life may be biased if the individuals in the treatment group differ systematically from those in the control group (Rosenbaum and Rubin, 1984). Different techniques have been developed to establish causal inference in observational studies where the RCT approach is not possible. One such technique is Propensity Score Matching (PSM), which is designed to mimic an RCT by matching individuals in the treatment group with similar individuals in the control group (D'Agostino, 2007). Technically, PSM is a two-step approach: First, a logit or probit regression model is run to estimate the propensity of a unit to be exposed to treatment, while controlling for a set of observable characteristics (labelled the *propensity score*). Next, units in the treatment group (living in car owning households in 2007) are matched with units in the control group (living in car free households in 2007) with similar propensity scores, and the average treatment effect (ATE) of all matched pairs is calculated. In addition, it is common to also present the average treatment effect of the treated (ATET), which measures the effect only for those who have experienced the treatment. The success of a PSM analysis is determined by whether it achieves to match treatment group units with similar units in the control group. To evaluate this, we can investigate how the matching contributes to creating balance between the two groups on the observed characteristics. D'Agostino states that the focus of PSM analyses, unlike conventional regression models, should be on including variables that contribute to balancing between the treated and control groups, rather than whether they are related to the outcome of interest (D'Agostino,

[2] https://www.oecd.org/economy/growth/OECD-Note-EquivalenceScales.pdf

2007, p. 315). The strength of the PSM technique is thus that it deals better with endogeneity and selection-bias than conventional statistical techniques, such as logistic or linear regression analysis.

In transportation research, PSM has been applied to study the effects of the built environment on travel behaviour (Cao, 2010; Cao and Fan, 2012; Cao et al., 2010), health-related outcomes of long commutes (Sandow et al., 2014), and to evaluate the impact of public transport investments (Dai et al., 2020; Gimenez-Nadal and Molina, 2016), residential housing policies, (Liu et al., 2018), car sharing (Mishra et al., 2015), and e-shopping (Nasri et al., 2020) on mobility and transport mode use. The technique has proven powerful in documenting the causal links between contextual factors and travel behaviour, and to overcome the problem with residential self-selection (Mokhtarian and Cao, 2008).

To the author's knowledge, the current study is the first to apply PSM to investigate travel socialisation. From other fields of the social sciences, PSM analyses have provided evidence on the effect of childhood experience on outcomes later in life, such as educational achievement (Li and Hamlin, 2019) and mental health (Duan et al., 2023). In terms of travel socialisation, the PSM is a valid tool, because of its ability to balance the treatment and control groups. In the case of car ownership, it is likely that residential location characteristics, as well as attitudes toward certain residential locations, varies between individuals who grew up in a car owning household and those who grew up without a car. Those who grew up without a car are likely to have lived in more urban areas, which in turn could affect their preference for an urban residential location later in life. By applying PSM, we can isolate the effect of car ownership in the parental household, without selection bias stemming from differences in residential location, attitudes or other characteristics.

In the next section, results from PSMs are presented and compared with the results of a binary logistic regression model. Afterwards, the quality of the PSM estimates are evaluated.

4. Results

We report four coefficients for the association and influence of car ownership in the parental household (at age 18) on car ownership later in life (at age 30): the observed difference between the treatment and control group, the coefficient from a binary logistic regression model, and two treatment effect coefficients from PSM models – the average treatment effect (ATE) and the average treatment effect of the treated (ATET). Coefficients from both the national level and the Oslo region level analyses are reported in Table 2.

The observed difference in car ownership at age 30 dependent on car ownership status at age 18 is high: the level of car ownership is 23 % higher in the treatment group (living in a car owning household in 2018) compared to the control group (living in a car free household at age 30), both at the national and the Oslo region level. However, as previously discussed, this difference is likely biased by other differences between the two groups. This is confirmed by the logit and PSM coefficients, where relevant background variables are controlled for.

In the logit estimates, which are estimates without matching, we observe significant coefficients of 0.255 and 0.246 (National and Oslo region level, respectively) of car ownership at age 18 on car ownership later in life. The full model results are reported in appendix A1. For the other control variables, we find the expected effects. A more central residential location (higher centrality index) at the age of 30 is associated with lower car ownership, whereas there is no significant effect of the residential location at age 18. The explanation of this could be that there is a high correlation between residential location at the two time points. For the Oslo region analyses, higher population density and building use diversity, as well as a closer proximity to Oslo, are all associated with lower levels of car ownership. In other words, a more urban residential location is related to lower car ownership levels. Income is positively associated with car ownership, although with a slight curve linear relationship at the national level, explained by the negative effect of the quadratic term. For education, we find slightly higher car ownership levels among those with high school and higher education at the bachelor level, compared to those with no education and those with a master's degree. Women experience lower car ownership levels than men, while car ownership is higher in couple households and families with children. For commute distance we find a small, but still significant effect. This variable is, however, likely to be correlated with other control variables in the models.

With the PSM estimates, we find similar treatment effects. At the national level, the treatment effect is 5,1 % (both ATE and ATET). The fact that we find significant, positive, treatment PSM effects suggest that the impact of travel socialisation would still hold if individuals were randomly assigned to either car owning or car free households at adolescent age. In other words, the impact of socialisation and previous experience on mobility behaviour is present, independent of the influence of other background characteristics.

In order to evaluate the quality of the PSM technique, we can conduct different tests. The first test is done to check the assumption of common support, meaning that we check whether we have an overlap in the distribution of propensity scores among the treatment and control groups (Garrido et al., 2014). This assumption is tested by graphing the propensity scores of each group, shown in Appendix A2. We see clearly that the two groups overlap, confirming that the assumption of common support is met.

Next, we test whether the PSM, with the chosen covariates, have contributed to balancing the characteristics of the treatment and control group. This is done in several ways, both by plotting the propensity scores of the raw and matched observations, and by calculating the standardized differences and variance ratios between the raw and matched samples of each covariate. Box plots showing the propensity scores of the raw and matched samples (balance plots) are shown in Appendix A3. For both the National and the Oslo region level, we see that the treatment and control group become more similar after

Table 2
Estimated effects of car ownership in 2007 on car ownership in 2019. Logit and PSM coefficients. Norway as a whole and the Oslo region.

	Observed association[1]	binary logit model coefficient[2]	PSM ATE[3]	PSM ATET[4]
Norway				
Coefficient	0.232 (0.69/0.56)	0.255*** (0.049)	0.051*** (0.011)	0.051*** (0.012)
Oslo region				
Coefficient	0.238 (0.52/0.42)	0.246** (0.071)	0.043* (0.018)	0.042* (0.019)

*$p < .05$, **$p < .01$, ***$p < .001$.
[1] Based on the descriptive statistics shown in Table 1. Shares shown in parentheses.
[2] Full model results are provided in Appendix A1.
[3] Average Treatment Effect.
[4] Average Treatment Effect of the Treated.

Table 3
Covariate balance summary, based on PSM. Norway as a whole and the Oslo region.

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Norway				
Centrality (2007)	−0.447	0.0.010	0.0.955	0.983
Centrality (2019)	−0.233	−0.115	1.108	1.019
Household income	0.237	−0.003	1.066	0.838
Education level	0.280	−0.009	0.853	0.997
Gender	−0.026	−0.014	1.000	1.000
Couple	0.094	0.0.001	0.945	1.000
Children in household	0.031	0.000	1.013	1.000
Commute distance	0.032	0.113	1.186	1.005
Oslo region				
Centrality (2007)	0.473	0.015	1.276	0.966
Population density	0.021	0.011	1.088	1.032
Building use diversity	0.019	−0.000	1.000	0.955
Distance to Oslo	0.059	−0.017	1.215	1.009
Household income	0.291	−0.019	1.066	0.858
Education level	0.387	−0.001	0.778	1.008
Gender	−0.015	0.001	1.000	1.000
Couple	0.077	−0.032	0.973	1.013
Children in household	−0.053	0.022	0.945	1.025
Commute distance	0.068	0.070	1.987	2.931

matching, suggesting a successful balancing. Table 3 shows the standardized differences and variance ratios of the raw and matched samples. In both cases, we see that the values become more balanced after matching: the standardized differences are closer to zero, while the variance ratios are closer to one. In social epidemiology, a recommended threshold of standardized differences is 10 % (Oakes and Johnson, 2006), a threshold that has also been applied in mobility research (Cao et al., 2010). From Table 3, we see that, after matching, all covariates are below this threshold, suggesting that the matching technique has been satisfactory.

5. Discussion and conclusion

This study has documented that growing up in a car-owning household has an influence on car ownership later in life. Although the effect is small (between 4 and 5 %), experiences in the parental household has an influence on car ownership, independent of other sociodemographic and neighbourhood level factors. This is relevant information for planners and policymakers working to reduce car ownership and car use. Reducing the influence of previous experiences may require different measures than the influence of structural and sociodemographic factors. For example, it may not be sufficient to introduce fees on car ownership and use, or to invest in sustainable transport services (public transport and bicycling infrastructure), if people still want to acquire a car because they are socialized into this behaviour. For this subgroup of the population, who have a preference to use a car "no matter what", alternative measures may be necessary. For example, public awareness campaigns, directed to change the people's mobility attitudes, may be useful supplements to traditional transport policies.

The current study has several important limitations that need to be acknowledged, and that shows the need for more research on this topic. First, car ownership of the parental household is only measured at one time point, i.e. when the individuals were 18 years old. While we can assume that car ownership is relatively stable over time, it might be the case that 18-year-olds living in a car owning household had spent most of their childhood without a car. The opposite might also be true: individuals that we have registered as car-less at age 18 may have been living in car-owning households previously. For privacy reasons, our data did not contain information about individuals before they turned 18 years old, which is the reason we limited the treatment variable to this time point. Because of this, the current study could not uncover more in detail how car ownership levels influence mobility behaviour. For example, the number of cars in the childhood home, as well as the timing and duration of car ownership could influence car ownership later in life. Similarly, other factors could moderate the effect of car ownership in the childhood home, such as public transport accessibility and the prevalence of active mobility (cycling and walking). Future research using data with longer observation periods and more detailed information about the childhood years may supplement this study. A similar limitation lies in the outcome variable, which measures car ownership at age 30. Previous research has established that mobility patterns – including car ownership levels – change after families enter parenthood (McCarthy et al., 2017, 2021). In modern societies, families may wait well into their thirties before starting a family, and car acquisition may be similarly postponed. Again, age 30 was selected because this was the longest time frame that was available with these data. Future studies utilizing data with a longer time frame would be useful to investigate the more long-term mobility effects of adolescent and childhood experiences. Another limitation is that socialisation into specific mobility behaviors may not be limited to the parental household. Car ownership levels in the local neighbourhood, or among childhood friends may also influence later in life decisions to own a car. Future research could investigate this, to get a better understanding of mobility socialisation at different levels.

Finally, the current study investigates *car ownership* as both the treatment and outcome variable. While car ownership is closely related to mobility – it strongly influences car use (Van Acker and Witlox, 2010) – this study does not answer how travel behaviour is influenced by childhood experiences. Such a study would require more detailed travel behaviour data, over a long period of time, than what is currently available.

CRediT authorship contribution statement

Erik B. Lunke: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

Acknowledgments

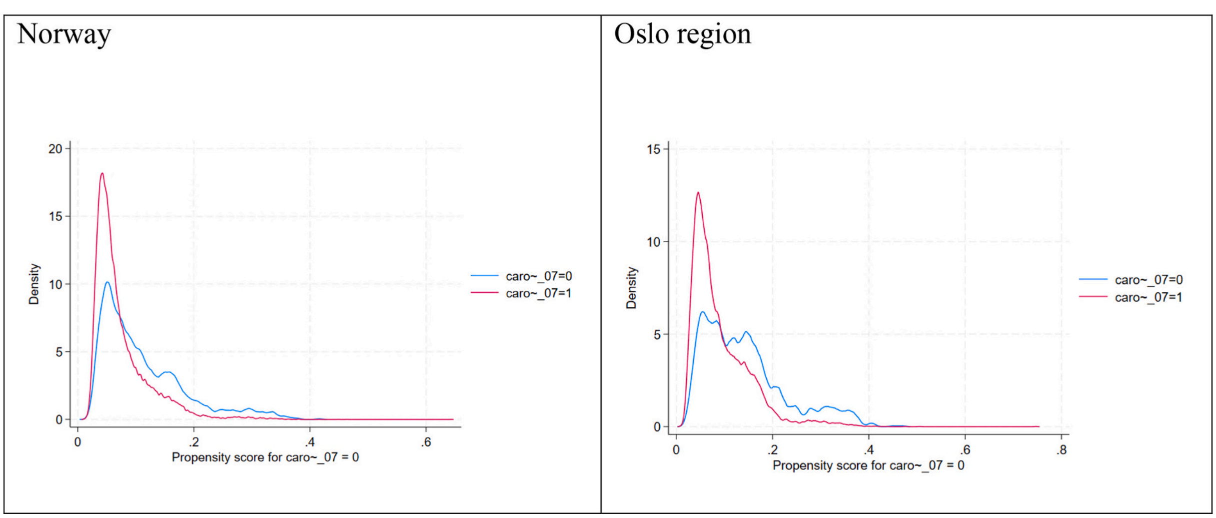
This work has been funded by The Research Council of Norway, grant no. 302059. Data on loan from Statistics Norway have been essential.

Appendix A. Appendix

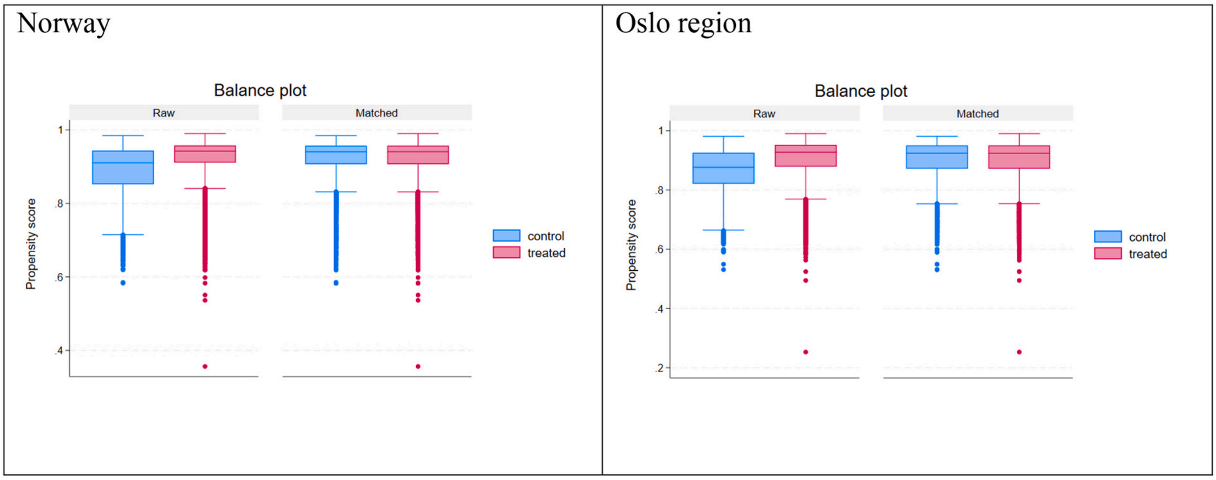
A.1. Logistic regression model

	Norway	Oslo region
Car ownership (2007)	0.255*** (0.049)	0.246** (0.071)
Centrality index (2007) 1	ref.	ref.
2	0.113 (0.075)	0.292 (0.164)
3	−0.010 (0.069)	0.034 (0.151)
4	−0.012 (0.066)	0.019 (0.142)
5	−0.007 (0.069)	0.066 (0.143)
6	0.021 (0.070)	0.112 (0.140)
Centrality index (2019) 1	ref.	–
2	0.040 (0.128)	–
3	−0.133 (0.117)	–
4	−0.574*** (0.112)	–
5	−1.056*** (0.113)	–
6	−2.397*** (0.112)	–
Population density	–	−0.023*** (0.003)
Building use diversity	–	−0.534*** (0.081)
Distance to Oslo centre	–	0.046*** (0.002)
Household income (1000 nok)	0.004*** (0.000)	0.003*** (0.000)
Household income^2	−0.000*** (0.000)	0.000 (0.000)
No education	ref.	ref.
High school	0.502*** (0.048)	0.229** (0.085)
Higher education (bachelor)	0.164*** (0.045)	0.056 (0.077)
Higher education (master)	−0.100* (0.051)	−0.110 (0.083)
Gender (female)	−0.091** (0.029)	−0.120** (0.043)
Couple	1.028*** (0.031)	0.964*** (0.047)
Children in household	0.903*** (0.037)	0.853*** (0.058)
Commute distance (10 km)	−0.005** (0.002)	0.009* (0.004)
Commute distance^2	−0.000 (0.000)	−0.000* (0.000)
Constant	−0.241 (0.131)	−2.900*** (0.208)
R2	0.275	0.248
N	37,933	13,559

A.2. Propensity score overlap



A.3. Balance plot



Data availability

The data that has been used is confidential.

References

Angrist, J.D., Pischke, J.-S., 2009. Mostly Harmless Econometrics: An empiricist's Companion. Princeton university press.

Baslington, H., 2008. Travel socialization: a social theory of travel mode behavior. Int. J. Sustain. Transp. 2, 91–114. https://doi.org/10.1080/15568310601187193.

Beige, S., Axhausen, K.W., 2012. Interdependencies between turning points in life and long-term mobility decisions. Transportation 39, 857–872.

Cao, X., 2010. Exploring causal effects of neighborhood type on walking behavior using stratification on the propensity score. Environ. Plan. A 42, 487–504.

Cao, J., Cao, X., 2014. The impacts of LRT, Neighbourhood characteristics, and self-selection on auto ownership: evidence from Minneapolis-St. Paul. Urban Stud. 51, 2068–2087. https://doi.org/10.1177/0042098013505887.

Cao, X., Fan, Y., 2012. Exploring the influences of density on travel behavior using propensity score matching. Environ. Plan B 39, 459–470.

Cao, X., Mokhtarian, P.L., Handy, S.L., 2009. Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. Transp. Rev. 29, 359–395. https://doi.org/10.1080/01441640802539195.

Cao, X., Xu, Z., Fan, Y., 2010. Exploring the connections among residential location, self-selection, and driving: propensity score matching with multiple treatments. Transp. Res. A Policy Pract. 44, 797–805. https://doi.org/10.1016/j.tra.2010.07.010.

Cervero, R., 2002. Built environments and mode choice: toward a normative framework. Transp. Res. Part D: Transp. Environ. 7, 265–284. https://doi.org/10.1016/S1361-9209(01)00024-4.

Cervero, R., Duncan, M., 2003. Walking, bicycling, and urban landscapes: evidence from the San Francisco Bay Area. Am. J. Public Health 93, 1478–1483. https://doi.org/10.2105/AJPH.93.9.1478.

Cervero, R., Kockelman, K., 1997. Travel demand and the 3Ds: density, diversity, and design. Transp. Res. Part D: Transp. Environ. 2, 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6.

Clark, B., Lyons, G., Chatterjee, K., 2016. Understanding the process that gives rise to household car ownership level changes. J. Transp. Geogr. 55, 110–120. https://doi.org/10.1016/j.jtrangeo.2016.07.009.

D'Agostino, R.B., 2007. Estimating treatment effects using observational data. JAMA 297, 314–316. https://doi.org/10.1001/jama.297.3.314.

Dai, F., Diao, M., Sing, T.F., 2020. Effects of rail transit on individual travel mode shares: a two-dimensional propensity score matching approach. Transp. Res. Part D: Transp. Environ. 89, 102601. https://doi.org/10.1016/j.trd.2020.102601.

Dargay, J.M., 2001. The effect of income on car ownership: evidence of asymmetry. Transp. Res. A Policy Pract. 35, 807–821. https://doi.org/10.1016/S0965-8564(00)00018-5.

Döring, L., Albrecht, J., Scheiner, J., Holz-Rau, C., 2014. Mobility biographies in three generations – socialization effects on commute mode choice. In: Transportation Research Procedia, Planning for the future of transport: challenges, methods, analysis and impacts - 41st European Transport Conference Selected Proceedings, 1, pp. 165–176. https://doi.org/10.1016/j.trpro.2014.07.017.

Duan, Z., Feng, Y., Xu, S., Gao, D., Ji, Y., Sun, X., Chen, R., Wang, Y., 2023. The role of childhood left-behind experience on childhood trauma exposure and mental health outcomes: a propensity score matching (PSM) analysis. J. Public Health fdad060. https://doi.org/10.1093/pubmed/fdad060.

Elster, J., 1989. Social norms and economic theory. J. Econ. Perspect. 3, 99–117.

Engebretsen, Ø., Næss, P., Strand, A., 2018. Residential location, workplace location and car driving in four Norwegian cities. Eur. Plan. Stud. 26, 2036–2057. https://doi.org/10.1080/09654313.2018.1505830.

Ewing, R., Cervero, R., 2010. Travel and the built environment. J. Am. Plan. Assoc. 76, 265–294. https://doi.org/10.1080/01944361003766766.

Ewing, R., Handy, S., 2009. Measuring the unmeasurable: Urban Design qualities related to walkability. J. Urban Des. 14, 65–84. https://doi.org/10.1080/13574800802451155.

Garrido, M.M., Kelley, A.S., Paris, J., Roza, K., Meier, D.E., Morrison, R.S., Aldridge, M.D., 2014. Methods for constructing and assessing propensity scores. Health Serv. Res. 49, 1701–1720. https://doi.org/10.1111/1475-6773.12182.

Gimenez-Nadal, J.I., Molina, J.A., 2016. Commuting time and household responsibilities: evidence using propensity score matching. J. Reg. Sci. 56, 332–359. https://doi.org/10.1111/jors.12243.

Grue, B., Landa-Mata, I., Langset Flotve, B., 2021. 2018/19 Norwegian Travel Survey - key results (No. 1835/2021). Institute of Transport Economics, Oslo.

Hägerstrand, T., Carlstein, T., Parkes, D., Thrift, N., 1978. Survival and Arena: On the Life-History of Individuals in Relation to their Geographical Environment in Human Activity and Time Geography.

Handy, S., 2020. Is accessibility an idea whose time has finally come? Transp. Res. Part D: Transp. Environ. 83, 102319. https://doi.org/10.1016/j.trd.2020.102319.

Haque, M.B., Choudhury, C., Hess, S., Sourd, R.C. dit, 2019. Modelling residential mobility decision and its impact on car ownership and travel mode. Travel Behav. Soc. 17, 104–119. https://doi.org/10.1016/j.tbs.2019.07.005.

Haustein, S., Klöckner, C.A., Blöbaum, A., 2009. Car use of young adults: the role of travel socialization. Transport. Res. F: Traffic Psychol. Behav. 12, 168–178. https://doi.org/10.1016/j.trf.2008.10.003.

Hjorthol, R., Engebretsen, Ø., Uteng, T.P., 2014. 2013/14 Norwegian Travel Survey - key results (No. 1383/2014). Oslo, TØI.

Høydahl, E., 2020. Sentralitetsindeksen (No. 2020/4). Norway, Statistics.

Kenworthy, J., Newman, P., 2015. The End of Automobile Dependence: How Cities Are Moving beyond Car-Based Planning. Island Press.

Li, A., Hamlin, D., 2019. Is daily parental help with homework helpful? Reanalyzing national data using a propensity score–based approach. Sociol. Educ. 92, 367–385. https://doi.org/10.1177/0038040719867598.

Liu, C., Sun, Y., Chen, Y., Susilo, Y.O., 2018. The effect of residential housing policy on car ownership and trip chaining behaviour in Hangzhou, China. Transp. Res. Part D: Transp. Environ. 62, 125–138. https://doi.org/10.1016/j.trd.2018.02.008.

Macfarlane, G.S., Garrow, L.A., Mokhtarian, P.L., 2015. The influences of past and present residential locations on vehicle ownership decisions. Transp. Res. A Policy Pract. 74, 186–200. https://doi.org/10.1016/j.tra.2015.01.005.

McCarthy, L., Delbosc, A., Currie, G., Molloy, A., 2017. Factors influencing travel mode choice among families with young children (aged 0–4): a review of the literature. Transp. Rev. 37, 767–781. https://doi.org/10.1080/01441647.2017.1354942.

McCarthy, L., Delbosc, A., Currie, G., Molloy, A., 2021. Trajectories and transitions: mobility after parenthood. Transportation 48, 239–256. https://doi.org/10.1007/s11116-019-10051-5.

Mishra, G.S., Clewlow, R.R., Mokhtarian, P.L., Widaman, K.F., 2015. The effect of carsharing on vehicle holdings and travel behavior: a propensity score and causal mediation analysis of the San Francisco Bay Area. Res. Transp. Econ. Sustain. Transp. 52, 46–55. https://doi.org/10.1016/j.retrec.2015.10.010.

Mjahed, L.B., Frei, C., Mahmassani, H.S., 2015. Walking behavior: the role of childhood travel experience. Transp. Res. Rec. 2495, 94–100.

Mokhtarian, P.L., Cao, X., 2008. Examining the impacts of residential self-selection on travel behavior: a focus on methodologies. Transp. Res. Part B: Methodol. A Tribute Career Frank Koppelman 42, 204–228. https://doi.org/10.1016/j.trb.2007.07.006.

Næss, P., 2009. Residential self-selection and appropriate control variables in land use: travel studies. Transp. Rev. 29, 293–324. https://doi.org/10.1080/01441640802710812.

Nasri, A., Carrion, C., Zhang, L., Baghaei, B., 2020. Using propensity score matching technique to address self-selection in transit-oriented development (TOD) areas. Transportation 47, 359–371. https://doi.org/10.1007/s11116-018-9887-2.

Oakes, J.M., Johnson, P.J., 2006. Propensity score matching for social epidemiology. Methods Soc. Epidemiol. 1, 370–393.

Oakil, A.T.M., Ettema, D., Arentze, T., Timmermans, H., 2014. Changing household car ownership level and life cycle events: an action in anticipation or an action on occurrence. Transportation 41, 889–904.

Oakil, A.T.M., Manting, D., Nijland, H., 2016. Determinants of car ownership among young households in the Netherlands: the role of urbanisation and demographic and economic characteristics. J. Transp. Geogr. 51, 229–235. https://doi.org/10.1016/j.jtrangeo.2016.01.010.

Prillwitz, J., Harms, S., Lanzendorf, M., 2007. Interactions between residential relocations, life course events, and daily commute distances. Transp. Res. Rec. 2021, 64–69. https://doi.org/10.3141/2021-08.

Ralph, K.M., 2022. Childhood Car access: long-term consequences for education, employment, and earnings. J. Plan. Educ. Res. 42, 36–46. https://doi.org/10.1177/0739456X18798451.

Rosenbaum, P.R., Rubin, D.B., 1984. Reducing Bias in observational studies using subclassification on the propensity score. J. Am. Stat. Assoc. 79, 516–524. https://doi.org/10.1080/01621459.1984.10478078.

Sandow, E., Westerlund, O., Lindgren, U., 2014. Is your commute killing you? On the mortality risks of long-distance commuting. Environ. Plan. A 46, 1496–1516. https://doi.org/10.1068/a46267.

Scheiner, J., 2018. Transport costs seen through the lens of residential self-selection and mobility biographies. Transp. Policy, Household Transp. Cost. Econ. Stress Energy Vulnerabil. 65, 126–136. https://doi.org/10.1016/j.tranpol.2016.08.012.

Shannon, C.E., 1948. A mathematical theory of communication. Bell Syst. Tech. J. 27, 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.

Smart, M.J., Klein, N.J., 2018. Remembrance of cars and buses past: how prior life experiences influence travel. J. Plan. Educ. Res. 38, 139–151. https://doi.org/10.1177/0739456X17695774.

Thigpen, C., 2019. Do bicycling experiences and exposure influence bicycling skills and attitudes? Evidence from a bicycle-friendly university. Transp. Res. Part A: Policy Pract. Walk. Cycling Better Transp. Health Environ. 123, 68–79. https://doi.org/10.1016/j.tra.2018.05.017.

Van Acker, V., Witlox, F., 2010. Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. J. Transp. Geogr. 18, 65–74.

Van Acker, V., Mulley, C., Ho, L., 2019. Impact of childhood experiences on public transport travel behaviour. Transp. Res. A Policy Pract. 130, 783–798. https://doi.org/10.1016/j.tra.2019.10.008.

Van Acker, V., Ho, L., Stevens, L., Mulley, C., 2020. Quantifying the effects of childhood and previous residential experiences on the use of public transport. J. Transp. Geogr. 86, 102759. https://doi.org/10.1016/j.jtrangeo.2020.102759.

Wolday, F., Næss, P., Cao, X., 2019. Travel-based residential self-selection: a qualitatively improved understanding from Norway. Cities 87, 87–102. https://doi.org/10.1016/j.cities.2018.12.029.