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Causes and effects between attitudes, the built environment and car kilometres: A longitudinal analysis

Paul van de Coevering [a,*], Kees Maat [b], Bert van Wee [c]

[a] Academy for Urban Development Logistics & Mobility, Breda University of Applied Sciences, P.O. Box 3917, 4800, DX, Breda, the Netherlands
[b] Department of Transport & Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, P.O. Box 5048, 2600, GA, Delft, Netherlands
[c] Transport and Logistics Group, Faculty Technology, Policy and Management, Delft University of Technology, P.O. Box 5015, 2600, GA, Delft, Netherlands

A R T I C L E I N F O

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Attitudes
Residential self-selection
Reverse causality
Longitudinal approach

A B S T R A C T

Travel-related attitudes are believed to affect the connections between the built environment and travel behaviour. Previous studies found supporting evidence for the residential self-selection hypothesis which suggests that the impact of the built environment on travel behaviour could be overestimated when attitudes are not accounted for. However, this hypothesis is under scrutiny as the reverse causality hypothesis, which implies a reverse direction of influence from the built environment towards attitudes, is receiving increased attention in recent research. This study tests both directions of influence by means of cross-sectional and longitudinal structural equation models. GPS tracking is used to assess changes in travel behaviour in terms of car kilometres travelled. The outcomes show stronger reverse causality effects than residential self-selection effects and that land-use policies significantly reduce car kilometres travelled. Moreover, the longitudinal models show that the built environment characteristics provide a better explanation for changes in car kilometres travelled than the travel-related attitudes. This contradicts the cross-sectional analysis where associations between car kilometres travelled and travel-related attitudes were stronger. This highlights the need for more longitudinal studies in this field.

1. Introduction

Land-use policies and concepts aiming at compact cities have been developed to curtail urban sprawl, reduce car dependency, and promote active and multi-modal travel behaviour. An important assumption behind these policies and concepts is that people will shift to more sustainable travel behaviour when sufficient opportunities are provided by the built environment and the transportation system. In general, study outcomes provide some support for these assumptions. Ceteris paribus, people in dense, mixed-use environments with good facilities for sustainable transport modes tend to use the car less and sustainable alternatives such as walking, biking and public transport more often (Krizek 2003; Ewing and Cervero 2010; Gim 2013, Chatman 2014; Næss 2014; Cao et al., 2019).

However, the built environment is only one of the many factors that influence travel behaviour. Many studies have shown that socioeconomic and demographic characteristics are at least as important. Over the last two decades, the role of attitudes has received increased attention. Where socioeconomic and demographic characteristics can be incorporated as control variables in statistical analyses, the role of attitudes is more complex. Previous studies suggested reciprocal and indirect relationships with residential choices and travel behaviour. This direction of influence is of great importance as it may lead to under- or overestimations of the extent that travel behaviour is affected by land-use policies (Cao and Chatman, 2016; Bohte 2010). Therefore, this article applies a longitudinal design and structural equations modelling, unravelling the role of attitudes and their dominant direction of influence.

One direction of influence is related to the well-known 'residential self-selection hypothesis'. According to this hypothesis, people locate themselves in neighbourhoods with conducive circumstances for their preferred travel modes. If studies would not control for this role of attitudes, the extent to which travel behaviour is influenced by the built environment may be overestimated or underestimated, depending on the extent to which people can self-select themselves (Cao et al. 2009; Bohte et al. 2009; Lin et al. 2017; Næss 2009). For instance, the influence of high-density urbanisation on public transport use appears to be strong, but this may be partly because people with strong public

* Corresponding author.
E-mail addresses: coevering.p@buas.nl (P. van de Coevering), c.maat@tudelft.nl (K. Maat), G.P.vanWee@tudelft.nl (B. van Wee).

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transport attitudes opt for high-density neighbourhoods. Studies evaluating the role of attitudes arrive at different conclusions. Bagley and Mokhtarian (2002) found that miles travelled for car, public transport and active modes were strongly associated with attitudes and lifestyle variables and that the influence of the built environment characteristics was limited. Lund (2003) found comparable results for the frequency of walking trips. Conversely, Schwanen and Mokhtarian (2005), Bohte (2010), Næss (2009), Ewing et al. (2016) and Van Herick and Mokhtarian (2020), did find significant influences of the built environment on car use when attitudes and mismatches were controlled for. For more extensive insight, we refer to Mokhtarian and Cao (2008), Bohte et al. (2009), Gim, (2013) and Heinen et al. (2018).

The 'reverse causality hypothesis' (Bohte et al. 2009; Chatman 2009; Van Wee et al. 2019), also called 'residential environment determinism' (Ewing et al. 2016), assumes an opposite direction of influence where the residential environment influences attitudes. Reverse causality occurs when people adapt travel-related attitudes to align them with their previously selected residential environment. First, this adjustment process may be related to the cognitive dissonance theory. This theory suggests that people tend to harmonise their attitudes and behaviour and reduce dissonance (Festinger 1957; Golob et al. 1979). For example, people that favour car use may experience cognitive dissonance when they start living in a compact neighbourhood. Aligning their attitudes towards this new, compact environment would cause them to develop a less positive car attitude and a more positive attitude towards alternative transport modes such as biking and public transport. Secondly, reverse causality may occur due to new experiences and resulting positive or negative emotions during people's daily routines in their social and spatial environment (Cullen 1978; Van Wee et al. 2019). For instance, people living near the railway station experience that car use is less convenient and conditions are more favourable for public transport, cycling or walking. This may influence people's perceptions and encourage more positive attitudes towards public transport, cycling and walking over time. Although many scholars have acknowledged the possibility of this reverse causal direction (Næss 2009; Næss 2014; Cao et al. 2009; Chatman 2009), few empirical studies have been conducted to date. To the best of our knowledge, Bagley and Mokhtarian (2002) were the first to explicitly analyse reverse causal influences. They found no significant reverse influences. Bohte (2010) did find reverse causal influences: living further from the nearest railway station had a negative impact on people's public transport attitudes. Some recent studies also found evidence for reverse causality (Van Acker et al., 2014; de Abreu e Silva, 2014; Ewing et al. 2016; Van De Coevering et al. 2016; Lin et al. 2017; De Vos et al. 2018).

There are four conditions for identifying causal relationships (Singleton and Straits, 2009; Shadish et al. 2002): (1) association, (2) non-spuriousness, (3) time precedence and (4) plausibility. Previous studies mostly applied quantitative cross-sectional research designs and found significant associations after controlling for confounding factors. However, the time precedence and plausibility criterion received less attention (Handy et al. 2005). To determine the direction of influence and disentangle the cause and effect, a longitudinal research design and controlling for confounding variables is necessary. In a cross-sectional study, all variables are measured at one moment in time. This enables the identification of associations between variables, e.g. people living in denser environments use the car less often. In a longitudinal study, variables are measured at two or more moments in time. This enables the identification of intra-personal change over time, e.g. people use the car less often after a move to a denser environment. This provides more evidence for a causal relationship (Van De Coevering et al. 2015). To date, few longitudinal studies include attitudes at multiple moments in time which is remarkable since the direction of influence is very important (Cao et al. 2009; Gim 2013). Sometimes attitudes were simply not part of the research focus (e.g. Krizek 2003; Meurs and Haaijer 2001) and in other studies retrospective longitudinal designs were used (Handy et al. 2005; Cao et al. 2007). As retrospective questioning is considered unreliable to assess changes in attitudes, retrospective studies often include current attitudes only (e.g. Handy et al. 2005). The studies by De Vos et al. (2018) and De Vos et al. (2020) are exceptions. They conducted retrospective questioning on attitudes after relocation and found reciprocal influences that revealed self-selection effects during the move and gradual changes in attitudes after the relocation. We only found two studies that applied longitudinal designs that incorporated attitudes on two occasions (Van De Coevering et al. 2016; Wang and Lin 2019). Interestingly, these studies indicated reverse causality, but no evidence was found for residential self-selection.

Taken together, there is some evidence for both directions of influence, but it is still inconclusive. In other words, we do see that different people in different residential environments have different attitudes. However, to what extent are people's attitudes the cause of this, due to people choosing a neighbourhood with characteristics that are aligned with their preferred travel behaviour? And to what extent are they the effect of people adjusting their attitudes to their residential environment? The answers to these questions are vital for the effectiveness of land-use policies. If residential self-selection is dominant, the effectivities of land-use policies and concepts in achieving more sustainable travel behaviour would be limited. The key role would be to enable people that already have a positive disposition towards sustainable travel behaviour to select a conducive neighbourhood and next travel in the desired way. If reverse causality would be dominant, the impact of the built environment is significantly larger. In addition to a direct effect on travel behaviour, the built environment would also have an indirect effect by its influence on people's attitudes.

This study aims to add to the academic debate and to assess the practical relevance of modifying the built environment to reduce the number of car kilometres driven. Therefore, we identify the dominant direction of influence between attitudes and the built environment, and determine the resulting impact of the built environment on car kilometres driven. The inclusion of multiple directions of causality and the use of longitudinal designs are both at an early stage in this field. That is why it is interesting, from a methodological viewpoint, to assess whether potential differences in results between previous cross-sectional studies and our longitudinal study originate from the inclusion of multiple directions of causality or from the longitudinal design. Therefore, this study starts with cross-sectional analyses, testing rival assumptions regarding the directions of influence, which will show which hypothesis fits the data best. Subsequently, a longitudinal analysis will be conducted that will assess the direction of causality over time.

We specifically focus on the following research questions:

1. Which assumed direction of influence fits the cross-sectional data best, residential self-selection, or reverse causality?
2. To what extent are residential self-selection and reverse causality able to explain changes in residential location characteristics and travel-related attitudes over time?
3. What is the remaining influence of the built environment on car kilometres driven over time?

This study builds on previous work of (Van De Coevering et al. 2016). It is based on the same questionnaire which includes attitudes at two moments in time (2005–2012), however, partially with other variables. This study adds to the current knowledge by using data from GPS tracking to specifically determine the number of car kilometres driven. The GPS dataset includes car trips during one week, which provides a better overall picture of kilometres driven than if only one day would be included, without placing a burden on the respondents (Bohte 2010). To the best of our knowledge, a longitudinal dataset with a time span of seven years incorporating detailed information about attitudes and travel behaviour is unique. Furthermore, the effects of two built environment indicators are compared: the distance to the nearest railway station and residential density. Lastly, this study includes cross-sectional and longitudinal SEMs, explicitly comparing their results. This will demonstrate to what extent the cross-sectional associations reflect causal influences over time.

Data are described in the next section. The modelling approach is described in the third section and the results in the fourth one. Finally, conclusions are drawn, and the scientific and societal implications discussed.

2. Data

2.1. Data collection, study area and sample

The data collection encompasses two research rounds both including an internet questionnaire and GPS tracking. The internet questionnaire will only be described briefly here. A more detailed description is available in Van De Coevering et al. (2016). The questionnaire was carried out in the Netherlands and included questions relating to demographics, socioeconomics, attitudes, and travel behaviour. A random sample was taken from homeowners and their partners living in three typical municipalities in the central part of the Netherlands, in the medium sized-city of Amersfoort (150,000 inhabitants), the smaller town of Veenendaal (62,500) and the remote town of Zeewolde (20,000). The research was limited to homeowners because renting in the Netherlands is regulated and does not provide many opportunities for residential self-selection. The sample represented people living in residential areas with diverse built environment characteristics. In the first round, 31% of the people in the sample participated, yielding a total response of 3979 respondents (Bohte 2010). In the second round, we were able to contact 3300 (83%) of these respondents again and 1788 of them participated in the survey, which equals a response rate of 54%. At the end of the questionnaires in 2005 and 2012, respondents were asked to participate in the subsequent GPS surveys. In the first round, 1200 respondents took part in the GPS fieldwork that was conducted in early 2007. The participants logged their trips for one week with a handheld GPS device. Subsequently, the data was downloaded and analysed using various rule-based algorithms to derive travel behaviour determinants such as mode use, kilometres travelled and travel times (Bohte 2010). Afterwards, participants were able to validate their trips via an online portal. This eventually resulted in 936 usable GPS surveys. For more details on this method see Biljecki et al. (2013). The GPS fieldwork in the second round involved 896 participants, but not all of them also took part in the first round. In total 595 people participated in both rounds. The same rule-based algorithms were used to analyse the new data. However, in 2013 we did not have an online portal available for the validation of the GPS trips. Therefore, we asked respondents to fill in a travel diary containing only the essential travel characteristics - departure time, trip purpose and travel mode - to validate the GPS trips in the second round. During data cleaning and validation, we removed respondents that did not validate their data online in 2007 or with the travel diary in 2013. Moreover, we only selected participants that recorded at least four days of travel or indicated that they stayed at home during one of these four days. This resulted in 479 longitudinal cases. Dependence on observations is prevented by a random selection of one partner per couple. This led to a dataset of 344 respondents for the present paper. Distances over the network towards important destinations, such as supermarkets, shopping centres and the railway station, were calculated using GIS software.

2.2. Variables

The variables are described in Table 1. Travel behaviour was operationalised by the average number of car kilometres driven per weekday. The average of 50 km is high by Dutch standards, which may be due to the relatively high education and income levels and to the fact that a large share of the respondents has a paid job. The sample is evenly distributed among males and females. The average age in the sample is relatively high because of the selection of homeowners (Bohte 2010).

Table 1
Variables ($N = 344$)

Variables	Description	2005 Mean (st.dev) & shares (%)	2012 Mean (st.dev) & shares (%)
Behaviour			
Kilometres driven by car	Kilometres on an average weekday	54,498/ (39,068)	50,397 (44,126)
Residential move between 2005 and 2012	No	n.a.	287 (83%)
	Yes	n.a.	57 (17%)
Attitudes			
Travel-related attitudes	Car attitude	3.4 (4.6)	4.3 (4.3)
	Public transport attitude	−3.6 (5.8)	−2.8 (5.7)
	Bicycle attitude	9.8 (4.7)	10.3 (4.8)
Built environment			
Average distance	To municipal centre [m]	1949 (775)	1955 (870)
	To nearest shopping centre [m]	1123 (778)	1161 (819)
	To nearest railway station [m]	6431 (5473)	5868 (5814)
	To nearest bus stop [m]	604 (566)	495 (483)
	To nearest highway ramp [m]	5491 (5001)	5255 (5048)
Density	Surrounding addresses density	1459 (732)	1515 (736)
Socio-demographics			
Age	Average	46.7 (9.4)	53.7 (9.4)
Gender	Female	45.0%	45.0%
	Male	55.0%	55.0%
Household composition	Single household	5.6%	6.1%
	Single parent	1.4%	3.1%
	Partners without children	25.0%	38.1%
	Partners with children	67.2%	51.7%
	Other	0.8%	1.1%
Education	Low:	4.2%	4.2%
	Medium	30.6%	28.9%
	High	65.3%	66.9%
Net personal income (monthly)	Low (< € 1000)	18.9%	11.9%
	Middle (≥€1000 < €2000)	40.0%	33.6%
	High (≥€2000)	41.1%	54.4%
Paid work	No job	14.2%	21.8%
	Part-time job (〈30h)	24.7%	22.7%
	Full-time job (≥ 30 h)	61.0%	55.5%

The majority of respondents live together with a partner and children, but this has significantly decreased while the share of partners living without children significantly increased between 2005 and 2012.

The travel-related attitudes were determined for three specific transport modes: car, public transport and bicycle. Respondents rated nine statements for each mode on a five-point Likert scale. The statements included cognitive (e.g. "public transport is timesaving") and affective (e.g. "car driving is fun") items and were rated on a range from −2 'completely disagree' to +2 'strongly agree'. Subsequently, we summed up the individual items to determine a person's overall attitude for each transport mode. The internal consistency of the scales proved to be satisfactory (Cronbach's Alpha for all attitudes >0.75). Interestingly, the mean values of all mode-related attitudes became more positive towards that mode between 2005 and 2012.

The built environment was operationalised by two types of measures. The first one is a measure of accessibility that represents the shortest route between respondents' homes to different types of facilities along the road network (NWB 2018). The second one is the surrounding address density, a density measure that was obtained from Statistics Netherlands (CBS). This measure represents the number of addresses per square kilometre. It is calculated per address by counting the number of addresses within a circular area with a radius of one kilometre, divided by the surface area. Subsequently, it is aggregated to the PC6 postal code level by averaging the scores of all addresses in the PC6 postal area (CBS, 2018). The small overall increase in density is probably due to new housing projects in and around the research areas.

3. Modelling approach and specification

3.1. Modelling approach

We applied Structural Equations Modelling (SEM) on cross-sectional and longitudinal data. SEM allows us to use multiple endogenous variables and identify and estimate directions of influence, while controlling for the confounding influence of exogenous variables such as socio-demographics. The cross-sectional analyses do not provide evidence for the causal direction, but they do enable us to compare the model fit indicators and the model parameters to determine which model fits the data best. The dominant direction of influence in the cross-sectional analysis was assessed by estimating separate models with different assumptions regarding the direction of causality. In addition, an attempt was made to develop a non-recursive model, including both directions of causality at the same time. However, this model posed challenges regarding identification, as the core of the model - represented by the links between the built environment indicator, car use and attitudes - was underidentified. With the inclusion of socio-demographic control variables, the model converged. However, all the coefficients between the variables of interest were insignificant and the overall modal fit was less favourable. Due to the lack of meaningful results, this approach was abandoned.

The longitudinal dataset enables us to analyse directions of influence over time, which provides stronger evidence for causality on these links (Mokhtarian and Cao 2008). We applied a Cross-lagged Panel Model (CLPM) which determines to what extent values of variables at an earlier point in time can explain ‘change’ in other variables over time. In our case with two time points, the CLPM for instance shows to what extent changes in people’s car attitudes between 2005 and 2015 can be explained by the characteristics of the residential location at baseline. To determine change, the baseline value of each endogenous variable is regressed on its value at the second point in time. This autoregressive effect reflects the stability of this variable over time and the remaining variance reflects the change of the variable over time. The higher the autoregressive effect, the higher the stability in the variable and the lower the change over time. The change is explained by what are called ‘cross-lagged effects’. A significant effect indicates that the baseline values of that particular variable explain the change in the variable of interest over time (Selig and Little 2012). Hence, the CLPM can meet the first criteria for identifying causal relationships, association, non-spuriousness and time precedence (Finkel 1995). Assumptions regarding causal mechanisms were derived from literature and are explained in the specification of the models in the next paragraph.

3.2. Specification

Fig. 1 shows the specification of the cross-sectional model including the built environment, mode-related attitudes, kilometres driven by car, and socio-demographics. To adjust for measurement errors in the composite scales of the mode attitudes, a latent variable was defined for each mode attitude. Each composite scale, measuring a mode attitude based on the nine items mentioned in Section 2, was then used as a single observed indicator for the associated latent construct. In line with published literature, the error variances were fixed to 1 minus the Cronbach’s alpha of the composite scales, multiplied by the variances of these scales (Bollen 2014), The mode-related attitudes in this model represent these latent constructs and are therefore visualised as circles.

The built environment variables are assumed to influence kilometres driven by car directly. Essential are the solid and dotted arrows between the built environment and the attitudes. The solid lines represent residential self-selection where attitudes influence kilometres driven by car via their influence on the built environment. The dotted arrows reflect reverse causality; the built environment influences attitudes (which are still assumed to affect kilometres driven by car). Similarly, both traditional and reverse influences are assumed between attitudes and kilometres driven by car. Socio-demographic characteristics are specified exogenously, influencing attitudes, built environment and kilometres travelled. To assess whether the residential self-selection or the reverse

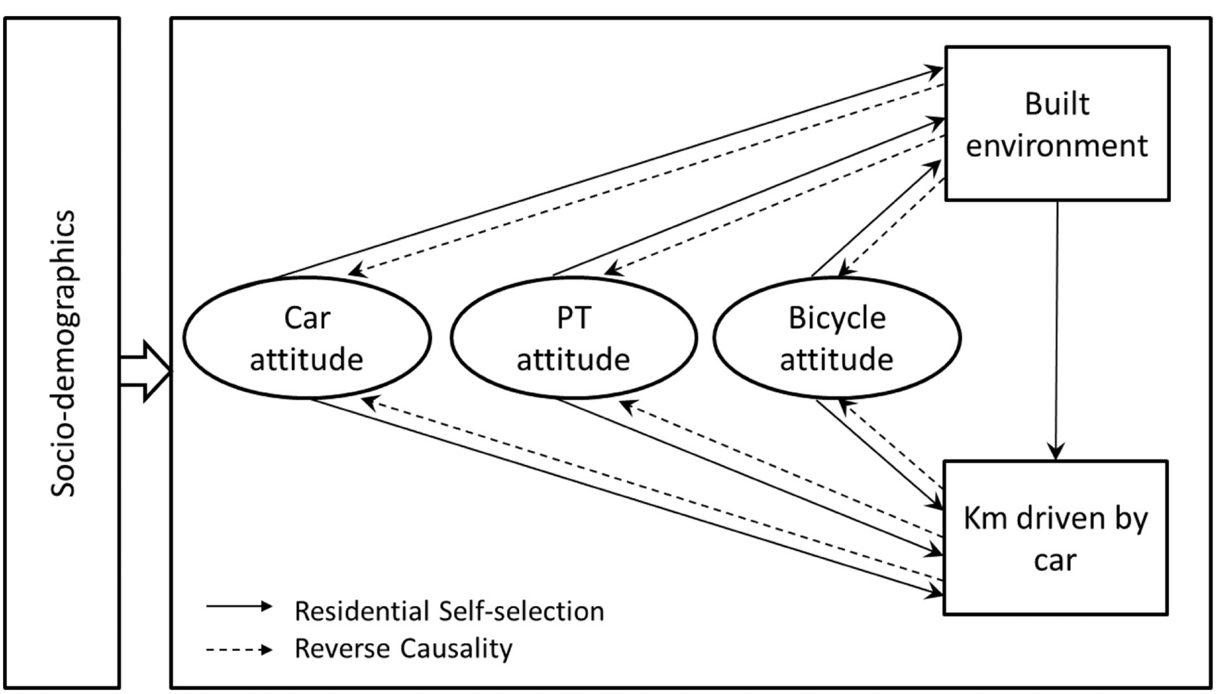

Fig. 1. specification of the cross-sectional model.

causality hypothesis fits the data best, we estimated three separate models. The first model reflects residential self-selection where attitudes are assumed to influence the built environment directly (solid lines). The second model reflects reverse causality, assuming an influence from the built environment towards the attitudes (dotted lines) but still the conventional influence of attitudes on kilometres driven by car. In addition to reverse causality from the built environment towards attitudes, the third model also assumes a reverse causal direction from car kilometres driven towards attitudes and not the converse.

The longitudinal CLPM is specified in Fig. 2. The model includes the values of the endogenous variables in 2012 and their counterparts in 2005. Socio-demographics are represented as exogenous variables and include the baseline values and their changes between 2005 and 2012.

The core of the model consists of the stability coefficients (S1-S3) of the built environment, attitudes and kilometres driven by car, and their related cross-lagged relationships (L1-L6) over time. In this model, the cross-lagged relationship from the baseline values of the mode attitudes towards the built environment characteristics in 2012 (L4) reflects residential self-selection. Reverse causality is represented by the cross-lagged relationship from the baseline values of the built environment characteristics towards mode attitudes in 2012 (L6). By testing the significance of these relationships and by comparing their strength we were able to determine the dominant direction of causality.

D1–D4 represent the influence of exogenous control variables. Socio-demographic characteristics are specified exogenously, influencing attitudes, built environment and kilometres travelled. The changes in socio-demographics also influence these variables, but only in 2012, as we only assume lagged effects in this model. For the sake of parsimony, lead effects (which involve people anticipating changes in their household circumstances by adjusting their current attitudes or choices regarding residential choice or car use) are not included. Finally, correlations are assumed between the error terms of the kilometres driven by car, mode-related attitudes and built environment characteristics These correlations represent the associations between these variables at baseline (C1-C3) and the remaining associations, after accounting for the lagged effects, the cross-lagged effects and the influence of the socio-demographics and their changes (C4 - C6). The socio-demographics and their changes are also assumed to be correlated themselves. Synchronous effects, for instance from the built environment indicators in 2012 to the attitudes in 2012, are not included in the model. Including them would lead to endogeneity issues as correlated error terms are assumed for variables at the same moment in time. What's more, including synchronous effects may cause challenges regarding identification, as this increases the number of parameters in the model. Even though we did not model synchronous effects, the associations between the error terms of these variables in 2005 and 2012 (C1-C6) indicate the presence of

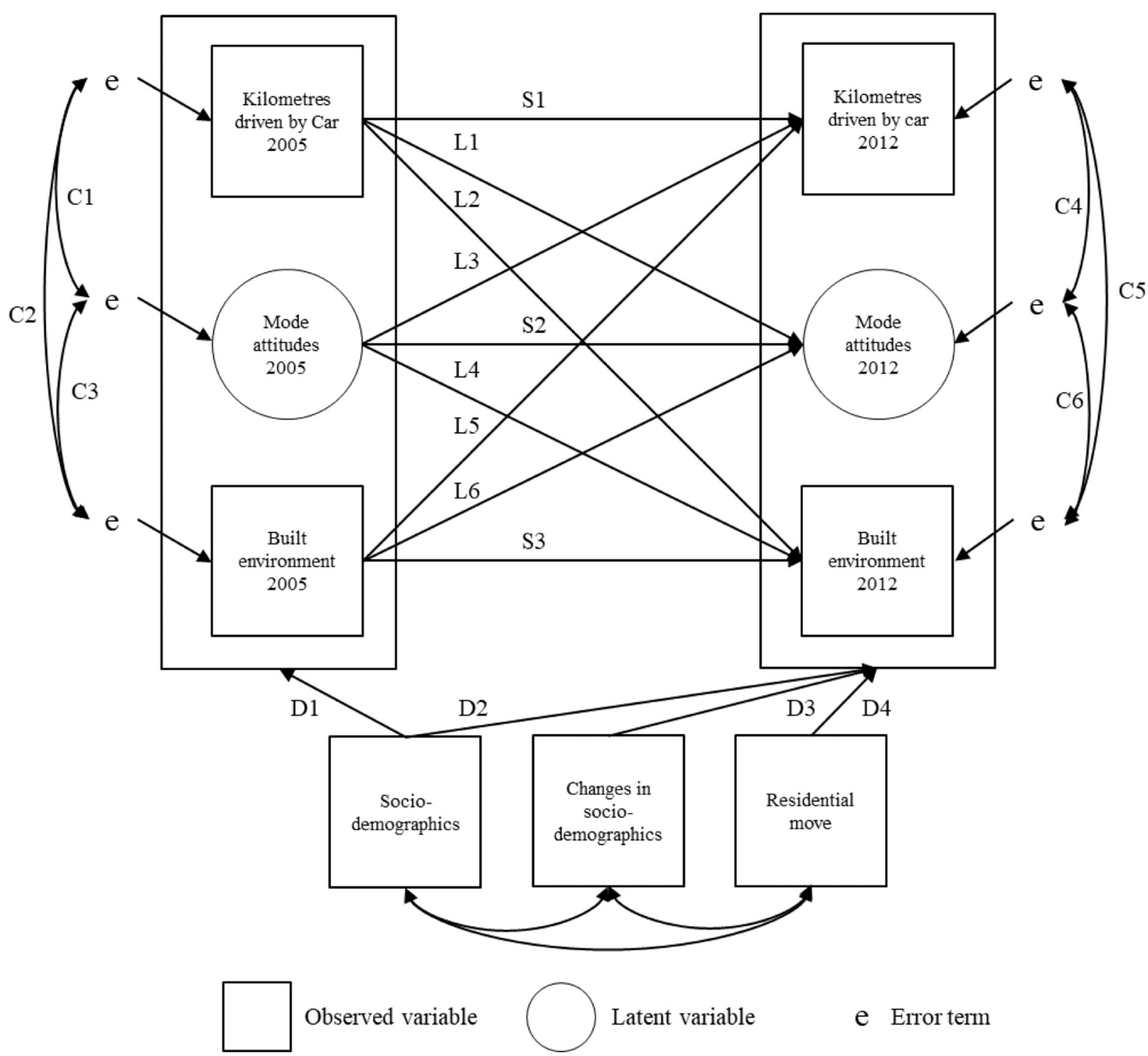

Fig. 2. Specification of the CLPM.

these effects.

We applied the commonly used maximum likelihood (ML) estimation, which assumes normally distributed endogenous variables, so we tested the distribution of the car kilometres per day and of the built environment characteristics. As their distribution deviated from normality, we took the natural logarithm of these variables.

4. Results

All models were constructed via the process of backward elimination, starting with the least significant relationship. All non-significant effects of the exogenous variables were removed, but the relationships between the endogenous variables were retained, as they concern the main research questions. During model development, all built environment indicators included in Table 1 were tested. As many show high levels of multicollinearity, it was infeasible to analyse all variables simultaneously. Therefore, we chose to take two strong indicators, the distance to the nearest railway station and residential density, and use them in all analyses. Both can be considered as a proxy reflecting among other things the quality of facilities for public transport and cycling, available parking space, function mix, accessibility of retail, etc. As they correlate strongly, they cannot both be included in one model. It was decided to estimate separate models for each determinant. By doing so we avoided limiting our analysis to just one determinant of the built environment, while enabling a comparison of their impact. For the sake of brevity we only report the results of the main variables of interest here. For the interested reader, full model results are available in the appendix to this article.

4.1. Cross-sectional results

Fig. 3 presents the standardised parameter estimates and model fit of six cross-sectional models for (I) residential self-selection, (II) reverse causality between attitudes and the built environment and (III) reverse causality between attitudes and the built environment and between attitudes and car kilometres driven. The models including the distance to the railway station as a determinant for the built environment are presented on the left and results for the residential density indicator on the right. Their outcomes are discussed together.

Overall, the cross-sectional analyses revealed that models assuming reverse causality and models assuming residential self-selection fit the data equally well. The insignificant chi-square and RMSEA *P*-values and the CFI and TLI close to 1, indicate an acceptable to good model fit for all models (Bollen 2014). The differences in the overall model fit between

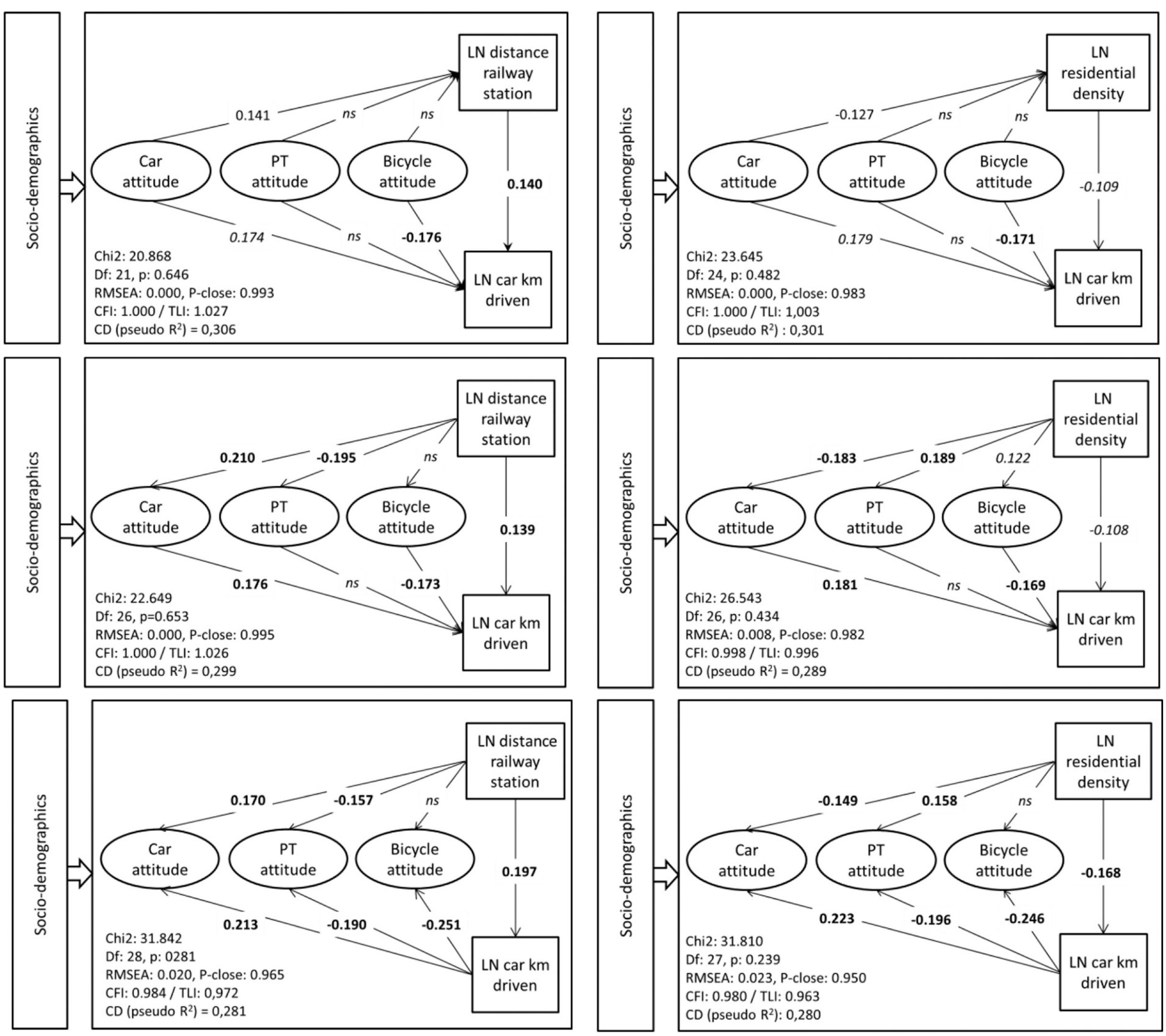

Fig. 3. cross-sectional results for car km driven based on the distance to the railway station (left) and residential density (right), and model 1 assuming residential self-selection (top), model 2 assuming reverse causality on the attitude-built environment link (middle) and model 3 assuming reverse causality on the attitude-built environment and the attitude-car km driven link (bottom). Significance: bold $p < .01$; italics $p < .05$; other $p < .1$.

the models are small and may also stem from the different influence of the socio-demographic variables in the models. As the cross-sectional analyses are based on similar - but different - models, a direct comparison of the strengths of the coefficients is not justified. However, comparing the models does indicate the direction and magnitude of effects on the links between attitudes, built environment and travel behaviour. A comparison of the coefficients of the first two models shows that the assumed direction of influence from the built environment towards attitudes is stronger than vice versa. In other words, reverse causality effects seem stronger than residential self-selection effects. Self-selection effects are small and only indicated for the car attitude. People with a stronger car attitude tend to self-select into lower-density neighbourhoods and further away from a railway station. The reverse causality coefficients are significant for the car and public transport attitudes. They indicate that living further from the railway station positively affects car attitudes, while the opposite holds for public transport attitudes. For the density indicator, the signs are opposite. A higher density has a negative influence on car attitudes and a positive influence on attitudes for public transport and cycling (the latter marginally significant). In line with expectations, travel-related attitudes have a direct effect on car kilometres driven. Stronger car attitudes have a positive effect and stronger bicycle attitudes have a negative effect on car kilometres driven. The results for public transport attitudes are insignificant, which may be an effect of the limited amount of public transport use in the sample. This is related to the nature of the sample with medium and small-sized Dutch municipalities where people often combine car and bicycle use, and the share of public transport is limited.

Results of the third model reveal that the reverse causal effects from the built environment indicators on attitudes are somewhat attenuated when reverse causality is assumed on the link between attitudes and car kilometres driven. This indicates that the effect of the built environment on attitudes is partially indirect. For example, people use the car more often when they live further from the railway station and this, in turn, has a positive effect on people's car attitude. In all models, the direct influence of the distance to the railway station and of the residential density on car kilometres travelled is significant. Larger distances to the railway station and lower densities have a positive influence on car kilometres travelled. The impact of the built environment indicator is somewhat smaller than the influence of the attitudes. So how large is this effect? When both independent and dependent variables are log-transformed, as in our case, the unstandardised regression coefficients can be interpreted as elasticities for small changes in the independent variable. For the distance to the railway station, the unstandardised coefficients vary between $b = 0.15$ (model 1 and 2) and $b = 0.21$ (model 3) and for residential density between $b = -0.20$ (model 1 and 2) and $b = -0.32$ (model 3). So, a 1% increase in the distance to the railway station leads to an approximate 0.15–0.21% increase in car kilometres travelled. A 1% increase in residential density leads to a 0.2–0.32% decrease in car kilometres travelled. For reasons of parsimony, the effects of socio-demographics, which are primarily used as control variables, are not described here. Their role will be elaborated on in the longitudinal models.

4.2. Longitudinal results

The results of the two longitudinal models are shown in Fig. 4 and will be described together. Note that non-significant links between the variables depicted in Fig. 4 have been retained in the statistical model, but they are not visualised here for the sake of clarity. The same holds for correlations between the error terms of these variables. With insignificant chi-square and RMSEA values, and CFI and TLI values close to one the model fit appears to be good for both models (Newsom 2015). We start with a description of the standardised effects on the relationships between the endogenous variables as shown in Fig. 4. We describe the autoregressive effects (indicators of stability), the cross-lagged effects (including residential self-selection and reverse causality) and the impact of the distance to the railway station and residential density on car kilometres driven. Finally, we present the effects of the socio-demographic variables and their changes on the endogenous variables in 2005 and 2012, as shown in Table 2.

The results in Fig. 4 show that autoregressive effects are strong in both models. In other words, the indicators in 2005 are a good predictor for their counterparts in 2012, which means that stability is rather high. The distance to the railway station shows high levels of stability. The stability of the residential density is lower but still rather high. The high stability of the built environment indicators reflects the fact that the

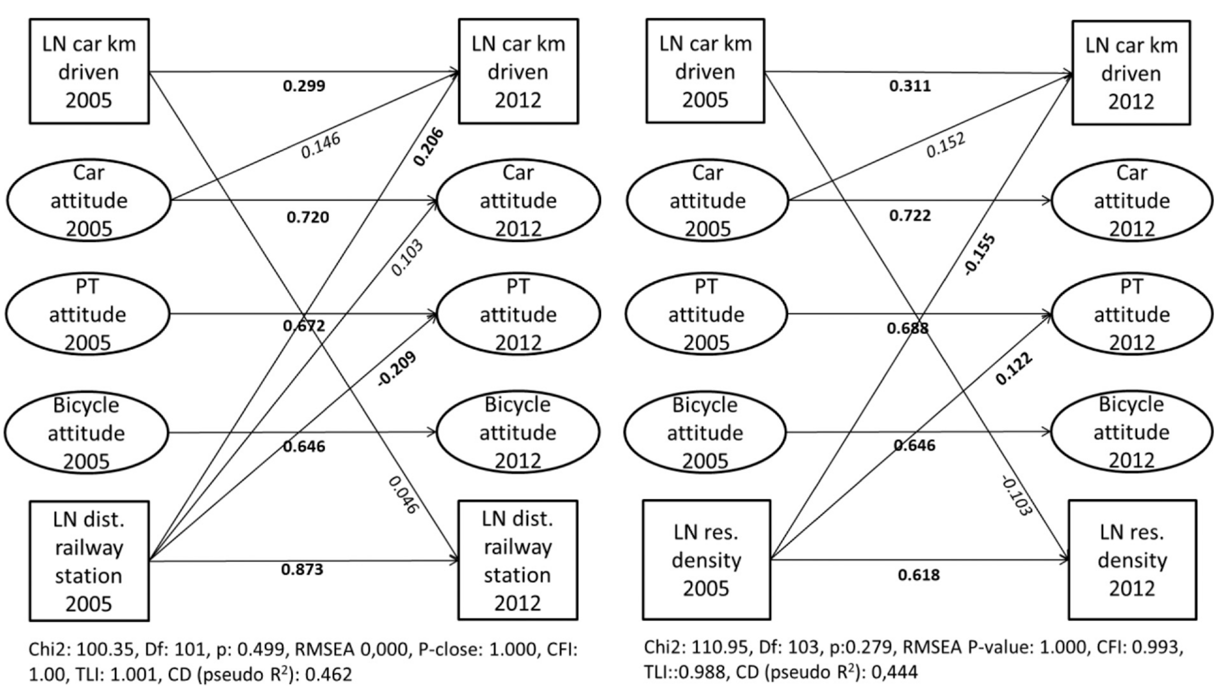

Fig. 4. Standardised effects for the longitudinal models based on the distance to the railway station and residential density. Significance: bold $p < .01$; italics $p < .05$; other $p < .1$.

Table 2
Standardised effects of socio-demographics on endogenous variables ($N = 344$).

Endogenous variables	Travel behaviour		Attitudes towards transport modes						Built Environment			
Exogenous variables	β Car use		β Att. car		β Att. PT		β Att. bicycle		β Distance to railway		β Density	
	2005	2012	2005	2012	2005	2012	2005	2012	2005	2012	2005	2012
Socio demographics (2005)												
Gender (ref. = female)			**0.223**									
Age			−0.091						**−0.228**		**0.212**	
Education Low education level							*−0.118*					
High education level (Ref. = Middle education level)		**0.184**			0.109							
Income and work Low income												
	−0.119						*0.138*			*0.060*		
High income	**0.202**											
(Ref = Middle income)												
Employed			*−0.145*	**0.130**								
Work full-time			**0.216**		*−0.119*		−0.114					
(Ref = No Job)												
Household												
Single parent household				*0.099*								
Couple without children				*0.210*						*0.105*		*−0.168*
Family with children				0.163						0.093		−0.153
Other household types (Ref. = single person hh)				0.080								
Residential move between 2005 and 2012										**−0.128**		

Significance: bold $p < .01$; italics $p < .05$; other $p < .1$

characteristics did not change a lot between 2005 and 2012. The attitudes seem to be more stable over time than the car kilometres driven. This was expected, as attitudes are generally assumed to be more stable than (travel) behaviour.

The cross-lagged effects between attitudes and the indicators for the built environment show that reverse causality effects prevail over residential self-selection effects. This is in line with the cross-section results in Fig. 3. This means that the built environment indicators do a better job at explaining the changes in attitudes between 2005 and 2012 than vice versa. In the first model, the distance to the railway station in 2005 influences attitudes towards public transport negatively and car attitudes positively in 2012. Thus, living further away from a railway station leads to weaker public transport attitudes and stronger car attitudes over time. In the second model, the residential density in 2005 significantly affects the public transport attitude. Thus, living in denser neighbourhoods leads to stronger public transport attitudes over time. In both models, the attitude-based residential self-selection effects are all insignificant. Thus, people's travel-related attitudes in 2005 do not explain the changes in the proximity towards the railway station or residential density between 2005 and 2012. This may be related to a rather small share of people in the sample (17%) moving house between 2005 and 2012, which reduces the statistical power to determine self-selection effects. Furthermore, travel-related attitudes are only one of the aspects of people's residential choices and arguably not the most important ones. So even if people take travel-related attitudes into account in their residential choice, they may need to trade them off against other aspects in their residential decision.

Interestingly, there is a significant lagged effect of car use on residential density and distance to the railway station in 2012 (the latter marginally significant). So instead of attitude-induced self-selection, this indicates self-selection based on previous behaviour where people who used the car more often in 2005 tend to end up in less dense areas and at larger distances from the railway station in 2012. Finally, it seems that the changes in car kilometres driven are relatively strongly affected by the built environment indicators compared to the other indicators. The positive impact of the distance to the railway station and the negative impact of residential density in 2005 on the change of car kilometres driven between 2005 and 2012 are stronger than the impact of the car attitude in 2005. Interestingly, this contradicts the findings of the cross-sectional analysis. This analysis found that the associations between attitudes and car kilometres driven were stronger than the associations between proximity to the railway station and residential density, and car kilometres driven. The unstandardised coefficients of the longitudinal models reveal that a 1% increase in the distance to the railway station leads to a 0.23% increase in car kilometres travelled. A 1% increase in residential density leads to a decrease of 0.3% in car kilometres travelled.

Due to the time lag of seven years, it is likely that unobserved events took place or that changes in the endogenous variables occurred after 2005. These may have affected the relationships between the variables in 2012. The correlations between the error terms of these variables (see C1-C6 in Fig. 4) indicate the presence of these effects. Not surprisingly, most correlations between these error terms are strongly significant in 2005. For instance, the distance to the railway station is strongly associated with car and public transport attitudes. These correlations are considerably weaker in 2012. The correlations between the error terms of the built environment indicators and attitudes in particular are much lower in 2012 and often insignificant. This indicates that the model explains the changes in these variables quite well. For the relationships between car kilometres driven and built environment indicators, significant error term correlations remain in 2012. Apparently, unobserved events or synchronous effects influenced the relationship between these variables.

Table 2 presents the influence of the socio-demographics and their changes on the endogenous variables for the model including the proximity to the nearest railway station. For reasons of parsimony, we do not present a separate table for the model with residential density, as both models yielded almost identical results. Instead, the effects of the socio-demographics on residential density are included in a separate column in this table.

As the socio-demographics are mainly included as control variables and do not concern the main research questions, we do not go into detail here. Overall, their effects on the baseline endogenous variables in 2005 seem plausible. For example, people with higher incomes and education levels drive more, whereas people with lower incomes drive less. People with a low education level express weaker bicycle attitudes, whereas people with a high education level have stronger public transport attitudes in 2005. Compared to not having a paid job, working full-time is related to more positive car attitudes and also to more negative public transport and cycling attitudes. A less intuitive outcome is that working part-time is negatively associated with the car attitude in 2005. Perhaps people in part-time jobs work closer to home and are less reliant on the car, which may affect their car attitude. Finally, higher age is associated with a weaker car attitude, living closer to the railway station, and living in higher density areas. This effect is probably related to the high average age (around 50 years old) in our sample. So, as people age, they tend to become less car-oriented and move more often to denser areas and areas nearer to the railway station.

Interestingly, the effects of the socio-demographics on changes in the endogenous variables over time are not aligned with the baseline results in 2005. In other words, the fact that exogenous variables are associated with endogenous variables in 2005, does not mean that these exogenous variables can also account for changes in the endogenous variables between 2005 and 2012. Results reveal that people with a higher education level are more inclined to drive more kilometres and people in larger households tend to develop a stronger car attitude. Surprisingly, people with a part-time job tend to develop a more positive car attitude between 2005 and 2012. This finding is at odds with the negative effect of working part-time on the car attitude in 2005. Furthermore, couples and families end up at larger distances from the railway station and in lower-density areas in 2012. The effect of a residential move has a negative sign for distance to the railway station as well as for residential density. This indicates that people who moved between 2005 and 2012 tend to end up in areas that are closer to the railway station but also in less dense residential environments. The fact that people moved between 2005 and 2012 did not have a significant effect on their car kilometres driven or their attitudes. So, it seems that moving house did not break current habits and mobility patterns. This may be because most households in our sample moved over small distances within the same municipality, reducing their necessity to re-evaluate their travel behaviour choices. Changes in socio-demographics and job changes also did not significantly affect changes in travel behaviour in 2012. This may be due to the limited number of changes and/or because the majority of the influence of these variables is already included in the stability effect of travel behaviour from 2005 to 2012.

4.3. Multi-group analysis

It is not an easy task to statistically prove residential self-selection as it requires respondents to:

1. move over time;
2. be able to select themselves in an area conducive to their travel attitudes and preferences;
3. experience significant changes in BE characteristics to an area more aligned with their travel attitudes and preferences.

In the previous models, movers and non-movers were included. The fact that only 57 out of the 344 people moved house may have affected the ability to find significant self-selection effects. To get a sharper understanding of the respondents who moved and took the opportunity to self-select, we conducted a multi-group analysis for both built environment indicators. We created two groups: (1) people that moved house and (2) people that did not move house between 2005 and 2012. The model with the railway station indicator yielded an interesting result. Within the movers' group, a more positive car attitude in 2005 resulted in a larger distance to the nearest station in 2012. This suggests self-selection of people with a positive car attitude that choose, for instance, a more suburban car-oriented residential environment after their move. No other significant self-selection effects were found in the model with the distance to the railway station or in the model with residential density. Furthermore, the results show that reverse causality effects are stronger, regardless of whether people moved house or not.

5. Conclusions and implications for policy and research

This study aimed to add to the academic debate regarding the residential self-selection and reverse causality hypotheses and to assess the practical relevance of modifying the built environment to reduce the number of car kilometres driven. Six cross-sectional SEMs were developed involving alternative directions of influence and two separate built environment indicators (distance to the railway station and residential density). Subsequently, two longitudinal Cross-Lagged Panel Models (2005–2012) were developed in SEM for both built environment indicators.

Overall, the models show that reverse causality effects are dominant. In other words, the impact of the built environment on attitudes is stronger than vice versa. This finding is in line with recent findings by Van De Coevering et al. (2016), Ewing et al. (2016) and Wang and Lin (2019). Furthermore, travel-related attitudes are more strongly influenced by the distance to the nearest railway station than they are by residential density. Living further from the railway station positively affects car attitudes while the opposite applies to public transport attitudes in the cross-sectional and longitudinal models. Attitudes towards the car, bicycle and public transport are significantly affected by higher densities in the cross-sectional analysis. However, in the longitudinal analysis, only the positive influence of higher densities on public transport attitudes is significant and, overall, standardised effects are lower. This may be since Dutch suburbs, even though they are dense, are still well-suited to car use. In general, older neighbourhoods nearby railway stations are less conducive for the car and more for public transport. Therefore, the proximity to the nearest railway station could be a stronger proxy for a neighbourhood's conduciveness to mode use than residential density.

Even though reverse causality effects prevail over residential self-selection effects, it seems that the latter ones also occur. The cross-sectional models showed that stronger car attitudes were associated with living in lower-density neighbourhoods and at larger distances from the railway station. Although residential self-selection effects were not present in the overall longitudinal analysis, a group analysis revealed that people with stronger car attitudes who moved house tended to end up in residential areas further from the railway station. This indicates reciprocal influences between attitudes and the built environment. Somewhat surprisingly, the longitudinal analysis also revealed an influence of car kilometres driven on built environment indicators. As this car-use related self-selection does not originate from attitudes, it probably originates from constraints. In other words, it could be that people do not self-select themselves in more car-oriented areas because they want to, but because they feel they have to. This perceived car dependency may be a consequence of their long-term and medium-term choices regarding lifestyles, work, household structure, etc. (Van Acker et al., 2010).

In addition, the distance to the railway station and residential density have a significant and direct influence on car use when the influence of attitudes and socio-demographics is controlled for. The cross-sectional analysis shows that the direct influence of travel-related attitudes on car kilometres driven is stronger than the effects of the built environment. Somewhat surprisingly, in the longitudinal analysis, this is the other way around, the influence of the built environment indicators prevails over the impact of the attitudes. In other words, even though attitudes have a strong direct relationship with travel behaviour, changes in travel behaviour are more strongly affected by the opportunities and constraints provided by the built environment. This is at odds with findings of a recent longitudinal study by Wang and Lin (2019) who found that attitudes affect total travel time and the number of trips by different modes more strongly than built environment indicators. This may be due to the longer time span of seven years in our study, enabling us to estimate long-term effects that are generally higher compared to short-term effects. However, our results are in line with previous findings by Handy et al. (2005). They also found that the influence of the built environment prevailed over the influence of travel-related attitudes in their quasi-longitudinal analysis, while it was the opposite in their cross-sectional analysis.

This study took many methodological issues into account, such as the reliance on cross-sectional designs and the lack of travel-related attitudes in most previous studies in this field. Nevertheless, some limitations apply. First, due to model complexity it was not possible to estimate comprehensive models including all determinants and directions of causality. Instead, a more explorative approach was chosen using multiple simplified models with different underlying assumptions. Thus, research outcomes represent an accumulation of results based on separate models. Second, the sample is restricted to homeowners, as renters have fewer opportunities to self-select in the Netherlands. Third, the number of movers in the sample is limited. This may have reduced the statistical power to determine self-selection effects. The smaller numbers of participants in the GPS survey may also have reduced the overall representativeness of the study sample. However, the outcomes of a previous study based on a similar but larger dataset, but without the GPS data, support the outcomes of this study. This suggests that the smaller size of the sample did not affect the overall outcomes of this study. In addition, the longer time span of seven years enabled us to estimate long-term effects, but it also increased the opportunity that unobserved events affected the outcomes of this study. Finally, the GPS survey to determine the number of car kilometres driven was carried out approximately one year after the household survey. Changes in household circumstances and attitudes during that timeframe may have influenced the results.

The results of this study have major implications for researchers as well as practitioners. First, and in line with previous studies, this study shows the relevance of including attitudes in studies that study the connection between land-use policies and travel behaviour. Secondly, the bi-directional nature of the relationship between attitudes and the built environment should be considered. Only controlling for residential self-selection will probably lead to an underestimation of the influence of the built environment, as the attitudes themselves are conditioned by people's residential environment. Furthermore, our results indicate that self-selection may not always be attitude induced, but may also originate from previous behaviour and constraints related to car dependence. So additionally, it is interesting to take reverse causality related to travel behaviour into account in future research. Finally, the differences between the cross-sectional and longitudinal models regarding the impact of built environment indicators and travel-related attitudes on car use show the importance of conducting more longitudinal studies in this field.

For practitioners, these findings provide support that spatial policies are important to reduce car kilometres driven. Densification and developing new dwellings within the catchment area of public transport stations significantly reduce car use. Even though the impact of built environment characteristics on travel behaviour changes is strong compared to other determinants, the elasticities show that their practical impact is fairly modest. In other words, major changes in the built environment would be necessary to achieve a shift towards sustainable travel behaviour. The impact of these policies can be enhanced by encouraging people with supportive attitudes to self-select in these areas. In addition, we found that the built environment affects people's attitudes, so the impact of these policies is not restricted to population segments with already favourable attitudes. This means that even in areas with people with less supportive attitudes, densification, TOD and other spatial policies could promote sustainable travel behaviour. What is important, is that - at least in the Dutch situation - the distance to the railway station has a stronger influence on car kilometres travelled than residential density alone. This implies that when compact developments are considered, locations closer to railway stations are preferable.

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Appendix A. Supplementary data

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References

Bagley, M.N., Mokhtarian, P.L., 2002. The impact of residential neighborhood type on travel behaviour: a structural equations modeling approach. Ann. Reg. Sci. 36, 279–297.
Biljecki, F., Ledoux, H., van Oosterom, P., 2013. Transportation mode-based segmentation and classification of movement trajectories. Int. J. Geogr. Inf. Sci. 27 (2), 385–407.
Bohte, W., 2010. Residential Self-Selection and Travel: The Relationship between Travel-Related Attitudes, BE Characteristics and TB. Doctoral Dissertation, Sustainable Urban Areas 35. IOS Press, Delft.
Bohte, W., Maat, K., van Wee, B., 2009. Measuring attitudes in research on residential self-selection and travel behaviour: a review of theories and empirical research. Transp. Rev. 29 (3), 325–357.
Bollen, K.A., 2014. Structural Equations with Latent Variables. John Wiley and Sons.
Cao, X., Chatman, D., 2016. How will smart growth land-use policies affect travel? A theoretical discussion on the importance of residential sorting. Environ. Plan. B: Plan. Design 43, 58–73.
Cao, X., Mokhtarian, P.L., Handy, S.L., 2007. Do changes in neighborhood characteristics lead to changes in travel behaviour? A structural equations modeling approach. Transportation 34 (5), 535–556.
Cao, X., Mokhtarian, P.L., Handy, S.L., 2009. Examining the impact of residential self-selection on travel behaviour: a focus on empirical findings. Transp. Rev. 29 (3), 359–395.
Cao, X., Næss, P., Wolday, F., 2019. Examining the effects of the built environment on auto ownership in two Norwegian urban regions. Transp. Res. D 67, 464–474.
CBS, 2018. Definition Surrounding Address Density. Retrieved from. http://www.cbs.nl.
Chatman, D.G., 2009. Residential choice, the built environment, and nonwork travel: evidence using new data and methods. Environ. Plan. A 41 (5), 1072–1089.
Chatman, D.G., 2014. Estimating the effect of land use and transportation planning on travel patterns: three problems in controlling for residential self-selection. J. Trans. Land Use 7 (3), 47–56.
Cullen, I., 1978. The treatment of time in the explanation of spatial behaviour. In: Carlstein, T., Parkes, D., Thrift, N. (Eds.), Human Activity and Time Geography. Halstead Press, New York, pp. 27–38.
De Abreu e Silva, J., 2014. Spatial self-selection in land-use–travel behavior interactions: accounting simultaneously for attitudes and socioeconomic characteristics. J. Trans. Land Use 7 (2), 63–84.
De Vos, J., Ettema, D., Witlox, F., 2018. Changing travel behaviour and attitudes following a residential relocation. J. Transp. Geogr. 73, 131–147.
De Vos, J., Cheng, L., Witlox, F., 2020. Do changes in the residential location lead to changes in travel attitudes? A structural equation modeling approach. Transportation 2020. https://doi.org/10.1007/s11116-020-10119-7.
Ewing, R., Cervero, R., 2010. Travel and the built environment. J. Am. Plan. Assoc. 76 (3), 265–294.
Ewing, R., Hamidi, S., Grace, J.B., 2016. Compact development and VMT—environmental determinism, self-selection, or some of both? Environ. Plan. B: Plan. Design 43 (4), 737–755.
Festinger, L., 1957. A Theory of Cognitive Dissonance. Row, Peterson, Evanston, IL.
Finkel, S.E., 1995. Causal Analysis with Panel Data. Sage Publications, Thousand Oaks, CA, US.
Gim, T., 2013. The relationships between land use measures and travel behaviour: a meta-analytic approach. Transp. Plan. Technol. 36 (5), 413–434.
Golob, T.F., Horowitz, A.D., Wachs, M., 1979. Attitude-behaviour relationships in travel-demand modeling. In: Hensher, D.A., Stopher, P.R. (Eds.), Behavioural Travel Modeling. Croom Helm, London, pp. 739–757.
Handy, S., Cao, X., Mokhtarian, P., 2005. Correlation or causality between the built environment and travel behaviour? Evidence from northern California. Transp. Res. D 10 (6), 427–444.
Heinen, E., Van Wee, B., Panter, J., Mackett, R., Ogilvie, D., 2018. Residential self-selection in quasi-experimental and natural experimental studies: an extended conceptualization of the relationship between the built environment and travel behaviour. J. Trans. Land Use 11 (1), 939–959.
Krizek, K., 2003. Residential relocation and changes in urban travel: does neighborhood-scale urban form matter? J. Am. Plan. Assoc. 69 (3), 265–281.
Lin, T., Wang, D., Guan, X., 2017. The built environment, travel attitude, and travel behavior: residential self-selection or residential determination? J. Transp. Geogr. 65, 111–122.
Lund, H., 2003. Testing the claims of new urbanism: local access, pedestrian travel, and neighboring behaviours. J. Am. Plan. Assoc. 69 (4), 414–429.
Meurs, H., Haaijer, R., 2001. Spatial structure and mobility, transportation research part D. Trans. Environ. 6 (6), 429–446.

Mokhtarian, P.L., Cao, X., 2008. Examining the impacts of residential self-selection on travel behaviour: a focus on methodologies. Transp. Res. B 42 (3), 204–228.
Næss, P., 2009. Residential self-selection and appropriate control variables in land use: travel studies. Transp. Rev. 29 (3), 293–324.
Næss, P., 2014. Tempest in a teapot: the exaggerated problem of transport-related residential self-selection as a source of error in empirical studies. J. Trans. Land Use 7 (2), 57–79.
Newsom, J.T., 2015. Longitudinal Structural Equation Modeling: A Comprehensive Introduction. Routledge. ISBN 9781848726970.
NWB, 2018. Nationaal Wegen Bestand [National Roads Stock]. Available at: https://data.overheid.nl/data/dataset/nationaal-wegen-bestand-wegen-wegvakken.
Schwanen, T., Mokhtarian, P.L., 2005. What if you live in the wrong neighborhood? The impact of residential neighborhood type dissonance on distance travelled. Transp. Res. D 10 (2), 127–151.
Selig, J.P., Little, T.D., 2012. Autoregressive and cross-lagged panel analysis for longitudinal data. In: Laursen, B., Little, T.D., Card, N.A. (Eds.), Handbook of Developmental Research Methods. London, The Guilford Press, pp. 265–278.
Shadish, W.R., Cook, T.D., Campbell, D.T., 2002. Experimental and Quasi-experimental Designs for Generalized Causal Inference. Houghton-Mifflin, Boston, MA.
Singleton Jr., R.A., Straits, B.C., 2009. Approaches to Social Research, Fifth ed. Oxford University Press, New York.
Van Acker, V., Van Wee, B., Witlox, F., 2010. When transport geography meets social psychology: toward a conceptual model of travel behaviour. Transp. Rev. 30 (2), 219–240.
Van De Coevering, P.P., Maat, K., Van Wee, B., 2015. Multi-period research designs for identifying causal effects of built environment characteristics on travel behaviour. Transp. Rev. 35 (4), 512–532.
Van De Coevering, P.P., Maat, K., Kroesen, M., van Wee, B., 2016. Causal effects of built environment characteristics on travel behaviour: a longitudinal approach. EJTIR 16 (4), 674–697.
Van Herick, D., Mokhtarian, P.L., 2020. How much does the method matter? An empirical comparison of ways to quantify the influence of residential self-selection. Travel Behav. Soc. 18, 68–82.
Van Wee, B., De Vos, J., Maat, K., 2019. Impacts of the built environment and travel behaviour on attitudes: theories underpinning the reverse causality hypothesis. J. Transp. Geogr. 80, 102540.
VanAcker, V., Mokhtarian, P.L., Witlox, F., 2014. Car availability explained by the structural relationships between lifestyles, residential location, and underlying residential and travel attitudes. Transp. Policy 35, 88–99.
Wang, D., Lin, T., 2019. Built environment, travel behavior, and residential self-selection: a study based on panel data from Beijing, China. Transportation 46, 51–74.