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# Spatial and sociodemographic determinants of energy consumption for personal mobility in the Netherlands

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ABSTRACT

We used a combination of logistic and multilinear regression models to analyze how the built environment and people's sociodemographic characteristics are related to energy consumption for personal mobility in the Netherlands. This energy consumption was accurately and comprehensively quantified based on distances travelled with a large number of modes, distances travelled with different types of cars, the occupancy of cars, and the probability of staying home. Local density was found to be the most important aspect of the built environment: it strongly reduced both the probability of using a passive mode of transportation and the associated energy consumption. Other relevant spatial variables included the landuse mix entropy, green space, and distances to city centers, supermarkets, and train stations. Sociodemographic characteristics were, however, more important overall. In particular, full-time employment was associated with higher energy consumption. Males, respondents from high-income households, and respondents with a higher education degree also consumed significantly more energy despite owning the most efficient cars. Our results thus highlight the importance of an energy policy mix that goes beyond the stimulation of technological progress.

## 1. Introduction

Climate change can cause a mass extinction of species as well as famines, epidemics, and even wars. At the Paris Conference in 2015, the world's leaders therefore agreed to limit global warming to well below 2.0 degrees. The Netherlands has accordingly adopted the National Climate Agreement, aimed at decarbonizing society before 2050 (Ministry of Economic Affairs and Climate Policy, 2019). The mobility sector is responsible for 17% of Dutch $CO_2$-emissions and makes an approximately equal contribution on a global scale (Abels-van Overveld et al., 2019; Sustainable Mobility for All, 2017). The transport of goods accounts for a third of road-related emissions, but is difficult to decarbonize (Abels-van Overveld et al., 2019; Hilbers et al., 2016). Reducing the energy consumption and associated $CO_2$-emissions of cars and other forms of personal mobility is thus a clear priority.

The Climate Agreement includes a large-scale technological shift towards electric cars (Ministry of Economic Affairs and Climate Policy, 2019). All cars are inherently inefficient, however, as they rely on the displacement of around a thousand kilograms of steel and plastics. A technology-centered energy transition strategy therefore requires a significant increase of renewable power production and associated landuse (wind and solar parks) as well as an upgrade of the transmission network. Furthermore, electric vehicles will not solve the non-environmental externalities of car dependence such as obesity, congestion, and occupation of scarce public space. It is hence important to also look beyond technology by switching to more sustainable transport modes as well as reducing the need to travel long distances in general. Effective and equitable policy towards this goal requires detailed insight into the influence of the built environment and people's sociodemographic characteristics on mobility behavior and the resulting energy consumption.

Earlier research has mostly focused on the modal split and kilometers travelled by car. The models developed in this study analyze energy consumption far more comprehensively based on distances travelled with a large number of modes, distances travelled with different types of cars, the actual occupancy of each car, and the probability that people do not travel in the first place. As such, they are more accurate and help understand the various and sometimes opposing ways in which spatial and sociodemographic variables influence energy consumption. Furthermore, this study provides new insights into the influence of the

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built environment on Dutch mobility behavior in general by including a comprehensive set of local spatial variables. Those working on the energy transition in the Netherlands and abroad may build on these insights to reduce energy consumption through urban planning. This study thus aims to inform energy policy by answering the following main question: how are the built environment and people's sociodemographic characteristics related to energy consumption for personal mobility in the Netherlands?

Section 2 first provides a concise overview of the scientific literature. Section 3 subsequently describes the datasets, energy calculations, and main regression models: a logistic model of whether respondents make a trip, a logistic model of whether respondents use a passive (energy consuming) mode, and a multilinear model of the energy consumed. The results are given in Section 4, after which the article is concluded in Section 5. See the appendix for the results of supplementary regressions of travel distances, modal choice, vehicle ownership, and the energy consumption of cars.

## 2. Scientific background

This scientific background covers American and European articles on the spatial and sociodemographic determinants of mobility behavior with a focus on the use of cars. Note that disaggregate studies of (the environmental effects of) mobility mostly analyze the number of trips made or kilometers travelled with this energy-intensive mode. The aim of this scientific background is to illuminate which variables are likely to be most influential in determining energy consumption for personal mobility in the Netherlands in general.

### 2.1. Spatial variables

City-residents are less dependent on cars. The landmark work of Newman, Kenworthy, and Laube highlighted the role of city-level density (Kenworthy and Laube, 1999; Newman and Kenworthy, 1989). Density reduces average distances to destinations and public transit stops (Limtanakool et al., 2006; Næss, 2012; Newman and Kenworthy, 2006; Van Acker and Witlox, 2010). Moreover, it facilitates high-quality transit, increases congestion, and limits parking space (Kenworthy and Laube, 1999; Limtanakool et al., 2006; Næss, 2012; Newman and Kenworthy, 2006; Van Acker and Witlox, 2010). Yet, recent research found the effect of average city-level density to be limited or absent (Ewing et al., 2017; Le Néchet, 2012; Santos et al., 2013). A number of studies based on disaggregate data found local density to be relevant, though other variables often had a larger effect (Dujardin et al., 2014; Ewing and Cervero, 2010; Næss, 2011, 2012; Stevens, 2017; Van Acker and Witlox, 2010).

Many studies for instance underlined the importance of short distances to city centers as local density does not reduce the use of cars if destinations are located far away and as people may prefer the "best" destinations in the city center over what is available nearby (Ewing and Cervero, 2010; Næss, 2011, 2012; Silva et al., 2017; Stevens, 2017; Van Acker and Witlox, 2010). A diffuse distribution of the city population has accordingly also been found to enhance mobility-related energy consumption (Le Néchet, 2012; Lefèvre, 2009). Travel distances and times to jobs in particular are correlated with car use as well (Chao and Qing, 2011; Ewing and Cervero, 2010; Silva et al., 2017; Stevens, 2017). The mixing of landuses should reduce car dependence by ensuring that shops and jobs are not spatially separated from residential areas, though recent research casts doubt on the sign and significance of this effect (Dujardin et al., 2014; Ewing and Cervero, 2010; Silva et al., 2017; Stevens, 2017; Van Acker and Witlox, 2010).

Design and infrastructure are also important. Greenery can for instance stimulate people to walk and cycle to destinations (Silva et al., 2017). Moreover, studies from the United States emphasize that well designed (highly connected) street networks can reduce car use by shortening real travel distances (Ewing and Cervero, 2010; Silva et al., 2017; Stevens, 2017). Yet, Northern-European studies only provide contradictory evidence (Næss, 2012). Various studies finally found correlations between mobility behavior and the provision of highways (Ewing et al., 2017; Le Néchet, 2012), bicycle paths (Santos et al., 2013), and public transit (Ewing and Cervero, 2010; Le Néchet, 2012; Næss, 2011; Santos et al., 2013; Silva et al., 2017; Stevens, 2017; Van Acker and Witlox, 2010).

The literature seems ambiguous overall. One likely reason is its methodological and contextual diversity. Another is the difficulty in separating different aspects of the built environment: people living close to the center of a major urban area are much more likely to live in a dense neighborhood with proper public transport. The ambiguity is enhanced by the use of inconsistent definitions and lack of comprehensive analyses (Silva et al., 2017). Yet, it seems clear that the combination of the spatial variables does significantly influence car use. We refer those readers interested in a more extensive analysis of the literature to the work of Ewing and Cervero (2010), Lefèvre (2009), Næss (2012), Silva et al. (2017), and Stevens (2017).

We could not find any analyses of Dutch national mobility data using the abovementioned local (intra-municipal) spatial variables. In general, Dutch studies did find people in urban areas to cover less distance and be less automobile dependent (Burgers, 2019; Dieleman et al., 2002; Kasraian et al., 2018; Limtanakool et al., 2006). Medium- to long-distance trips specifically are more often made by train when starting or ending in high-density, landuse-diverse, and service-oriented municipalities with a railstation (Limtanakool et al., 2006). Interesting is that public transport seems to compete with cycling within the main cities (Dieleman et al., 2002; Kasraian et al., 2018) though it can also stimulate cycling by generating access and egress trips (Ton et al., 2019). On a local (intra-municipal) level, the presence of shops has been shown to significantly increase walking and cycling (Ton et al., 2019). Moreover, local residential density in addition to density and functional mix at the workplace have been shown to significantly reduce distances travelled by car around the cities of Amsterdam and Utrecht (Maat and Timmermans, 2009). Research has lastly also shown local density and proximity to railway stations to reduce car use by homeowners in three small- to medium-sized municipalities (van de Coevering et al., 2016, 2021).

### 2.2. Sociodemographic and other variables

The main sociodemographic determinants of mobility behavior appear to be the income and the related variable of vehicle ownership as most studies find them to significantly increase car use and associated energy consumption (Burgers, 2019; Chao and Qing, 2011; Dieleman et al., 2002; Kasraian et al., 2018; Limtanakool et al., 2006; Maat and Timmermans, 2009; Matiaske et al., 2012; Næss, 2011; Van Acker and Witlox, 2010; van de Coevering et al., 2016, 2021). Education is postively correlated with using cars as well (Burgers, 2019; Dieleman et al., 2002; Matiaske et al., 2012; Næss, 2011; Scheiner and Holz-Rau, 2007; van de Coevering et al., 2021). A plausible explanation is that highly educated people tend to work specialized jobs, which may be located further away (Næss, 2011, 2012). Employment itself also significantly increases driving according to some studies (Chao and Qing, 2011; Næss, 2011; Scheiner and Holz-Rau, 2007; Van Acker and Witlox, 2010). Those with a job have more benefit from the flexibility offered by private vehicles due to the need to make more trips for a larger variety of reasons (van der Waard et al., 2013).

The demographic group most inclined to travel by car accordingly seems to be the middle-aged (Burgers, 2019; Kasraian et al., 2018; Limtanakool et al., 2006; van de Coevering et al., 2016). Student discount passes play a significant role in enhancing public transport use by young adults (Burgers, 2019; van der Waard et al., 2013). Gender has been shown to influence car travel as well, but it is unclear if it still has a significant effect in the Netherlands today. Both the Dutch and foreign literature appear inconclusive on whether household children significantly stimulate car use (by making it more convenient). None of the studies reviewed finally provides recent (European) evidence for an effect of ethnicity or migrant backgrounds on mobility behavior.

One of the most important remaining explanatory variables is the reason people travel as the time and place of certain activities are more flexible than others (Næss, 2011). The Dutch for instance walk and cycle more for shopping and leisure trips (Dieleman et al., 2002; Ton et al., 2019). Preferences, attitudes, and lifestyles are relevant as well. Germans for instance travel more kilometers by car if the household head enjoys driving and does not worry about the environment (Matiaske et al., 2012). The residential self-selection effect is a major intermediary mechanism as attitudes and lifestyles influence whether people will choose to live in the city center or the suburbs (Ewing and Cervero, 2010; Næss, 2011, 2012; Scheiner and Holz-Rau, 2007; Van Acker and Witlox, 2010). This can weaken or strengthen the effect of spatial variables without correction (Ewing and Cervero, 2010; Stevens, 2017). The opposite effect of the built environment on mobility attitudes may, however, be stronger (van de Coevering et al., 2016, 2021). The mobility-related variables finally influence one another: trip distance, time, and mode are highly interrelated (Burgers, 2019; Dieleman et al., 2002; Limtanakool et al., 2006; Ton et al., 2019). Studies have also shown old and inefficient cars to be driven less (Chao and Qing, 2011; Matiaske et al., 2012).

The many variables and interrelations highlighted in this scientific background underline the importance of comprehensively and carefully analyzing mobility behavior.

## 3. Data and methodology

This Section describes how Dutch mobility data has been analyzed to test and expand the scientific knowledge base. The different datasets and processing techniques are first elaborated upon in subsection 3.1. Subsection 3.2 then describes how this data has been used to quantify energy consumption after which subsection 3.3 elucidates how the energy consumption has been analyzed using logistic and multilinear regression models.

### 3.1. The data

Data on the mobility-related variables as well as most of the independent variables has been obtained from the research project "Onderzoek Verplaatsingen in Nederland" from Statistics Netherlands and Rijkswaterstaat (2017), from hereon referred to as OViN2017. For this dataset, 36,594 individuals of all age-categories have been asked about their trips within the Netherlands for one day (Statistics Netherlands, 2018b). The specific date has been predetermined to ensure enough responses for every day of the year (Statistics Netherlands, 2018a). The respondents were sampled randomly from a number of localities, which were in turn obtained through stratified sampling whereby the probability of being sampled was proportional to the population size in order to ensure a proper spatial spread of the data over the country (Statistics Netherlands, 2018a). Weight factors are available to make the data representative of the Dutch population (Statistics Netherlands, 2018a).

Trips for holiday purposes, trips for professional purposes (e.g. taxi- and truck-drivers), and trips that were partly conducted across the Dutch border are labelled and could thus easily be excluded. Three "daily mobility" trips made by airplane have additionally been removed since this data was deemed unreliable upon visual inspection. Trips made by persons younger than 10 years have been excluded since these children typically do not travel independently. A final 427 trips were removed because the respondent's postcode of residence could not be determined. In the end, 89,096 trips made by 25,019 respondents plus 6628 respondents who stayed home were analyzed from a total of 110,428 entries in the main dataset. Multimodal trips have hereby been recorded as multiple trips.

The mobility behavior of these respondents has been analyzed in python using twenty-two spatial and sociodemographic variables. See Table 1 for an overview. Table 2 provides the descriptive statistics. The presence of multicollinearity has been tested by computing the variance inflation factors (VIFs) with the statsmodels library, whereby a threshold of 5.0 has been applied (James et al., 2013; Seabold and Perktold, 2010).

**Table 1**
The twenty-two independent spatial and sociodemographic variables included in the data analysis.

| Spatial variables | Unit or categories | Source |
|---|---|---|
| Municipal level of urbanity | Five categories of average number of addresses per km$^2$ in a 1 km buffer around the addresses of inhabitants with category one denotating the most urban municipalities | OViN2017 |
| Municipal population size | Eight categories of number of inhabitants with category eight denotating the most populous municipalities | OViN2017 |
| Randstad area | Whether the resident is located in the larger Randstad area | OViN2017 |
| Metro | Whether the resident is located in Amsterdam or Rotterdam | OViN2017 |
| Local address density | The average number of addresses per km$^2$ in a 1 km buffer around the addresses of inhabitants postcode area | PC2017 |
| Distance to supermarket | Average travel distance of inhabitants postcode area to nearest major supermarket | PC2017 |
| Distance to train station | Average travel distance of inhabitants postcode area to nearest train station | PC2017 |
| Distance to road entry | Average travel distance of inhabitants postcode area to nearest major road entry point | PC2017 |
| Distance to center | Distance of center postcode area to the nearest center of a postcode area containing more than 50 known destinations on average in 1 km travel distance of inhabitants | PC2017 |
| Distance to larger center | Distance of center postcode area to the nearest center of a postcode area containing more than 200 known destinations on average in 1 km travel distance of inhabitants | PC2017 |
| PT stops density | Number of bus-, tram-, and metro-stops per km$^2$ of postcode area | NDOV2020 |
| Green space | Average Normalized Difference Vegetation Index for each postcode area | VDC2020 |
| Landuse mix entropy | Average entropy index of mix between five landuse categories for each postcode area | VDC2020 |
| **Sociodemographic variables** | | |
| Income | Standardized spendable household income in categories of 10 percentile points | OViN2017 |
| Household size | Number of people in household | OViN2017 |
| Number of children | Number of people in household of less than 12 years old | OViN2017 |
| Household position | Single / single member core of multi-member household (including single parents) / partner, husband or wife (reference) / (grand)child (in law) / other | OViN2017 |
| Gender | Male / female (reference) | OViN2017 |
| Migrant background | None (reference) / Western migrant / non-Western migrant | OViN2017 |
| Societal position | Working 12–30 h per week / working 30+ hours per week (reference) /student / retired / teenager / other | OViN2017 |
| Education | No education / primary education / vocational secondary education /advanced vocational or theoretical secondary education (reference) /higher education / other / unknown | OViN2017 |
| Student transport pass | Yes / no (reference) | OViN2017 |

**Table 2**
The descriptive statistics of the independent variables for the 25,019 respondents who made a trip. For the numerical and ordinal variables, the minimum, mean, maximum, and standard deviation (std) are given.

| Spatial variables | Most freq. category | Frequency | Min | Mean | Max | Std |
|---|---|---|---|---|---|---|
| Municipal level of urbanity (ordinal) | | | 1.0 | 2.7 | 5.0 | 1.3 |
| Municipal population size (ordinal) | | | 1.0 | 5.1 | 8.0 | 1.6 |
| Randstad area | Not in the Randstad area | 13,561 | | | | |
| Metro | Not in Ams. or Rott. | 23,357 | | | | |
| Local address density (addresses/km$^2$) | | | 11.0 | 1758.7 | 11,456.0 | 1596.3 |
| Distance to supermarket (km) | | | 0.2 | 0.9 | 9.5 | 0.7 |
| Distance to train station (km) | | | 0.5 | 5.1 | 58.6 | 5.7 |
| Distance to road entry (km) | | | 0.1 | 1.7 | 46.3 | 1.2 |
| Distance to center (km) | | | 0.0 | 5.8 | 39.6 | 5.4 |
| Distance to larger center (km) | | | 0.0 | 21.7 | 99.9 | 19.6 |
| PT stops density (stops/km$^2$) | | | 0.0 | 5.5 | 57.3 | 6.1 |
| Green space (NDVI) | | | 0.162 | 0.464 | 0.730 | 0.094 |
| Landuse mix entropy (index) | | | 0.045 | 0.632 | 0.956 | 0.154 |
| **Sociodemographic variables** | | | | | | |
| Income (ordinal) | | | 1 | 6.3 | 10 | 2.7 |
| Household size (# people) | | | 1 | 2.8 | 10 | 1.4 |
| Number of children (# people) | | | 0 | 0.4 | 6 | 0.8 |
| Household position | Partner, husband, or wife | 14,914 | | | | |
| Gender | Female | 12,992 | | | | |
| Migrant background | No migrant background | 20,937 | | | | |
| Societal position | Working 30+ hours/week | 8898 | | | | |
| Education | Advanced vocational or theoretical secondary | 8527 | | | | |
| Student pass | No student pass | 23,735 | | | | |

The rest of this subsection will elaborate on the independent variables.

The first two independent variables are the level of urbanity and population size category of the respondents' municipality of residence as included in the OViN2017 dataset. In total, there were 388 municipalities in the Netherlands in 2017. The municipality of residence can additionally be used to determine whether the respondent lives in the main urban region (the Randstad area) and whether the respondent lives in a city with metro (Amsterdam or Rotterdam). For the sake of consistency, the borders of the larger Randstad area by Limtanakool et al. (2006) are used (see Fig. 1).

Additional variables were added from a second dataset from Statistics Netherlands containing detailed information on the Netherlands' approximately 4000 four digit postcode areas in 2017, from hereon referred to as PC2017 (Statistics Netherlands, 2017; van Leeuwen, 2019). The postcode of each OViN2017-respondent has been taken to be the starting postcode of the first trip of the day. The postcode of the 4% of respondents who indicated to have started the day elsewhere was taken to be the ending postcode of the trips with the indicated purpose of "going home". To be precise, the average address density in a 1 km buffer around the addresses of the postcode area's inhabitants as well as the average distance of these inhabitants to the nearest major supermarket, train station, and major road entry point were added to the dataset. These distances have been computed as the shortest distance over the (car) road network.

To get an objective proxy for the distance of respondents to the city center, those postcode areas with a large concentration of destinations were filtered out. These destinations included supermarkets, other daily-visited shops, places that serve food or drinks, entertainment services, out-of-school care facilities, and nurseries within a 1 km travel distance of inhabitants. The shortest distance of the spatial center of the respondent's postcode area to the spatial center of the closest destination-rich area was then computed using QGIS. If a postcode consisted of multiple continuous areas, the spatial center of the largest area was used. Two variables were added: the distance to the clostest center of a postcode area where inhabitants have access to more than 50 (distance to center) and more than 200 destinations on average (distance to larger center). Note that the larger city center proxies are by definition also included in the set of city center proxies. See the distribution of these city center proxies in Fig. 1.

The number of bus-, tram-, and metro-stops per square kilometer for each postcode area was also computed in QGIS using the national database on public transport (NDOV Loket, 2020), from hereon referred to as NDOV2020. The accuracy was verified by visual inspection.

Furthermore, two additional spatial variables were added from the ongoing Vitality Data Center Project (Wang, 2020), from hereon referred to as VDC2020, which studies the relationship between the built environment and physical activity (Ren et al., 2019; Wang et al., 2021). An average landuse mix entropy index, $S$, was included to better represent the diversity of the built environment. This index is based on the area, $A$, of five landuse categories, $i$, namely: residential, recreational (including green and blue areas), commercial, industrial, and other (including public facilities and infrastructure). It was computed with Eq. (1) below (Christian et al., 2011) using data from Statistics Netherlands from 2015:

$$S = -\sum_{i=1}^{5} \frac{A_i}{A_{total}} \ln\left(\frac{A_i}{A_{total}}\right) \Big/ \ln(5). \tag{1}$$

The index takes on a number of 0 if only one landuse category is present and 1 if landuses are divided completely equally. The relative amount of green space, as part of a pleasant urban environment, is represented by the average Normalized Difference Vegetation Index. This index is based on NASA satellite imagery with values close to 0 generally indicating urban areas and 1 indicating dense vegetation cover. Both VDC-variables had to be averaged as they have been computed for a 1 km buffer around the centroid of six digit postcode areas - a higher level of spatial resolution than the four digit postcode areas. See Wang et al. (2021) for more insight into the influence of different buffer sizes.

Through combination with other government databases, Statistics Netherlands also added a rich variety of background-information on the respondents to the OViN2017 dataset (Statistics Netherlands, 2018a). The available sociodemographic variables that have been included in this study are the household income category, household size, number of children under the age of 12 in the household, position in the household, gender, migrant background, (employment-related) societal position, highest obtained education level, and possession of a student public transport pass. An extra societal position category was created for the energy-relevant age-group of teenagers (who are not allowed to drive).

The ownership of vehicles was not included as people who can afford to buy a vehicle are likely to only do so when their living location and


**Fig. 1.** The city center proxies. The historic centers of the four most populous cities are tagged for reference purposes. In line with Limtanakool et al. (2006), the Randstad area is defined as the larger region and contains non-urban municipalities.

personal circumstances demand it. Vehicle ownership is thus not independent from the spatial and sociodemographic variables. Including it can consequently cloud the correlations between these variables and mobility behavior, which is the primary focus of this article (Næss, 2011, 2012; Van Acker and Witlox, 2010). As it can be relevant for policy purposes, we have instead executed a separate regression of vehicle ownership as a dependent variable (see Table A.5 of the Appendix). The travel motive and distance have additionally been omitted from the main regressions as these are also not independent variables. People living in urban areas can for instance be expected to go shopping more frequently. Moreover, the travel distance largely reflects short-term circumstances and is thus less relevant to determine people's overall energy consumption.

### 3.2. Quantifying energy consumption

The OViN2017 dataset specifies a number of mobility-related variables. Of these, distances travelled and modal choice are most important in determining final energy consumption. In this research project, the specific energy consumption (SEC) has been quantified for eight main passive modes (see Table 3).

The overview of vehicle-specific emission factors and their fuel's $CO_2$-intensities by independent research institute CE Delft can be used to derive that standard gasoline cars consumed 2.64 MJ per vehicle kilometer (vkm) in real-life conditions in 2011 (Otten et al., 2015; Zijlstra and Rietkerk, 2020). This figure was subsequently corrected for the vehicle fuel type and age (see a further elaboration below). Next, it was

**Table 3**
The original modal split and corresponding (final) SEC-values. The energy consumption of car-trips was corrected for the occupancy, age, and fuel type of the vehicle. Trips made by other (reclassified) modes - such as disability vehicles - are omitted for the sake of brevity. In addition to actual trips, the OViN2017 dataset also contains 6628 "non-trips": respondents who stayed home.

| Mode | Modal split | SEC | Source | Year data | Scope data |
|---|---|---|---|---|---|
| Car | 39,325 Trips | 2.64 MJ/vkm (corrected) | CE Delft | 2011 | The Netherlands |
| Train | 2180 Trips | 0.28 MJ/pkm | CE Delft | 2016 | The Netherlands |
| Tram/metro | 1329 Trips | 0.57 MJ/pkm | CE Delft | 2016 | The Netherlands |
| Bus | 1949 Trips | 1.53 MJ/pkm | CE Delft | 2016 | The Netherlands |
| Touringcar | 190 Trips | 0.37 MJ/pkm | CE Delft | 2011 | The Netherlands |
| Moped | 810 Trips | 0.52 MJ/pkm | CE Delft | 2011 | The Netherlands |
| Motorcycle | 172 Trips | 1.40 MJ/pkm | CE Delft | 2011 | The Netherlands |
| Boat | 75 Trips | 0.21 MJ/pkm | DEFRA | 2011 | The UK |
| Walking | 18,396 Trips | 0 MJ/pkm | – | – | – |
| Cycling | 23,854 Trips | 0 MJ/pkm | – | – | – |

**Table 4**
The number of corrected trips and associated (final) SEC-values used for different types of cars, as computed using data from CE Delft (Otten et al., 2015). Conversion to MJ/pkm was made based on the actual car-occupancy.

| Fuel type | Modal split | SEC | Source | Year data | Scope data |
|---|---|---|---|---|---|
| Gasoline | 21,220 Trips | 2.64 MJ/vkm (age-corrected) | CE Delft | 2011 | The Netherlands |
| Diesel | 5805 Trips | 2.34 MJ/vkm (age-corrected) | CE Delft | 2011 | The Netherlands |
| LPG | 304 Trips | 2.75 MJ/vkm (age-corrected) | CE Delft | 2011 | The Netherlands |
| Electric | 117 Trips | 0.84 MJ/vkm (no correction) | CE Delft | 2011 | The Netherlands |
| PHEV | 404 Trips | 1.24 MJ/vkm (no correction) | CE Delft | 2011 | The Netherlands |
| Other | 262 Trips | 2.64 MJ/vkm (average age) | CE Delft | 2011 | The Netherlands |
| Unknown | 6321 Trips | 2.64 MJ/vkm (average age) | CE Delft | 2011 | The Netherlands |

divided by the vehicle's occupancy as recorded in the OViN2017 dataset to obtain the SEC in MJ per passenger kilometer (pkm). This occupancy was assumed equal to the mean for the car-driver (1.46) and -passenger (2.71) categories in case of missing data.

The SEC for the operation of trains was 0.28 MJ/pkm in 2016, relative to 0.57 MJ/pkm for light rail and metro, and 1.53 MJ/pkm for buses according to a recent CE Delft assessment of the energy consumption and $CO_2$-emissions in Dutch public transport ('t Hoen et al., 2018). The SEC of non-public touringcars is lower at an estimated 0.37 MJ/pkm due to their higher average occupancy (Otten et al., 2015; Zijlstra and Rietkerk, 2020).

Mopeds and motorcycles were estimated to consume 0.52 and 1.40 MJ/pkm respectively (Otten et al., 2015; Zijlstra and Rietkerk, 2020). The SEC of mopeds is likely a slight overestimation due to technological advances between 2011 and 2017 and the omission of a small share of electric devices (Geilenkirchen et al., 2016; Otten et al., 2015). Motors are unlikely to become more efficient in time because of their increasing average weight (Otten et al., 2015).

The SEC of trips made by boat can be roughly estimated using a 2011 report of the Department for Environment, Food and Rural Affairs of the United Kingdom (Hill et al., 2011). This report specifies UK ferries - carrying both passengers and freight - to emit 19.3 g of $CO_2$ per pkm travelled without car. This translates into 0.21 MJ/pkm when assuming the ferries to run on the same diesel as cars (Otten et al., 2015; Zijlstra and Rietkerk, 2020).

The remaining mode categories were reclassified to the main mode with the most similar energy-characteristics. Specifically, trips for personal mobility made by delivery vans (213 trips), taxis (189), trucks

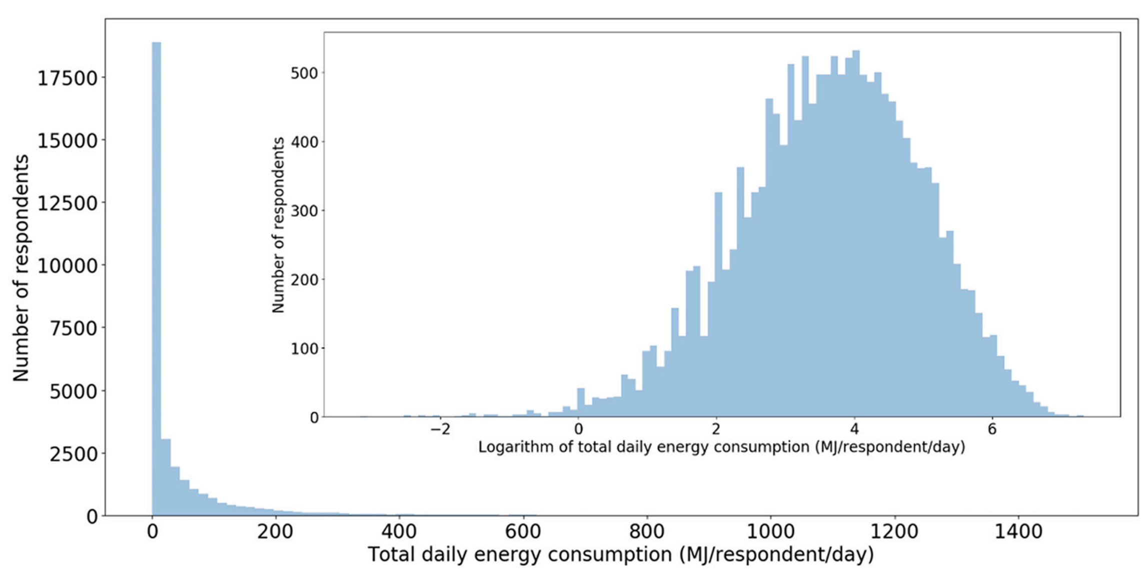


**Fig. 2.** A 100-bin histogram of the daily energy consumption distribution of the 31,647 respondents. Some respondents consumed up to 1500 MJ, equivalent to 570 km of driving a standard gasoline vehicle. In contrast, 14,950 respondents did not consume any energy because they stayed home or only walked and cycled during the day. When excluding this last group, the daily energy consumption is approximately lognormally distributed, as shown in the inset.

(22), campers (16), and agricultural vehicles (4) were reclassified as single-occupancy car-driving trips; trips made by disability vehicles (274) were reclassified as moped-trips; and trips made by skates, skeelers, steps (47 combined), and prams (1) have been reclassified as walks. The 50 trips made by still other (non-specified) modes were given zero energy consumption.

Most studies investigating the energy-related impact of household mobility focus on distances travelled by personal vehicles. In this study, the specific energy consumption of cars has been corrected for the household vehicle's fuel type and age for car-drivers and for car-passengers who travelled with household members only (which was usually the case). No corrections could be made for vehicle weights and driving styles due to data limitations.

The OViN2017 dataset specifies the (household vehicles') following fuel types: gasoline, diesel, LPG (Liquified Petroleum Gas), and electricity. The SEC can be computed in the same manner as for gasoline vehicles (see Table 4). Cars using a combination of electricity and gasoline or diesel as fuel inputs are both treated as (gasoline) plug-in hybrid vehicles (PHEVs). The gasoline-powered vehicle was chosen as the default.

A second important determinant of energy consumption is the vehicle age. In the Netherlands, autonomous improvements in the efficiency of cars are enhanced by (fiscal) policies and increasingly stringent environmental regulations (Geilenkirchen et al., 2016; Hilbers et al., 2016; Otten et al., 2015). CE Delft's emission-report includes correction factors for the real-life energy consumption of gasoline, diesel, and LPG cars built from 2002 to 2011 (Otten et al., 2015). These have been extrapolated to cover the full range of building years in the dataset. The average age of cars for which corrections were made is 8.58 years. This age has been chosen as the default.

The (final) energy consumption for each trip and for each person in total was computed by multiplying the distance travelled by each mode with the corresponding SEC-value. The daily energy consumption of those respondents using a passive mode of transportation was approximately lognormally distributed (see Fig. 2). Together, the respondents consumed 1.35 TJ, equivalent to 265.0 PJ for the Netherlands in 2017 as a whole. 95% Of this energy was consumed by the (reclassified) car-driver and -passenger trips. These numbers appear plausible as the final energy consumption by personal vehicles on Dutch roads was 266 PJ in 2013 (Geilenkirchen et al., 2016).

### 3.3. Data analysis

The influence of the spatial and sociodemographic variables on the energy consumption was analyzed by fitting multilinear and logistic regression models. The models were made representative by using the respondent-specific weight factors provided by Statistics Netherlands. Although the mobility behavior of a single OViN respondent may vary from day to day, the reported travel was assumed representative for the rest of the year on average because of the large number of respondents. Moreover, non-regular trips such as holiday-trips are not part of the analysis. See Fig. 3 below for a flowchart of the regression models used. The rest of this subsection further elaborates on these models.

The effects of the $z$ independent variables $x_i$ on the daily final energy consumption $E_{passive}$ for each person could be tested by fitting a multilinear regression model to the data (James et al., 2013). It was decided to transform the variable to account for its lognormal distribution. The final model was thus as follows:

$$\ln\left(E_{passive}\right) = \beta_0 + \sum_{i=1}^{z} \beta_i x_i. \tag{2}$$

In order to fit this model, it was necessary to first exclude those people who did not cover any distance or consume any energy. Two logistic regression models have been constructed for this purpose, whereby the effects of the $z$ independent variables $x_i$ on the relative probability $P$ that a certain trip falls into a certain category has been assessed by fitting the model in Eq. (3) below to the data (James et al., 2013):

$$P = \frac{e^{\beta_0 + \sum_{i=1}^{z} \beta_i x_i}}{1 + e^{\beta_0 + \sum_{i=1}^{z} \beta_i x_i}}. \tag{3}$$

A first binary logistic model analyzed the influence of the sociodemographic and municipal-level spatial variables on the probability that someone covers any distance by making a trip. Note that many spatial variables could not be included in this model since an absence of any trips inhibits an accurate deduction of the respondents' postcode of residence. The second binary logistic model was used to analyze the influence of the full set of spatial and sociodemographic variables on the probability that people who left the house actually consumed any energy by using a passive transportation mode.

The (mean) final daily energy consumption $E$ of a type of respondent can be estimated by multiplying the estimations of the probability of leaving the house $\widehat{P}_{leaving}$, the probability of using a passive mode $\widehat{P}_{passive}$, and the energy consumption if using a passive mode $\widehat{E}_{passive}$:

$$\widehat{E} = \widehat{P}_{leaving} \cdot \widehat{P}_{passive} \cdot \widehat{E}_{passive}. \tag{4}$$

We thereby estimate that $\widehat{E}_{passive} = Ce^{\widehat{\ln}\left(E_{passive}\right)}$. The bias correction factor $C$ is meant to compensate for the larger impact of positive deviations from the mean compared to their negative counterparts after the exponential transformation. We found $C := \langle E_{passive} \rangle / \left\langle e^{\widehat{\ln}\left(E_{passive}\right)} \right\rangle = 1.94$ where $\langle \dots \rangle$ denotes the weighted average over the entire set of energy consuming respondents.

Several other models were fitted for further insight into the results obtained, namely: 1) a multilinear model of the logarithm transformed distance travelled per respondent for both the entire set of travelling

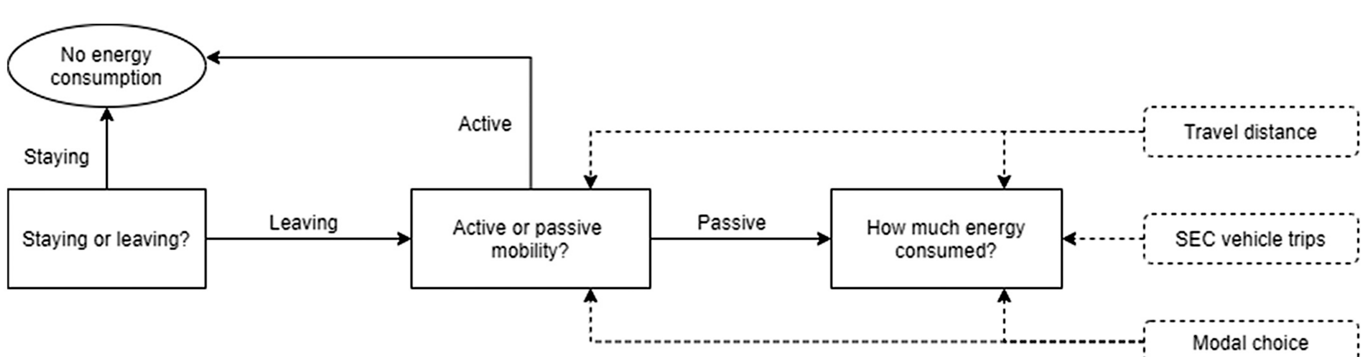


**Fig. 3.** The regression models used to analyze energy consumption for mobility. The supporting regressions in the dashed boxes on the right provide further insight into the main results and can be found in the Appendix.

respondents and for the separate subset of respondents who consumed energy, 2) a multilinear model of the distance-weighted SEC of vehicle trips per respondent, and 3) an extended multinomial logistic model of the specific mode used for each trip. The SEC of vehicle trips has in turn been further analyzed with multilinear models of vehicle efficiency and distance-weighted average occupancy. The precise results of the supporting regressions are provided in the Appendix.

All models have been fitted using the scikit-learn python-library for machine learning (Pedregosa et al., 2011). The independent input variables were standardized and 20% of the data has been reserved for testing each model's performance.

## 4. Results

The results of the analyses are described below. First, subsection 4.1 describes which sociodemographic and municipal-level spatial factors determine whether someone makes any trip at all. Subsection 4.2 then analyzes the factors determining whether people who leave the home use a passive mode of transportation. The energy used by this subgroup is finally analyzed by means of a multilinear regression analysis, as described in subsection 4.3. Subsection 4.4 brings it all together and assesses the relative importance of the spatial and sociodemographic variables.

### 4.1. Staying or leaving

See the results of the logistic regression of whether people stay home or leave the house in Table 5 below. Leaving the house is the reference category 1 and is thus associated with positive coefficients. The underlying data shows that people mostly stay home due to day-to-day circumstances such as absent outside activities, holidays, and illnesses. The model's receiver operating curve does, however, deviate from the diagonal with an Area Under the Curve (AUC) (Mandrekar, 2010) of 65%.

**Table 5**
The results of the binary logistic regression model of whether the 31,647 respondents included in this research project made any trip. The second column provides the factor change in the odds ratio per change of standard deviation (Std) in the independent variable, which is then converted in a percentage change for easier interpretation. Results with a *P*-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Factor change | % Change | Std | *P*-values |
|---|---|---|---|---|---|
| Municipal level of urbanity | −0.043 | 0.958 | −4.2 | 1.275 | 0.104 |
| Municipal population size | −0.006 | 0.994 | −0.6 | 1.551 | 0.824 |
| Randstad area | −0.000 | 1.000 | 0.0 | 0.498 | 0.990 |
| Metro | 0.012 | 1.012 | 1.2 | 0.248 | 0.508 |
| **Sociodemographic variables** | | | | | |
| **Income** | **0.056** | **1.058** | **5.8** | **2.711** | **0.002** |
| Household size | −0.040 | 0.961 | −3.9 | 1.378 | 0.162 |
| **Number of children** | **0.105** | **1.111** | **11.1** | **0.739** | **0.000** |
| **Living alone HP** | **−0.099** | **0.906** | **−9.4** | **0.389** | **0.000** |
| Single core HP | −0.006 | 0.994 | −0.6 | 0.205 | 0.725 |
| Child HP | −0.033 | 0.968 | −3.2 | 0.385 | 0.307 |
| Other HP | −0.006 | 0.994 | −0.6 | 0.044 | 0.707 |
| Male | 0.004 | 1.004 | 0.4 | 0.499 | 0.827 |
| **Western MB** | **−0.070** | **0.932** | **−6.8** | **0.283** | **0.000** |
| **Non-Western MB** | **−0.100** | **0.905** | **−9.5** | **0.280** | **0.000** |
| Part-time worker SP | −0.001 | 0.999 | −0.1 | 0.342 | 0.971 |
| Student SP | −0.021 | 0.979 | −2.1 | 0.219 | 0.412 |
| **Retired SP** | **−0.368** | **0.692** | **−30.8** | **0.434** | **0.000** |
| **Other SP** | **−0.177** | **0.838** | **−16.2** | **0.324** | **0.000** |
| **Teenager SP** | **0.137** | **1.147** | **14.7** | **0.321** | **0.000** |
| **No Edu.** | **−0.042** | **0.959** | **−4.1** | **0.106** | **0.004** |
| **Primary Edu.** | **−0.204** | **0.815** | **−18.5** | **0.351** | **0.000** |
| **Vocational Sec. Edu.** | **−0.078** | **0.925** | **−7.5** | **0.400** | **0.000** |
| **Higher Edu.** | **0.066** | **1.068** | **6.8** | **0.455** | **0.001** |
| Other Edu. | −0.012 | 0.988 | −1.2 | 0.107 | 0.420 |
| **Unknown Edu.** | **−0.090** | **0.914** | **−8.6** | **0.063** | **0.000** |
| Student pass | 0.020 | 1.020 | 2.0 | 0.216 | 0.429 |

A number of independent variables are accordingly significant. Unsurprisingly, retired people seem most likely to stay home. People in the "other" societal category - mainly unemployed people, disabled people, and people working in the household - are also more inclined to stay home. Additional factors that are correlated with staying home are "only" having received primary or vocational secondary education, having an unknown education status, having received no education, having a migrant background, and living alone. Teenagers and people in households with many children seem most likely to leave the house. Having a high level of education and a high household income are correlated with making at least one trip as well. None of the municipal-level spatial variables are statistically significant.

### 4.2. Active or passive mobility

A second binary logistic regression model was constructed to analyze which of the 25,019 respondents who left the house actually consumed any energy rather than only walking and cycling during the day. See the results in Table 6 below whereby consuming any energy by using a passive transportation mode is the reference category 1. The prediction accuracy and AUC were 70% and 69% respectively. The accuracy and AUC can be increased to 80% and 88% respectively by including the distance and trip motive variables in the model (see the extended regression in the Appendix, Table A.4). Tables A.1 and A.3 of the Appendix provide the results of the supporting regressions of total daily travel distance and modal choice for further insight.

Teenagers appear least inclined to use passive modes. Members of the retired, "other", student, and part-time employed societal categories also tend to walking and cycling. These groups - and in particular the retired group - cover less distance than the reference full-time employed category and thus have less need for using passive transportation modes. Yet, all correlations stay significant when including the distance and trip motive variables in the extended regression.

A high local address density is the next most important contributor to walking and cycling. Other spatial variables that are significantly correlated with active mode use are the landuse mix, green space, and short distances to city centers and supermarkets. The effect of greenery is larger in the extended regression. In contrast, the distances to supermarkets and city centers become insignificant in the extended regression. This is probably due to their correlations with travel distances (which can be exhaustive to walk or cycle).

The remaining variables stimulating walking and cycling are living alone and living in a large household, "only" having received primary or vocational secondary education, and having received no education. The effect of living alone seems partly intermediary by reducing travel distances. The education categories seem to become insignificant in the extended regression for this reason.

In contrast, being a full-time working adult, having a high (household) income, living in a household with many children, being the child in the household, and having a non-Western migrant background are correlated with making at least one trip with a passive, energy consuming, mobility mode. The effect of income is mainly intermediary whereas the influence of having a child household position or a non-Western migrant background is partly concealed by (shorter) distances travelled and different trip motives. Specifically, those with a non-Western migrant background appear to have a preference for public transport.

People who have a student public transport pass or who live in the metro-cities of Amsterdam and Rotterdam are also more likely to consume energy. Combined with the supporting regression results, this

**Table 6**
The results of the binary logistic regression model of whether the 25,019 respondents who made at least one trip actually consumed any energy. The second column provides the factor change in the odds ratio per change of standard deviation (Std) in the independent variable, which is then converted in a percentage change for easier interpretation. Results with a *P*-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Factor change | % Change | Std | P-values |
|---|---|---|---|---|---|
| Municipal level of urbanity | 0.002 | 1.002 | 0.2 | 1.270 | 0.960 |
| Municipal population size | −0.025 | 0.975 | −2.5 | 1.548 | 0.369 |
| Randstad area | 0.022 | 1.022 | 2.2 | 0.498 | 0.309 |
| **Metro** | **0.062** | **1.064** | **6.4** | **0.247** | **0.002** |
| **Local address density** | **−0.248** | **0.780** | **−22.0** | **1606.742** | **0.000** |
| **Distance to supermarket** | **0.053** | **1.054** | **5.4** | **0.718** | **0.020** |
| Distance to train station | −0.004 | 0.996 | −0.4 | 5.704 | 0.827 |
| Distance to road entry | 0.011 | 1.011 | 1.1 | 1.134 | 0.562 |
| **Distance to center** | **0.062** | **1.064** | **6.4** | **5.454** | **0.006** |
| Distance to larger center | −0.033 | 0.968 | −3.2 | 19.631 | 0.108 |
| PT stops density | −0.026 | 0.974 | −2.6 | 6.054 | 0.279 |
| **Green space** | **−0.104** | **0.901** | **−9.9** | **0.095** | **0.002** |
| **Landuse mix entropy** | **−0.137** | **0.872** | **−12.8** | **0.153** | **0.000** |
| **Sociodemographic variables** | | | | | |
| **Income** | **0.114** | **1.121** | **12.1** | **2.686** | **0.000** |
| **Household size** | **−0.079** | **0.924** | **−7.6** | **1.380** | **0.004** |
| **Number of children** | **0.073** | **1.076** | **7.6** | **0.766** | **0.001** |
| **Living alone HP** | **−0.110** | **0.896** | **−10.4** | **0.372** | **0.000** |
| Single core HP | 0.011 | 1.011 | 1.1 | 0.206 | 0.529 |
| **Child HP** | **0.073** | **1.076** | **7.6** | **0.393** | **0.031** |
| Other HP | −0.000 | 1.000 | 0.0 | 0.040 | 0.978 |
| Male | 0.023 | 1.023 | 2.3 | 0.500 | 0.171 |
| Western MB | 0.011 | 1.011 | 1.1 | 0.274 | 0.500 |
| **Non-Western MB** | **0.056** | **1.058** | **5.8** | **0.273** | **0.001** |
| **Part-time worker SP** | **−0.120** | **0.887** | **−11.3** | **0.352** | **0.000** |
| **Student SP** | **−0.200** | **0.819** | **−18.1** | **0.223** | **0.000** |
| **Retired SP** | **−0.332** | **0.717** | **−28.3** | **0.409** | **0.000** |
| **Other SP** | **−0.252** | **0.777** | **−22.3** | **0.314** | **0.000** |
| **Teenager SP** | **−0.606** | **0.546** | **−45.4** | **0.329** | **0.000** |
| **No Edu.** | **−0.031** | **0.969** | **−3.1** | **0.098** | **0.041** |
| **Primary Edu.** | **−0.098** | **0.907** | **−9.3** | **0.345** | **0.000** |
| **Vocational Sec. Edu.** | **−0.054** | **0.947** | **−5.3** | **0.388** | **0.003** |
| Higher Edu. | −0.027 | 0.973 | −2.7 | 0.464 | 0.176 |
| Other Edu. | −0.025 | 0.975 | −2.5 | 0.104 | 0.098 |
| Unknown Edu. | −0.013 | 0.987 | −1.3 | 0.047 | 0.406 |
| **Student pass** | **0.128** | **1.137** | **13.7** | **0.221** | **0.000** |

supports the notion that public transport competes with cycling as a main mode in the Netherlands: people are inclined to make use of cheaper or easier access.

A final important observation is that having received higher education significantly reduces the probability of using passive modes in the extended regression. This effect appears to be concealed by the positive correlation with travel distances.

### *4.3. Energy consumption*

The last main regression shows how much energy those that do use a passive transportation mode consume by means of a multilinear model.

**Table 7**
The results of the multilinear regression model of the natural logarithm of the energy consumed by the 16,697 respondents who used a passive mode of transportation. The second column provides the factor change in the energy consumption per change of standard deviation (Std) in the independent variable, which is then converted in a percentage change for easier interpretation. Results with a *P*-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Factor change | % Change | Std | P-values |
|---|---|---|---|---|---|
| Constant | 3.624 | – | – | – | – |
| Municipal level of urbanity | −0.021 | 0.979 | −2.1 | 1.276 | 0.323 |
| Municipal population size | −0.012 | 0.988 | −1.2 | 1.530 | 0.508 |
| Randstad area | −0.008 | 0.992 | −0.8 | 0.497 | 0.591 |
| **Metro** | **−0.038** | **0.963** | **−3.7** | **0.239** | **0.004** |
| **Local address density** | **−0.118** | **0.889** | **−11.1** | **1494.708** | **0.000** |
| Distance to supermarket | 0.025 | 1.025 | 2.5 | 0.796 | 0.076 |
| **Distance to train station** | **0.029** | **1.029** | **2.9** | **5.851** | **0.026** |
| Distance to road entry | −0.017 | 0.983 | −1.7 | 1.186 | 0.142 |
| **Distance to center** | **0.030** | **1.030** | **3.0** | **5.484** | **0.044** |
| Distance to larger center | 0.023 | 1.023 | 2.3 | 19.310 | 0.089 |
| PT stops density | 0.027 | 1.027 | 2.7 | 5.764 | 0.106 |
| Green space | 0.004 | 1.004 | 0.4 | 0.093 | 0.842 |
| Landuse mix entropy | −0.027 | 0.973 | −2.7 | 0.160 | 0.172 |
| **Sociodemographic variables** | | | | | |
| **Income** | **0.069** | **1.071** | **7.1** | **2.644** | **0.000** |
| Household size | −0.033 | 0.968 | −3.2 | 1.325 | 0.063 |
| **Number of children** | **−0.082** | **0.921** | **−7.9** | **0.766** | **0.000** |
| Living alone HP | −0.004 | 0.996 | −0.4 | 0.362 | 0.770 |
| Single core HP | 0.011 | 1.011 | 1.1 | 0.210 | 0.323 |
| Child HP | −0.000 | 1.000 | 0.0 | 0.356 | 0.995 |
| Other HP | 0.015 | 1.015 | 1.5 | 0.045 | 0.163 |
| **Male** | **0.079** | **1.082** | **8.2** | **0.500** | **0.000** |
| Western MB | −0.016 | 0.984 | −1.6 | 0.273 | 0.139 |
| Non-Western MB | −0.022 | 0.978 | −2.2 | 0.267 | 0.053 |
| **Part-time worker SP** | **−0.097** | **0.908** | **−9.2** | **0.363** | **0.000** |
| **Student SP** | **−0.065** | **0.937** | **−6.3** | **0.222** | **0.000** |
| **Retired SP** | **−0.298** | **0.742** | **−25.8** | **0.396** | **0.000** |
| **Other SP** | **−0.146** | **0.864** | **−13.6** | **0.301** | **0.000** |
| **Teenager SP** | **−0.177** | **0.838** | **−16.2** | **0.261** | **0.000** |
| No Edu. | −0.015 | 0.985 | −1.5 | 0.089 | 0.169 |
| **Primary Edu.** | **−0.100** | **0.905** | **−9.5** | **0.284** | **0.000** |
| **Vocational Sec. Edu.** | **−0.034** | **0.967** | **−3.3** | **0.382** | **0.005** |
| **Higher Edu.** | **0.072** | **1.075** | **7.5** | **0.475** | **0.000** |
| Other Edu. | −0.001 | 0.999 | −0.1 | 0.102 | 0.910 |
| Unknown Edu. | −0.010 | 0.990 | −1.0 | 0.048 | 0.367 |
| Student pass | −0.026 | 0.974 | −2.6 | 0.227 | 0.127 |

The coefficient of determination ($R^2$) is 14%. See the model coefficients in Table 7. A description in order of importance is provided below. The Appendix provides the supporting regressions of total daily travel distance (Table A.2), modal choice (Table A.3), the SEC of vehicle trips (Table A.6), vehicle efficiency (Table A.7), and vehicle occupancy (Table A.8). Note that the determinants of distances travelled within the subset of energy consuming respondents are significantly different. Also note that a sizable majority of trips are made by car.

The societal position categories are again most important with retired people using the least energy. Those in the retired, "other", and part-time employed categories cover much less distance than the reference full-time employed group. The non-reference categories also seem to prefer mopeds and public transport over cars. When travelling by car, especially the teenager and retired groups tend to consume less energy because of a positive correlation with occupancy.

The local address density is once more the most relevant spatial variable: the daily energy consumption of respondents is 11.1% lower for every 1495 extra addresses per square kilometer. It appears to increase the probability of using mopeds and public transport. Within the subset of people travelling by energy consuming modes, local address density does not reduce travel distances though: apparently it is correlated with a higher probability of making short active trips only. Living in Amsterdam and Rotterdam appears negatively correlated with energy consumption due to the expected correlation with using the tram and metro instead of cars and a negative correlation with travel distances. People living close to city centers and train stations also consume significantly less energy. People living close to city centers cover less distance while those living close to stations naturally tend to travel by train, which is a very energy efficient long-distance mode.

The remaining variables reducing energy consumption are “only” having received primary or vocational secondary education and living in a household with many children. The “lower” education groups travel less kilometers per day and appear more likely to use mopeds. Respondents from households with many children seem inclined to use a car, but also to share these cars and cover little distance.

Being full-time employed, being male, having received higher education, and having a high (household) income are most correlated with consuming more energy. These groups tend to cover more distance. Interestingly, they also appear to own the most efficient vehicles. This seems to be counteracted by a tendency to drive and low occupancies for the full-time employed, male, and high income groups. It is likely that these are not distinct effects: these privileged respondents have more financial means to buy modern and electric cars, but may also anticipate their greater use of these vehicles (self-selection) or drive more in response to the lower energy costs (rebound effect).[1]

### 4.4. General results

See Fig. 4 below for a visual overview of the results. Sometimes, the effect of variables is very clear. Being retired for instance strongly reduces the probability of covering any distance in the first place, the probability of using a passive mode of transportation when a trip is made, and the amount of energy consumed when still using a passive mode. A number of spatial and sociodemographic variables, including for instance gender, are only significant in one or two of the regressions. In four cases, variables have opposing effects on energy consumption. Finally, there are six spatial variables and three sociodemographic categories that are not significant in any of the main regressions.

The impact of the variables can be further illuminated by estimating the energy consumption of four sociodemographic profiles:

A. Very low income (category 1) retired male with a non-Western migrant background of unknown education status who lives alone
B. Very low income (1) female graduate student with a Western migrant background who lives alone
C. Full-time working female with no migrant background, an advanced vocational education degree and an average (household) income (6), living together with her partner and a third household member of 12 years or older
D. Highly educated, very high income (10), full-time employed male with no migrant background who lives alone

These estimations were made for two postcode areas. PC 1053 in

| Spatial variables | Staying or leaving | Active or passive mobility | Energy consumption |
|---|---|---|---|
| Municipal level of urbanity | | | |
| Municipal population size | | | |
| Randstad area | | | |
| Metro | | | |
| Local address density | - | | |
| Distance to supermarket | - | | |
| Distance to train station | - | | |
| Distance to road entry | - | | |
| Distance to center | - | | |
| Distance to larger center | - | | |
| PT stops density | - | | |
| Green space | - | | |
| Landuse mix entropy | - | | |
| **Sociodemographic variables** | | | |
| Income | | | |
| Household size | | | |
| Number of children | | | |
| Living alone HP | | | |
| Single core HP | | | |
| Child HP | | | |
| Other HP | | | |
| Male | | | |
| Western MB | | | |
| Non-Western MB | | | |
| Part-time worker SP | | | |
| Student SP | | | |
| Retired SP | * | | * |
| Other SP | | | |
| Teenager SP | | * | |
| No Edu. | | | |
| Primary Edu. | | | |
| Vocational Secondary Edu. | | | |
| Higher Edu. | | | |
| Other Edu. | | | |
| Unknown Edu. | | | |
| Student Pass | | | |

**Fig. 4.** An overview table of the results. Green means that the variable was found to significantly reduce energy consumption at the 5% level. Red means that the variable significantly increased energy consumption at the 5% level. Variables that influence the odds ratio of the logistic regressions or the energy consumption in the multilinear regression by more than 10% have been given a darker colour. Yellow means insignificant. The variable with the largest coefficient in each regression has lastly been highlighted with a star (*).

Old-West Amsterdam is the densest postcode area in the dataset with 11,456 addresses/km$^2$in the vicinity of its inhabitants. It is located within walking distance of the Canal District World Heritage Site. In contrast, PC 3453 (Veldhuizen, 1479 addresses/km$^2$) is representative for the Dutch built environment from an energy-perspective. It is a suburban neighborhood of Utrecht that can easily be reached by car, bus, and bicycle. See the results in Table 8 below. Please note that these estimations refer to the mean energy consumption associated with the sociodemographic profiles.

Table 9 finally shows the influence of the different types of variables on the overall regression performance. The first model can barely predict the probability that a respondent makes a trip on a particular day on the basis of the (municipal-level) spatial variables alone. The full set of (municipal- and postcode-level) spatial variables does help predict the probability that respondents who leave the house use a passive, energy consuming, mode of transportation. The models are aimed at analyzing averages and are thus less suited for predicting individual mobility behavior. Yet, the regression performances are consistently much higher when only using sociodemographic variables. The energy consumption of Dutch citizens thus seems to depend more on their personal characteristics and circumstances than their residential location. The spatial variables mainly help explain differences in mobility behavior by similar respondents who live in different neighborhoods. Such differences can nevertheless be major, as shown in Table 8.

[1] See Matiaske et al. (2012) for a more detailed analysis of the (non-linear) rebound effect.

**Table 8**
The estimated mean energy consumption associated with four sociodemographic profiles in two different spatial settings. The final estimation $\widehat{E}$ is the product of the outcomes of the three main regressions (see Eq. (4)).

| Profile in PC 1053 | $\widehat{P}_{leaving}$ | $\widehat{P}_{passive}$ | $\widehat{E}_{passive}$ | $\widehat{E}$ |
|---|---|---|---|---|
| Profile A | 25.2% | 25.0% | 13.1 MJ/day | 0.8 MJ/day |
| Profile B | 80.9% | 35.3% | 23.1 MJ/day | 6.6 MJ/day |
| Profile C | 86.4% | 53.1% | 34.6 MJ/day | 15.9 MJ/day |
| Profile D | 86.9% | 52.6% | 54.4 MJ/day | 24.8 MJ/day |
| **Profile when living in PC 3453 (Veldhuizen)** | | | | |
| Profile A | 24.2% | 52.7% | 34.9 MJ/day | 4.5 MJ/day |
| Profile B | 80.1% | 64.6% | 61.6 MJ/day | 31.9 MJ/day |
| Profile C | 85.8% | 79.1% | 92.2 MJ/day | 62.6 MJ/day |
| Profile D | 86.3% | 78.7% | 145.0 MJ/day | 98.5 MJ/day |

**Table 9**
The AUC and $R^2$ metrics of the main regressions when including different sets of variables.

| Variables included | AUC Staying or leaving | AUC Active or passive | $R^2$ Energy consumption |
|---|---|---|---|
| Spatial and sociodemographic | 65% | 69% | 14% |
| Only spatial | 51% | 57% | 2% |
| Only sociodemographic | 65% | 67% | 13% |

## 5. Conclusion and discussion

The extensive use of cars and associated energy consumption is a major driver of climate change. A technological shift towards electric vehicles can help, but these vehicles will burden the future electricity grid and will still contribute to the non-environmental externalities of car dependence. A wider approach is thus desired. This in turn demands more insight into the spatial and sociodemographic determinants of mobility behavior. Previous studies have omitted energy-relevant aspects of mobility such as distances travelled with non-car modes, distances travelled with different types of cars, the occupancy of cars, and the probability that people do not travel in the first place. Moreover, studies of national Dutch mobility data lack certain local spatial variables. This research project aimed to fill these gaps by using a combination of logistic and multilinear regression models to analyze how the built environment and people's sociodemographic characteristics are related to energy consumption for personal mobility in the Netherlands.

Local density turned out to be the most important aspect of the built environment: it strongly reduced both the probability of using a passive mode of transportation and the associated energy consumption. Short distances to the city center proxies also reduced energy consumption through both mechanisms. Other spatial variables had a singular effect. Landuse mix entropy and short distances to supermarkets for instance only reduced the probability of using energy consuming modes, presumably by reducing the effort required to reach destinations by foot or bicycle. Green space seemed to make walking and cycling more attractive. In contrast, living in the metro-cities of Amsterdam and Rotterdam increased passive mode use, which appears related to competition between public transport and cycling in the Netherlands. Public transport is energy efficient though. Living in a metro-city as well as living close to a train station accordingly did reduce the energy consumed when using a passive mode.

The influence of these spatial variables was surpassed by that of the respondents' sociodemographic characteristics, including most prominently people's societal position: full-time working respondents consistently consumed far more energy. Those with high (household) incomes and a high level of education also consumed more energy. These groups did own the most efficient vehicles. These results are generally in accordance with the literature. The strength of the societal position effect is somewhat surprising, but can be explained by the combination of energy-relevant employment- and age-related characteristics. The literature was not conclusive on whether gender, household children, and migrant backgrounds significantly influence car use and associated energy consumption in the Netherlands today. The results of this study show that males consume more energy because they cover more distance and tend to drive their (albeit energy efficient) vehicles alone. Being from a household with many children turned out to both increase the probability of making a trip by car and reduce the consumption of energy when doing so. Those with parents from non-Western countries were finally more likely to travel by public transport or to not travel at all. Lastly, the inclusion of a student societal category in the regression analyses revealed the add-on effect of the student pass itself, which turned out to increase energy consumption due to the abovementioned competition between public transport and cycling.

Several policy-recommendations can be provided using these results. Major energy savings can first of all be obtained by directly reducing the need for long-distance commutes. An effort should thus be made to retain the adoption of working from home. The differences in the computed specific energy consumption values also show the potential of electric and modern cars. On a more fundamental level, however, the results of this study underline the importance of looking beyond technology. The respondents with the most efficient vehicles were shown to drive longer distances with less people per car. Subsidizing these vehicles can therefore be seen as unfair to underprivileged groups that consume far less energy overall. An alternative may be to stimulate the construction of dense and diverse neighborhoods near existing cities. Finally, the results show that it is important to be careful that investments in - the main cities' - public transport infrastructure are well-targeted to get people out of their cars and not off their bikes.

The main strength of this study is its comprehensive analysis of energy consumption. This allowed for more accurate results and helped reveal the many and sometimes contradictory ways in which the spatial and sociodemographic variables influence energy consumption. Moreover, the coupling of different datasets allowed the inclusion of additional local (intra-municipal) spatial variables.

Yet, the influence of the spatial variables was limited overall and some were not significant in any of the main regressions. One explanation is that features specific to the Netherlands weakened the correlations. Think of the polycentric urban configuration with many smaller cities, the prominence of cycling as an alternative to driving and public transport on medium distances, the wide coverage of roads, and the relatively extensive public transport network. Future studies can help clarify the influence of such inter-country differences. Subsequently, they could also investigate whether the correlations between the built environment and mobility behavior hold in the rapidly growing cities of the global South where future energy consumption will be concentrated.

Future research can also analyze energy consumption for mobility more accurately by including variables related to people's travel preferences to account for residential self-selection. Further spatial additions may include the available infrastructure for walking and cycling, the accessibility of jobs, and an entropy-related measure of the concentration of people and jobs. Another key improvement would be to develop a more advanced econometric framework to test the various interrelationships between trip production, modal choice, distance travelled, and energy consumption as well as their relevance for understanding and predicting transport related energy consumption. Moreover, future studies can improve the computation of energy consumption by correcting for public transport occupancy and vehicle weights. And these studies do not have to stop at energy consumption. They can for instance account for the carbon- and nitrogen-footprint of different energy carriers. In these ways, they could truly make a contribution towards reducing the environmental impacts of car dependence.

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## Code availability

The code is available from the corresponding author on request.

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## Appendix A. Supporting regressions

See the results of the supporting regression models below for further insight into the main results.

### A.1. Travel distances

See the results of the regression of the natural logarithm of total daily distance travelled by the 25 019 respondents who made at least one trip in Table A.1 below ($R^2 = 11\%$).

**Table A.1**
The results of the multilinear regression model of the natural logarithm of the total daily distance travelled by the 25,019 respondents who made at least one trip. Results with a *P*-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Factor change | % Change | Std | P-values |
|---|---|---|---|---|---|
| Constant | 2.828 | – | – | – | – |
| Municipal level of urbanity | −0.029 | 0.971 | −2.9 | 1.270 | 0.116 |
| Municipal population size | −0.002 | 0.998 | −0.2 | 1.548 | 0.881 |
| Randstad area | 0.017 | 1.017 | 1.7 | 0.498 | 0.167 |
| Metro | 0.002 | 1.002 | 0.2 | 0.247 | 0.884 |
| **Local address density** | **−0.096** | **0.908** | **−9.2** | **1606.742** | **0.000** |
| **Distance to supermarket** | **0.042** | **1.043** | **4.3** | **0.718** | **0.000** |
| Distance to train station | 0.010 | 1.010 | 1.0 | 5.704 | 0.376 |
| Distance to road entry | −0.008 | 0.992 | −0.8 | 1.134 | 0.440 |
| **Distance to center** | **0.034** | **1.035** | **3.5** | **5.454** | **0.008** |
| Distance to larger center | −0.009 | 0.991 | −0.9 | 19.631 | 0.430 |
| PT stops density | −0.010 | 0.990 | −1.0 | 6.054 | 0.503 |
| Green space | 0.014 | 1.014 | 1.4 | 0.095 | 0.455 |
| **Landuse mix entropy** | **−0.035** | **0.966** | **−3.4** | **0.153** | **0.036** |
| **Sociodemographic variables** | | | | | |
| **Income** | **0.089** | **1.093** | **9.3** | **2.686** | **0.000** |
| Household size | −0.025 | 0.975 | −2.5 | 1.380 | 0.108 |
| **Number of children** | **−0.027** | **0.973** | **−2.7** | **0.766** | **0.024** |
| **Living alone HP** | **−0.054** | **0.947** | **−5.3** | **0.372** | **0.000** |
| Single core HP | 0.011 | 1.011 | 1.1 | 0.206 | 0.272 |
| Child HP | −0.006 | 0.994 | −0.6 | 0.393 | 0.743 |
| Other HP | 0.003 | 1.003 | 0.3 | 0.040 | 0.763 |
| **Male** | **0.061** | **1.063** | **6.3** | **0.500** | **0.000** |
| Western MB | −0.012 | 0.988 | −1.2 | 0.274 | 0.182 |
| Non-Western MB | −0.015 | 0.985 | −1.5 | 0.273 | 0.127 |
| **Part-time worker SP** | **−0.109** | **0.897** | **−10.3** | **0.352** | **0.000** |
| **Student SP** | **−0.053** | **0.948** | **−5.2** | **0.223** | **0.000** |
| **Retired SP** | **−0.291** | **0.748** | **−25.2** | **0.409** | **0.000** |
| **Other SP** | **−0.204** | **0.815** | **−18.5** | **0.314** | **0.000** |
| **Teenager SP** | **−0.200** | **0.819** | **−18.1** | **0.329** | **0.000** |
| **No Edu.** | **−0.019** | **0.981** | **−1.9** | **0.098** | **0.049** |
| **Primary Edu.** | **−0.103** | **0.902** | **−9.8** | **0.345** | **0.000** |
| **Vocational Sec. Edu.** | **−0.047** | **0.954** | **−4.6** | **0.388** | **0.000** |
| **Higher Edu.** | **0.086** | **1.090** | **9.0** | **0.464** | **0.000** |
| Other Edu. | 0.005 | 1.005 | 0.5 | 0.104 | 0.630 |
| Unknown Edu. | −0.005 | 0.995 | −0.5 | 0.047 | 0.617 |
| **Student pass** | **0.050** | **1.051** | **5.1** | **0.221** | **0.000** |

### A.2. Travel distances energy consuming subset

See the results of the regression of the natural logarithm of total daily distance travelled by the 16,697 respondents who made at least one trip with a passive mode in Table A.2 below ($R^2 = 9\%$).

**Table A.2**
The results of the multilinear regression model of the natural logarithm of the total daily distance travelled by the 16,697 respondents who made at least one trip with a passive mode. Results with a P-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Factor change | % Change | Std | P-values |
|---|---|---|---|---|---|
| Constant | 3.396 | – | – | – | – |
| Municipal level of urbanity | −0.003 | 0.997 | −0.3 | 1.276 | 0.862 |
| Municipal population size | 0.005 | 1.005 | 0.5 | 1.530 | 0.752 |
| Randstad area | 0.019 | 1.019 | 1.9 | 0.497 | 0.134 |
| **Metro** | **−0.031** | **0.969** | **−3.1** | **0.239** | **0.008** |
| Local address density | 0.003 | 1.003 | 0.3 | 1494.708 | 0.890 |
| **Distance to supermarket** | **0.035** | **1.036** | **3.6** | **0.796** | **0.004** |
| Distance to train station | 0.004 | 1.004 | 0.4 | 5.851 | 0.729 |
| Distance to road entry | −0.012 | 0.988 | −1.2 | 1.186 | 0.222 |
| **Distance to center** | **0.030** | **1.030** | **3.0** | **5.484** | **0.024** |
| Distance to larger center | 0.022 | 1.022 | 2.2 | 19.310 | 0.073 |
| PT stops density | 0.023 | 1.023 | 2.3 | 5.764 | 0.120 |
| Green space | 0.021 | 1.021 | 2.1 | 0.093 | 0.277 |
| Landuse mix entropy | 0.002 | 1.002 | 0.2 | 0.160 | 0.888 |
| **Sociodemographic variables** | | | | | |
| **Income** | **0.053** | **1.054** | **5.4** | **2.644** | **0.000** |
| Household size | −0.007 | 0.993 | −0.7 | 1.325 | 0.637 |
| **Number of children** | **−0.048** | **0.953** | **−4.7** | **0.766** | **0.000** |
| Living alone HP | 0.002 | 1.002 | 0.2 | 0.362 | 0.858 |
| Single core HP | 0.017 | 1.017 | 1.7 | 0.210 | 0.082 |
| Child HP | −0.005 | 0.995 | −0.5 | 0.356 | 0.769 |
| Other HP | 0.004 | 1.004 | 0.4 | 0.045 | 0.659 |
| **Male** | **0.049** | **1.050** | **5.0** | **0.500** | **0.000** |
| Western MB | −0.013 | 0.987 | −1.3 | 0.273 | 0.177 |
| **Non-Western MB** | **−0.032** | **0.969** | **−3.1** | **0.267** | **0.002** |
| **Part-time worker SP** | **−0.084** | **0.919** | **−8.1** | **0.363** | **0.000** |
| Student SP | 0.004 | 1.004 | 0.4 | 0.222 | 0.809 |
| **Retired SP** | **−0.204** | **0.815** | **−18.5** | **0.396** | **0.000** |
| **Other SP** | **−0.103** | **0.902** | **−9.8** | **0.301** | **0.000** |
| Teenager SP | −0.018 | 0.982 | −1.8 | 0.261 | 0.301 |
| No Edu. | −0.010 | 0.990 | −1.0 | 0.089 | 0.280 |
| **Primary Edu.** | **−0.074** | **0.929** | **−7.1** | **0.284** | **0.000** |
| **Vocational Sec. Edu.** | **−0.043** | **0.958** | **−4.2** | **0.382** | **0.000** |
| **Higher Edu.** | **0.119** | **1.126** | **12.6** | **0.475** | **0.000** |
| Other Edu. | 0.005 | 1.005 | 0.5 | 0.102 | 0.583 |
| Unknown Edu. | −0.017 | 0.983 | −1.7 | 0.048 | 0.078 |
| **Student pass** | **0.049** | **1.050** | **5.0** | **0.227** | **0.001** |

### *A.3. Modal choice*

See the results of the multinomial regression model of the specific mode used for each of the 89,096 trips in Table A.3 below (accuracy = 58%). Some sparsely used modes have been reclassified, as explained in subsection 3.2. The coefficients of the remaining modes used for less than 1% of the trips have been omitted to allow for a better overview. These are the touring bus, motorcycle, boat, and non-specified modes. A distinction is made between car-drivers and -passengers to reflect the difference in average occupancy. As the model is not intended for energy consumption calculations, the trip distance and motive variables were added. Note that the reference trip motive is commuting to school or work and that the free time motive includes sports-related activities.

**Table A.3**
The coefficients of the multinomial logistic regression model of the mode used for the 89,096 trips in the dataset when including the trip distance and motive variables.

| Spatial variables | Train | Tram/metro | Bus | Car-driver | Car-pass. | Moped | Cycling | Walking |
|---|---|---|---|---|---|---|---|---|
| Municipal level of urbanity | 0.020 | −0.454 | −0.059 | 0.049 | 0.084 | 0.131 | 0.086 | −0.056 |
| Municipal population size | 0.074 | 0.070 | 0.177 | 0.005 | 0.063 | 0.307 | 0.122 | 0.114 |
| Randstad area | −0.016 | 1.151 | −0.274 | −0.324 | −0.298 | −0.104 | −0.220 | −0.235 |
| Metro | −0.247 | 0.053 | −0.065 | −0.078 | −0.165 | −0.104 | −0.139 | −0.093 |
| Local address density | 0.118 | 0.114 | 0.024 | −0.252 | −0.032 | 0.181 | 0.175 | 0.091 |
| Distance to supermarket | −0.048 | −0.055 | −0.100 | −0.072 | −0.078 | −0.131 | −0.087 | −0.087 |
| Distance to train station | −0.998 | 0.264 | 0.172 | 0.031 | 0.052 | 0.022 | 0.041 | 0.035 |
| Distance to road entry | −0.051 | 0.077 | −0.064 | −0.019 | −0.044 | −0.058 | −0.024 | 0.002 |
| Distance to center | 0.068 | 0.259 | 0.005 | 0.048 | 0.048 | 0.052 | −0.012 | 0.051 |
| Distance to larger center | 0.048 | −0.448 | −0.179 | 0.051 | 0.047 | 0.011 | 0.098 | 0.018 |
| PT stops density | 0.004 | 0.004 | −0.000 | −0.018 | 0.059 | −0.162 | 0.015 | 0.068 |
| Green space | −0.000 | −0.037 | 0.131 | −0.081 | −0.052 | 0.065 | 0.149 | 0.085 |
| Landuse mix entropy | −0.058 | 0.022 | 0.005 | −0.106 | −0.033 | 0.127 | 0.050 | 0.017 |
| **Sociodemographic variables** | | | | | | | | |
| Income | 0.165 | 0.026 | 0.024 | 0.251 | 0.107 | −0.108 | 0.140 | 0.060 |
| Household size | −0.003 | 0.060 | 0.051 | 0.199 | 0.045 | 0.094 | 0.216 | 0.069 |

(continued on next page)

**Table A.3** (*continued*)

| Spatial variables | Train | Tram/metro | Bus | Car-driver | Car-pass. | Moped | Cycling | Walking |
|---|---|---|---|---|---|---|---|---|
| Number of children | 0.110 | −0.038 | −0.073 | 0.135 | 0.131 | −0.228 | 0.022 | 0.018 |
| Living alone HP | 0.232 | 0.201 | 0.254 | 0.090 | −0.185 | 0.191 | 0.142 | 0.081 |
| Single core HP | 0.266 | 0.220 | 0.193 | 0.144 | 0.009 | 0.125 | 0.110 | 0.114 |
| Child HP | 0.353 | 0.189 | 0.320 | −0.021 | 0.192 | 0.415 | −0.099 | −0.050 |
| Other HP | 0.095 | 0.142 | 0.101 | 0.147 | 0.160 | −0.242 | 0.147 | 0.121 |
| Male | −0.067 | −0.135 | −0.177 | 0.099 | −0.467 | 0.192 | −0.025 | −0.053 |
| Western MB | 0.080 | −0.020 | 0.141 | −0.023 | 0.036 | −0.048 | −0.069 | −0.002 |
| Non-Western MB | 0.214 | 0.356 | 0.367 | 0.156 | 0.126 | −0.088 | 0.008 | 0.195 |
| Part-time worker SP | 0.033 | −0.076 | 0.029 | −0.002 | 0.037 | 0.061 | 0.089 | −0.006 |
| Student SP | 0.190 | 0.032 | 0.214 | −0.034 | 0.159 | 0.080 | 0.272 | 0.139 |
| Retired SP | 0.007 | 0.256 | 0.287 | −0.006 | 0.155 | 0.118 | 0.208 | 0.227 |
| Other SP | 0.069 | 0.094 | 0.186 | −0.023 | 0.101 | 0.239 | 0.138 | 0.137 |
| Teenager SP | 0.109 | −0.064 | 0.105 | −1.339 | 0.130 | −0.298 | 0.363 | −0.048 |
| No Edu. | 0.048 | 0.049 | 0.109 | 0.035 | 0.068 | 0.159 | 0.093 | 0.105 |
| Primary Edu. | −0.278 | −0.044 | −0.203 | −0.139 | 0.121 | 0.115 | −0.013 | −0.014 |
| Vocational Sec. Edu. | 0.021 | −0.142 | −0.028 | −0.019 | 0.058 | 0.163 | −0.008 | 0.000 |
| Higher Edu. | 0.278 | 0.028 | −0.040 | −0.090 | −0.114 | −0.489 | 0.069 | 0.015 |
| Other Edu. | 0.130 | 0.120 | 0.144 | 0.106 | 0.141 | 0.189 | 0.165 | 0.173 |
| Unknown Edu. | −0.269 | 0.115 | 0.133 | 0.134 | 0.057 | 0.169 | 0.117 | 0.112 |
| Student pass | 0.442 | 0.413 | 0.396 | −0.103 | 0.026 | −0.017 | −0.002 | 0.105 |
| Other variables | | | | | | | | |
| Trip distance | 0.014 | −1.848 | −0.622 | 0.318 | 0.329 | −0.373 | −0.875 | 0.695 |
| Log trip distance | 2.497 | 0.573 | 0.679 | 0.350 | 0.623 | −0.435 | −0.827 | −2.819 |
| Shopping motive | 0.051 | −0.109 | −0.011 | 0.491 | 1.015 | 0.251 | 0.172 | 0.074 |
| Visits motive | −0.187 | −0.250 | −0.199 | 0.155 | 0.681 | −0.008 | −0.077 | −0.095 |
| Free time motive | −0.463 | −0.312 | −0.522 | −0.213 | 0.596 | −0.180 | −0.142 | 0.325 |
| Other motive | −0.321 | −0.299 | −0.249 | 0.242 | 0.544 | −0.056 | −0.169 | −0.219 |

### A.4. *Extended regression active versus passive mobility*

See the results of the extended binary logistic regression of whether the 25,019 respondents who made at least one trip used a passive mode of transportation in Table A.4 below. The daily distance and trip motive variables were added. This makes the model unsuitable for predicting energy consumption, but strongly increases the accuracy and AUC to 80% and 88% respectively. Note that the reference trip motive is commuting to school or work and that the free time motive includes sports-related activities. In this model, the trip motive variable refers to the motive of the first trip only.

**Table A.4**
The results of the binary logistic regression model of whether the 25,019 people who made at least one trip actually consumed any energy when including the distance travelled per day and the motive of the first trip. Results with a P-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Factor change | % Change | Std | P-values |
|---|---|---|---|---|---|
| Municipal level of urbanity | 0.065 | 1.067 | 6.7 | 1.270 | 0.103 |
| Municipal population size | −0.032 | 0.969 | −3.1 | 1.548 | 0.346 |
| Randstad area | −0.002 | 0.998 | −0.2 | 0.498 | 0.934 |
| **Metro** | **0.080** | **1.083** | **8.3** | **0.247** | **0.001** |
| **Local address density** | **−0.208** | **0.812** | **−18.8** | **1606.742** | **0.000** |
| Distance to supermarket | −0.002 | 0.998 | −0.2 | 0.718 | 0.931 |
| Distance to train station | −0.025 | 0.975 | −2.5 | 5.704 | 0.310 |
| Distance to road entry | 0.030 | 1.030 | 3.0 | 1.134 | 0.161 |
| Distance to center | 0.054 | 1.055 | 5.5 | 5.454 | 0.056 |
| Distance to larger center | −0.012 | 0.988 | −1.2 | 19.631 | 0.647 |
| PT stops density | −0.026 | 0.974 | −2.6 | 6.054 | 0.395 |
| **Green space** | **−0.163** | **0.850** | **−15.0** | **0.095** | **0.000** |
| **Landuse mix entropy** | **−0.096** | **0.908** | **−9.2** | **0.153** | **0.009** |
| **Sociodemographic variables** | | | | | |
| **Income** | **0.058** | **1.060** | **6.0** | **2.686** | **0.010** |
| **Household size** | **−0.074** | **0.929** | **−7.1** | **1.380** | **0.030** |
| **Number of children** | **0.125** | **1.133** | **13.3** | **0.766** | **0.000** |
| **Living alone HP** | **−0.091** | **0.913** | **−8.7** | **0.372** | **0.000** |
| Single core HP | 0.002 | 1.002 | 0.2 | 0.206 | 0.915 |
| **Child HP** | **0.146** | **1.157** | **15.7** | **0.393** | **0.001** |
| Other HP | 0.002 | 1.002 | 0.2 | 0.040 | 0.921 |
| Male | −0.035 | 0.966 | −3.4 | 0.500 | 0.099 |
| Western MB | 0.031 | 1.031 | 3.1 | 0.274 | 0.121 |
| **Non-Western MB** | **0.118** | **1.125** | **12.5** | **0.273** | **0.000** |
| **Part-time worker SP** | **−0.055** | **0.946** | **−5.4** | **0.352** | **0.022** |
| **Student SP** | **−0.218** | **0.804** | **−19.6** | **0.223** | **0.000** |
| **Retired SP** | **−0.182** | **0.834** | **−16.6** | **0.409** | **0.000** |
| **Other SP** | **−0.153** | **0.858** | **−14.2** | **0.314** | **0.000** |
| **Teenager SP** | **−0.610** | **0.543** | **−45.7** | **0.329** | **0.000** |
| No Edu. | −0.019 | 0.981 | −1.9 | 0.098 | 0.358 |

(continued on next page)

**Table A.4** (*continued*)

| Spatial variables | Coefficients | Factor change | % Change | Std | P-values |
|---|---|---|---|---|---|
| Primary Edu. | 0.006 | 1.006 | 0.6 | 0.345 | 0.844 |
| Vocational Sec. Edu. | −0.006 | 0.994 | −0.6 | 0.388 | 0.788 |
| **Higher Edu.** | **−0.142** | **0.868** | **−13.2** | **0.464** | **0.000** |
| **Other Edu.** | **−0.039** | **0.962** | **−3.8** | **0.104** | **0.043** |
| Unknown Edu. | −0.011 | 0.989 | −1.1 | 0.047 | 0.567 |
| **Student pass** | **0.123** | **1.131** | **13.1** | **0.221** | **0.000** |
| **Other variables** | | | | | |
| **Daily distance** | **1.249** | **3.487** | **248.7** | **57.420** | **0.000** |
| **Log daily distance** | **1.553** | **4.726** | **372.6** | **1.383** | **0.000** |
| **Shopping motive** | **0.286** | **1.331** | **33.1** | **0.400** | **0.000** |
| **Visits motive** | **0.256** | **1.292** | **29.2** | **0.293** | **0.000** |
| Free time motive | −0.003 | 0.997 | −0.3 | 0.402 | 0.899 |
| **Other motive** | **0.288** | **1.334** | **33.4** | **0.306** | **0.000** |

## *A.5. Vehicle ownership*

See the results of the binary logistic regression of vehicle ownership in Table A.5 below. Respondents who did not make any trips were excluded as their postcode area could not be determined. The teenagers aged below 18 were excluded as well because they are not legally allowed to drive. The precision accuracy and AUC of the model are 89% and 91% respectively. These high scores indicate that people indeed only buy a vehicle when their living location and personal circumstances demand it.

**Table A.5**
The results of the binary logistic regression model of whether the 21,934 adults who made at least one trip own one or more vehicles. Results with a P-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Factor change | % Change | Std | P-values |
|---|---|---|---|---|---|
| Municipal level of urbanity | 0.015 | 1.015 | 1.5 | 1.281 | 0.807 |
| Municipal population size | −0.059 | 0.943 | −5.7 | 1.561 | 0.229 |
| Randstad area | 0.024 | 1.024 | 2.4 | 0.498 | 0.530 |
| Metro | −0.005 | 0.995 | −0.5 | 0.253 | 0.875 |
| **Local address density** | **−0.367** | **0.693** | **−30.7** | **1637.315** | **0.000** |
| **Distance to supermarket** | **0.124** | **1.132** | **13.2** | **0.723** | **0.038** |
| Distance to train station | −0.007 | 0.993 | −0.7 | 5.692 | 0.869 |
| Distance to road entry | 0.037 | 1.038 | 3.8 | 1.101 | 0.316 |
| Distance to center | 0.092 | 1.096 | 9.6 | 5.430 | 0.051 |
| **Distance to larger center** | **0.131** | **1.140** | **14.0** | **19.738** | **0.001** |
| PT stops density | −0.050 | 0.951 | −4.9 | 6.214 | 0.153 |
| Green space | −0.002 | 0.998 | −0.2 | 0.095 | 0.975 |
| **Landuse mix entropy** | **−0.235** | **0.791** | **−20.9** | **0.155** | **0.000** |
| **Sociodemographic variables** | | | | | |
| **Income** | **0.718** | **2.050** | **105.0** | **2.681** | **0.000** |
| **Household size** | **0.411** | **1.508** | **50.8** | **1.290** | **0.000** |
| Number of children | −0.058 | 0.944 | −5.6 | 0.731 | 0.235 |
| **Living alone HP** | **−0.647** | **0.524** | **−47.6** | **0.391** | **0.000** |
| **Single core HP** | **−0.303** | **0.739** | **−26.1** | **0.220** | **0.000** |
| Child HP | 0.050 | 1.051 | 5.1 | 0.266 | 0.248 |
| Other HP | 0.010 | 1.010 | 1.0 | 0.039 | 0.733 |
| Male | −0.006 | 0.994 | −0.6 | 0.500 | 0.836 |
| **Western MB** | **−0.071** | **0.931** | **−6.9** | **0.280** | **0.005** |
| **Non-Western MB** | **−0.074** | **0.929** | **−7.1** | **0.259** | **0.003** |
| **Part-time worker SP** | **−0.092** | **0.912** | **−8.8** | **0.372** | **0.012** |
| **Student SP** | **−0.132** | **0.876** | **−12.4** | **0.234** | **0.002** |
| **Retired SP** | **−0.129** | **0.879** | **−12.1** | **0.429** | **0.000** |
| **Other SP** | **−0.200** | **0.819** | **−18.1** | **0.330** | **0.000** |
| **No Edu.** | **−0.104** | **0.901** | **−9.9** | **0.087** | **0.000** |
| **Primary Edu.** | **−0.149** | **0.862** | **−13.8** | **0.197** | **0.000** |
| Vocational Sec. Edu. | −0.021 | 0.979 | −2.1 | 0.396 | 0.499 |
| Higher Edu. | −0.067 | 0.935 | −6.5 | 0.480 | 0.057 |
| **Other Edu.** | **−0.098** | **0.907** | **−9.3** | **0.113** | **0.000** |
| Unknown Edu. | 0.020 | 1.020 | 2.0 | 0.052 | 0.464 |
| **Student pass** | **−0.217** | **0.805** | **−19.5** | **0.213** | **0.000** |

## *A.6. Specific energy consumption vehicle trips*

See the results of the multilinear regression of the distance-weighted average SEC of vehicle trips (in MJ/pkm) of the 12,873 respondents for whom the SEC was corrected because they drove a vehicle and/or travelled by vehicle with household members only in Table A.6 below ($R^2 = 11\%$). Note that the SEC of vehicle-trips is determined by both the vehicle's efficiency and occupancy. A distance-weighted average has been used in case the respondent made multiple trips with differing car-occupancies.

**Table A.6**
The results of the multilinear regression model of the distance-weighted average SEC of vehicle trips in MJ/pkm of the 12,873 respondents who drove a vehicle and/or travelled by vehicle with household members only. Results with a P-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Std | P-values |
|---|---|---|---|
| Constant | 1.952 | – | – |
| Municipal level of urbanity | 0.012 | 1.259 | 0.311 |
| Municipal population size | −0.009 | 1.462 | 0.366 |
| Randstad area | −0.003 | 0.494 | 0.676 |
| Metro | 0.001 | 0.202 | 0.908 |
| Local address density | −0.004 | 1279.716 | 0.738 |
| Distance to supermarket | 0.007 | 0.816 | 0.373 |
| Distance to train station | −0.006 | 5.900 | 0.399 |
| Distance to road entry | 0.003 | 1.167 | 0.613 |
| Distance to center | −0.011 | 5.462 | 0.207 |
| Distance to larger center | −0.001 | 19.382 | 0.860 |
| PT stops density | 0.009 | 5.244 | 0.363 |
| Green space | 0.005 | 0.091 | 0.669 |
| Landuse mix entropy | −0.013 | 0.162 | 0.247 |
| **Sociodemographic variables** | | | |
| **Income** | **−0.016** | **2.534** | **0.020** |
| **Household size** | **−0.053** | **1.297** | **0.000** |
| **Number of children** | **−0.081** | **0.781** | **0.000** |
| **Living alone HP** | **0.080** | **0.344** | **0.000** |
| **Single core HP** | **0.039** | **0.204** | **0.000** |
| **Child HP** | **0.051** | **0.295** | **0.000** |
| **Other HP** | **0.017** | **0.043** | **0.006** |
| Male | 0.010 | 0.500 | 0.135 |
| Western MB | −0.004 | 0.272 | 0.488 |
| Non-Western MB | 0.004 | 0.238 | 0.543 |
| **Part-time worker SP** | **−0.023** | **0.385** | **0.001** |
| **Student SP** | **−0.044** | **0.173** | **0.000** |
| **Retired SP** | **−0.152** | **0.381** | **0.000** |
| **Other SP** | **−0.068** | **0.306** | **0.000** |
| **Teenager SP** | **−0.194** | **0.187** | **0.000** |
| No Edu. | 0.003 | 0.076 | 0.656 |
| Primary Edu. | −0.006 | 0.226 | 0.470 |
| Vocational Sec. Edu. | −0.007 | 0.375 | 0.300 |
| **Higher Edu.** | **−0.031** | **0.482** | **0.000** |
| Other Edu. | 0.001 | 0.097 | 0.864 |
| **Unknown Edu.** | **0.014** | **0.045** | **0.022** |
| Student pass | −0.010 | 0.162 | 0.231 |

### *A.7. Vehicle efficiency*

See the results of the multilinear regression of vehicle SEC (without dividing by occupancy, in MJ/vkm) of the 12,873 respondents for whom the SEC was corrected because they drove a vehicle and/or travelled by vehicle with household members only in Table A.7 below ($R^2 = 11\%$). Note that allmost all cars are gasoline- and diesel-type vehicles of less than 25 years old, limiting the SEC-range.

**Table A.7**
The results of the multilinear regression model of the vehicle specific energy consumption in MJ/vkm of the 12,873 respondents who drove a vehicle and/or travelled by vehicle with household members only. Results with a P-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Std | P-values |
|---|---|---|---|
| Constant | 2.564 | – | – |
| Municipal level of urbanity | 0.003 | 1.259 | 0.555 |
| Municipal population size | 0.006 | 1.462 | 0.144 |
| Randstad area | 0.002 | 0.494 | 0.536 |
| Metro | 0.000 | 0.202 | 0.920 |
| Local address density | −0.001 | 1279.716 | 0.864 |
| Distance to supermarket | −0.003 | 0.816 | 0.398 |
| Distance to train station | −0.002 | 5.900 | 0.480 |
| Distance to road entry | −0.000 | 1.167 | 0.971 |
| Distance to center | −0.005 | 5.462 | 0.162 |
| Distance to larger center | −0.000 | 19.382 | 0.887 |
| PT stops density | 0.001 | 5.244 | 0.813 |
| Green space | 0.001 | 0.091 | 0.826 |
| Landuse mix entropy | −0.001 | 0.162 | 0.789 |
| **Sociodemographic variables** | | | |

(*continued on next page*)

**Table A.7** (*continued*)

| Spatial variables | Coefficients | Std | P-values |
|---|---|---|---|
| **Income** | **−0.042** | **2.534** | **0.000** |
| **Household size** | **−0.023** | **1.297** | **0.000** |
| Number of children | 0.000 | 0.781 | 0.941 |
| Living alone HP | 0.003 | 0.344 | 0.428 |
| Single core HP | 0.004 | 0.204 | 0.122 |
| **Child HP** | **0.030** | **0.295** | **0.000** |
| Other HP | 0.004 | 0.043 | 0.100 |
| **Male** | **−0.027** | **0.500** | **0.000** |
| **Western MB** | **0.007** | **0.272** | **0.008** |
| Non-Western MB | 0.004 | 0.238 | 0.167 |
| **Part-time worker SP** | **0.024** | **0.385** | **0.000** |
| **Student SP** | **0.010** | **0.173** | **0.012** |
| **Retired SP** | **0.014** | **0.381** | **0.000** |
| **Other SP** | **0.016** | **0.306** | **0.000** |
| Teenager SP | 0.002 | 0.187 | 0.569 |
| No Edu. | 0.002 | 0.076 | 0.441 |
| Primary Edu. | −0.001 | 0.226 | 0.764 |
| Vocational Sec. Edu. | 0.004 | 0.375 | 0.195 |
| **Higher Edu.** | **−0.022** | **0.482** | **0.000** |
| Other Edu. | −0.001 | 0.097 | 0.693 |
| Unknown Edu. | 0.005 | 0.045 | 0.058 |
| Student pass | −0.003 | 0.162 | 0.477 |

### *A.8. Occupancy*

See the results of the multilinear regression of the distance-weighted average occupancy of the 12,873 respondents for whom the SEC was corrected because they drove a vehicle and/or travelled by vehicle with household members only in Table A.8 below ($R^2 = 15\%$).

**Table A.8**
The results of the multilinear regression of the distance-weighted average occupancy of vehicle trips of the 12,873 respondents who drove a vehicle and/or travelled by vehicle with household members only. Results with a P-value lower than 5% have been made bold.

| Spatial variables | Coefficients | Std | P-values |
|---|---|---|---|
| Constant | 1.580 | – | – |
| Municipal level of urbanity | 0.002 | 1.259 | 0.880 |
| Municipal population size | 0.015 | 1.462 | 0.225 |
| Randstad area | 0.008 | 0.494 | 0.391 |
| Metro | 0.002 | 0.202 | 0.818 |
| Local address density | 0.011 | 1279.716 | 0.470 |
| Distance to supermarket | −0.009 | 0.816 | 0.337 |
| Distance to train station | 0.001 | 5.900 | 0.883 |
| Distance to road entry | −0.006 | 1.167 | 0.406 |
| Distance to center | 0.007 | 5.462 | 0.481 |
| Distance to larger center | 0.003 | 19.382 | 0.768 |
| PT stops density | −0.010 | 5.244 | 0.360 |
| Green space | −0.001 | 0.091 | 0.941 |
| Landuse mix entropy | 0.023 | 0.162 | 0.094 |
| **Sociodemographic variables** | | | |
| **Income** | **−0.023** | **2.534** | **0.006** |
| **Household size** | **0.090** | **1.297** | **0.000** |
| **Number of children** | **0.167** | **0.781** | **0.000** |
| **Living alone HP** | **−0.043** | **0.344** | **0.000** |
| **Single core HP** | **−0.036** | **0.204** | **0.000** |
| **Child HP** | **−0.027** | **0.295** | **0.018** |
| **Other HP** | **−0.018** | **0.043** | **0.013** |
| **Male** | **−0.036** | **0.500** | **0.000** |
| Western MB | 0.009 | 0.272 | 0.246 |
| Non-Western MB | 0.007 | 0.238 | 0.345 |
| **Part-time worker SP** | **0.038** | **0.385** | **0.000** |
| **Student SP** | **0.051** | **0.173** | **0.000** |
| **Retired SP** | **0.073** | **0.381** | **0.000** |
| **Other SP** | **0.083** | **0.306** | **0.000** |
| **Teenager SP** | **0.229** | **0.187** | **0.000** |
| No Edu. | −0.001 | 0.076 | 0.887 |
| Primary Edu. | 0.007 | 0.226 | 0.521 |
| Vocational Sec. Edu. | 0.010 | 0.375 | 0.233 |
| Higher Edu. | 0.014 | 0.482 | 0.113 |
| Other Edu. | −0.003 | 0.097 | 0.676 |
| Unknown Edu. | −0.010 | 0.045 | 0.158 |
| Student pass | 0.018 | 0.162 | 0.094 |

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