The influence of the built environment on real world car energy efficiency

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SHORT SUMMARY

To reduce CO_2 emissions and safeguard our energy security, we need to electrify our car-fleet, increase its efficiency, and limit car-dependence. This paper therefore answers the following research question: How and to what extent are features of residential neighborhoods and their residents currently related to energy relevant car type choice? For this purpose, it analyzes Dutch vehicles' real-world energy consumption with a multilevel discrete choice model of fuel- and weight-preferences in one- and multicar households. Small, lower-income, female households in non-green (urban) environments tended to own light, efficient vehicles. Households with a private parking spot tended to own heavy, electric vehicles. Lastly, households with multiple cars tended to live in non-urban areas and to prefer heavier vehicles. These correlations imply that studies that omit vehicle energy efficiency underestimate the environmental impact of urban planning interventions. However, improving vehicle testing procedures may be a more effective energy-saving strategy.

Keywords: built environment, car ownership, discrete choice modelling, energy efficiency, electric vehicles

1. INTRODUCTION

Vehicle gasoline consumption causes climate change and threatens energy security. Electric vehicles can reduce emissions. Yet, these EVs come with energy security concerns of their own due to their rare mineral requirements (International Energy Agency, 2022). Moreover, they can cause a prohibitive increase in electricity use (Galvin, 2022). Especially heavy EVs consume a lot of electricity (Galvin, 2022; Weiss et al., 2020). It is thus important to limit the deployment of heavy, energy inefficient vehicles as well as of cars in general.

A large body of earlier research has shown that a sustainable urban environment with high densities and limited distances to city centers can enable green-minded citizens to live a car-free life (Banister, 2011; Ewing and Cervero, 2010; Næss, 2012; Newman and Kenworthy, 1989; Silva et al., 2017; Stevens, 2017). Other studies have shown that residents of dense urban areas are less likely to own large (inefficient) vehicle designs like vans, trucks, and SUVs (Bhat et al., 2009; Brownstone and Fang, 2014; Cao et al., 2006; Chen et al., 2021; Eluru et al., 2010; Garikapati et al., 2014; Li et al., 2015; Liu and Shen, 2011; McCarthy and Tay, 1998; Potoglou, 2008; Prieto and Caemmerer, 2013; Song et al., 2016).

Yet, most of these studies ignored efficient compact cars. Most also did not actually compute car energy efficiency whereas an SUV does not necessarily consume more energy than a sedan (Li et al., 2015; Timmons and Perumal, 2016). Moreover, no articles could be found that directly analyze the correlation between the built environment and car weight: the major determinant of both conventional and electric vehicles' energy efficiency. A clear link between the built environment and the (future) energy consumption of cars has thus not been established.

The present paper will help fill this gap by answering the following research question: How and to what extent are features of residential neighborhoods and their residents currently related to energy relevant car type choice? For this purpose, it made use of real-world specific energy consumption data in megajoules per vehicle kilometer (MJ/vkm) of cars in the Netherlands. The energy-relevant car type choices were analyzed with a multilevel discrete choice modeling framework of fuel type and weight preferences in one- and multicar households.

2. METHODOLOGY

Travel, sociodemographic and built environment data

Travel and sociodemographic data were obtained from the Netherlands Mobility Panel (MPN) from KiM Netherlands Institute for Transport Policy Analysis (Hoogendoorn-Lanser, 2019). This panel consists of multiple surveys and a three-day travel diary. Household members complete these on a predetermined moment in September, October, or November.

This study analyzed data from households who participated in 2019, 2018, or 2017. Preference was given to the latest year available. The response rate is likely similar to the 64% in 2013 (Hoogendoorn-Lanser et al., 2015). In the end, 4316 households were included who together owned 3498 cars of which the energy use could be accurately determined. All vehicles were analyzed. The sample weight was used to avoid overrepresentation of the multicar households.

KiM provided us with the respondents' residential addresses on the postcode-6 level (1234 AB, representing part of a street). Specifically, we used the postcode-6 addresses to couple the local address density and distances to stations and big (transfer) stations from Statistics Netherlands (CBS; Statistics Netherlands, 2018, 2019). Moreover, this data was analyzed with Geopy to compute distances to city center proxies: destination-rich postcode-6 areas. We also included the NDVI green-space and land-use mix indexes from the Vitality Data Center (VDC) Project (Ren et al., 2019; Wang, 2020; 202). A number of other built-environment and sociodemographic variables were included from the MPN-survey itself. The variables are described in Table 1.

Car energy data

The discrete choice model assessed the effect of the above-described variables on direct (consumer) energy. This can be easily converted to tailpipe CO_2 emissions.

The Netherlands Vehicle Authority (RDW) registers fuel use (Team Open Data RDW, 2021) based on the standardized New European Driving Cycle (NEDC). However, the Netherlands Organization for Applied Scientific Research (TNO) has shown this data to be biased. The gap with the real-world fuel use varies systematically with vehicle building year and can be expected to depend on other vehicle characteristics as well. It was therefore decided to instead use real-world data from fuel-cards from Travelcard Nederland BV. The data were scraped from Praktijkverbruik.nl and coupled based on the MPN vehicles' fuel type, building year, and model.

Table 1: The explanatory variables included in the data analysis

Included variables	Resolution	Unit or categories	Source
Density_PC5	Postcode-5	The average number of addresses per km^2 in a 1 km buffer around the addresses of the inhabitants of the postcode-5 area	CBS
log_km_station	Postcode-6	The natural logarithm of the average travel distance of the inhabitants of the postcode-6 area to the nearest train station	CBS
log_km_bigstation	Postcode-6	The natural logarithm of the average travel distance of the inhabitants of the postcode-6 area to the nearest transfer train station	CBS
km_hugecenter	Postcode-6	Distance of center postcode area to the nearest center of a postcode-6 area containing ≥500 known destinations on average in 1 km travel distance of inhabitants: Amsterdam, Rotterdam, the Hague, and Utrecht.	CBS
km_largecenter	Postcode-6	Distance of center postcode area to the nearest center of a postcode-6 area containing ≥200 known destinations on average in 1 km travel distance o inhabitants. These are the centers of 23 cities, including the huge centers	CBS
NDVI	Postcode-6	Average Normalized Difference Vegetation Index for a 1 km buffer around each postcode-6 area	VDC
land-use	Postcode-6	Average entropy index of the mix between five land-use categories for a 1 km buffer around each postcode-6 area	VDC
km_bus	Household	Travel distance of the household to a bus stop with a frequency of at least 1 bus per hour	MPN
Parkingspot	Household	Whether the household has a private parkingspot	MPN
HH_under18	Household	Number of household members of less than 18 years old	MPN
HH_18to39	Household	Number of household members of 18 to 39 years old	MPN
HH_40to59	Household	Number of household members of 40 to 59 years old	MPN
HH_60plus	Household	Number of household members of at least 60 years old	MPN
inc<20k	Household	A household income of less than 20 thousand euros per year	MPN
inc40to60k	Household	A household income of 40 to 60 thousand euros per year	MPN
inc60to120k	Household	A household income of 60 to 120 thousand euros per year	MPN
inc≥120k	Household	A household income of ≥ 120 thousand euros per year	MPN
Males	Household	Fraction of adult household members who are male	MPN
Higheducation	Household	Fraction of adult household members who have a university degree	MPN
Workers	Household	Fraction of adult household members who work at least 24 hours per week	MPN

Travelcard data was available for 60% of the valid MPN vehicles. The energy used by remaining gasoline, diesel, and gasoline hybrid vehicles was instead computed using TNO-models calibrated with Travelcard-data (de Ruiter et al., 2021). These estimate emissions based on car weight, building year, and engine power. The precise energy efficiency of plug-in hybrid (PHEV) and battery electric (BEV) car-models was taken from TNO Travelcard-based research (van Gijlswijk et al., 2020; de Ruiter et al., 2021).

Non-electric cars with missing fuel type, building year, or weight data or with a registered weight under 500 kilograms were excluded from the analysis.

Data processing

Data cleaning and standardization was done using Pandas and Sklearn (pandas development team, 2020; Wes McKinney, 2010; Pedregosa et al., 2011). Variables that were insignificant at the 20% level or that were insignificant at the 10% level for all car ownership classes, fuel types, and weight classes were excluded. The sample-weights were scaled to avoid in- or deflated P-values.
The cars were lastly categorized into types based on fuel type and weight: the main determinants of energy consumption. The (hybrid) electric vehicles (HEVs) were given their own category

because of their importance for future energy consumption. Diesel vehicles were given their own fuel type class too since these efficient vehicles constitute a major fraction of the sample. The standard (mostly gasoline) and diesel cars were subdivided into the following weight categories: light (<1000 kg), midlight (1000-1250 kg), midheavy (1250-1500 kg), and heavy (>1500 kg).

Car energy exploration

The real-world energy consumption of the vehicles per car type category is shown in the boxplots of Figure 3. The BEVs are visible as a group of HEVs (green) consuming less than 1 MJ/vkm. Diesel vehicles (red) are also efficient, with the exception of heavy diesel vans. The old standard-fueled cars (blue) consume around 3-4 MJ/vkm, but these often have a low sample-weight. As expected, heavy standard cars also use considerably more energy than their lighter counterparts.

The energy consumption quantiles according to the NEDC test cycles are shown in gray for reference purposes. As expected, this official data consistently underestimates real-world energy consumption. The gap seems somewhat larger for light vehicles.

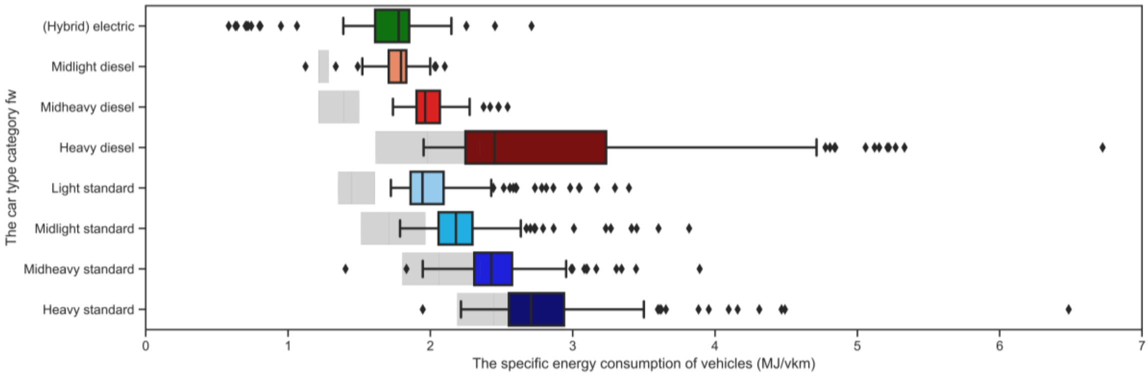

Figure 1: The real-world energy consumption of the eight car type categories *fw*

The discrete choice model

It was decided to analyze cars' real-world specific energy consumption using a multilevel discrete choice modeling framework. Given that decisions on car ownership cannot be disentangled from household preferences for fuel- and weight-based car types *fw*, both choices were modeled jointly, taking the multilevel characteristics of the decision-making process into account: the number of vehicles available to households influences the types of vehicles being purchased. Both decisions are fundamental to understanding households' travel energy use. Moreover, both decisions depend on the household's sociodemographic characteristics and the built environment.

At a first stage, car ownership classes were considered using a discrete choice model, whereby the utility U_{cn} of each of the three classes c (no car, one car, or two or more cars) for a household n was the sum of the utilities associated with the v sociodemographic and built environment variables x_{in} as determined by the estimated coefficients β_{ic}, the aspecific constant ASC_c and the (EV1 iid) unobserved utility term ε_{cn}:

$$U_{cn} = ASC_c + \sum_{i=1}^{v} \beta_{ic} x_{in} + \varepsilon_{cn} \quad (1)$$

Then, a car type model was specified, which considered the number of cars owned as discrete latent attributes. This car type model estimated household choices for car fuel types f and weight categories w explicitly by defining the utility of each of the eight fuel- and weight-based car types $U_{fwn|c}$ as the sum of the utility of the fuel type $U_{fn|c}$, the utility of the weight category $U_{wn|c}$, an aspecific constant ASC_{fw}, and the (EV1 iid) unobserved utility term ε_{fwn}. The utility of the fuel type and weight category were adjusted by a fixed amount β_{2car} in households that were estimated to own two or more vehicles.

$$U_{fwn|c} = ASC_{fw} + U_{fn|c} + U_{wn|c} + \varepsilon_{fwn} \quad (2)$$
$$U_{fn|c} = \sum_{i=1}^{v} \beta_{if} x_{in} + \beta_{2car,f} \quad (3)$$
$$U_{wn|c} = \sum_{i=1}^{v} \beta_{iw} x_{in} + \beta_{2car,w} \quad (4)$$

Attempted nested logit and mixed logit models collapsed into the multinomial model. It was thus decided to analyze car types using the above-explained Multinomial Logit specification. This allowed us to use the independence of irrelevant alternatives property such that a household's probability of choosing a light gasoline over a heavy gasoline vehicle was only determined by the weight coefficients β_{iw}. These weight category coefficients should therefore remain valid in a future sample with more electric vehicles.

The joint model was estimated in Biogeme (Bierlaire, 2020) by maximizing the loglikelihood LL function below. P_{cn} and $P_{fwn|c}$ are the respective probability of belonging to the car ownership class and having a car of a certain fuel- and weight-based type as given by the well-known multinomial logit equation. The dummy q is 1 if the household owns a valid car and 0 otherwise.

$$LL(\beta_{ic}, \beta_{if}, \beta_{iw}) = \ln\left(\prod_n \prod_c P_{cn}(c|x_i; \beta_{ic}, \varepsilon) \prod_n \prod_{fw} \left[\sum_c P_{fwn|c}(fw|x_i, c; \beta_{if}, \beta_{iw}, \varepsilon) \times P_{cn}(c|x_i; \beta_{ic}, \varepsilon)\right]^q\right) \quad (5)$$

3. RESULTS AND DISCUSSION

The study results are provided in Table 2 and described below.

As expected, large families with many employed individuals, a middle- to high-income, and a non-urban residential location tended to possess a car. Households owning multiple cars were especially likely to have many adult and working members, a high income, and a low-density residential environment. They had a preference for heavy, non-diesel vehicles.

Owning heavy rather than light vehicles was directly correlated with a large number of (older) family members, a higher household income, and a high fraction of males. Living in a green area and having a private parking spot increased (mid)heavy over light vehicle ownership as well, which is logical as compact cars are easier to park and maneuver in densely built areas. Yet, electric vehicles were also owned by households with a private parking spot. One explanation is that EV owners prefer to charge their vehicles at home (Westin et al., 2018).

Interestingly, the local address density, street connectivity, and distances to public transport had no significant direct effect on vehicle fuel type or weight. Previously found effects of these variables on vehicle choice may be due to correlations with open (green) space and parking possibilities. Earlier studies may also have captured indirect effects of the built environment through ownership of two or more cars and associated heavy car preferences.

The combined built environment effect was a noticeably higher vehicle energy consumption in non-urban areas. Building new residences in existing cities could therefore have a stronger effect on future energy consumption and CO_2 emissions than indicated by earlier studies that did not take vehicle energy efficiency into account.

The capturing of this indirect effect was made possible by the multilevel discrete choice modeling framework. In addition, this design allowed analysis of households' car fuel and weight preferences separately. This improved the model accuracy and increased its future relevance. The model was fed with built environment data from multiple sources on the fine-grained postcode-6 level. This helped achieve a high degree of accuracy and allowed testing of a wide variety of built environment variables. Moreover, the real-world car energy efficiency could be precisely determined by coupling data from the Netherlands Vehicle Authority, TNO, and Travelcard BV.

This also illuminated the large gap between vehicles' real world energy consumption and the official data based on the NEDC test. Further analysis showed this gap to be greater than the built environment effect on vehicle energy use. Potential consequences include undermining of CO_2 -emission standards, flawed estimates of (technologies') emission reduction potentials, and the misleading of consumers. It is therefore important that a new WLTP test-cycle has recently been introduced, which should reduce - but not eliminate - the real-world gap (Ligterink et al., 2016).

4. CONCLUSIONS

This paper investigated how and to what extent features of residential neighborhoods and their residents are currently related to energy relevant car type choice by analyzing real-world energy use with a multilevel model of fuel- and weight-preferences in one- and multicar households.

Small, female households with few older members, and a lower income in non-green (urban) environments were most likely to own light, efficient vehicles. Households with a private parking spot tended to own both heavy and electric vehicles. Small, lower-income, urban households were lastly less likely to own one or multiple cars, whereby the ownership of multiple cars was associated with the choice of heavier vehicles.

The combined effect was a mild preference for efficient, low-energy vehicles in urban environments. Earlier studies that focused on vehicle kilometers thus underestimated the environmental impact of urban planning interventions. However, the easiest way to reduce vehicles' energy consumption and CO_2 -emissions seems to further improve the testing procedures in order to tighten policies, stimulate innovation, and better inform consumers.

Table 2: The estimated coefficients for each of the utility functions. Variables with a P-value of 5% or less have been made bold. Coefficients give the change in utility when increasing the variable by 1 standard deviation (std).

Car ownership classification

Onecar class utility	Coef β_c	Std err	t-score	P-value	Twocar class utility	Coef β_c	Std err	t-score	P-value
Aspecific Constant	2.004	0.060	33.2	0.000	**Aspecific Constant**	0.763	0.076	10.1	0.000
HH_under18	0.435	0.066	6.6	0.000	**HH_under18**	0.533	0.071	7.5	0.000
HH_18to39	0.571	0.072	8.0	0.000	**HH_18to39**	1.571	0.084	18.8	0.000
HH_40to59	0.598	0.072	8.3	0.000	**HH_40to59**	1.579	0.084	18.8	0.000
HH_60plus	1.160	0.078	15.0	0.000	**HH_60plus**	2.032	0.107	19.1	0.000
inc<20k	-0.292	0.036	-8.2	0.000	**inc<20k**	-0.384	0.082	-4.7	0.000
inc40to60k	0.196	0.045	4.3	0.000	**inc40to60k**	0.304	0.061	5.0	0.000
inc60to120k	0.313	0.062	5.0	0.000	**inc60to120k**	0.613	0.070	8.7	0.000
inc≥120k	0.155	0.078	2.0	0.047	**inc≥120k**	0.252	0.080	3.1	0.002
					Males	0.164	0.057	2.9	0.004
Workers	0.375	0.050	7.5	0.000	**Workers**	1.052	0.076	13.8	0.000
Density_PC5	-0.307	0.041	-7.4	0.000	**Density_PC5**	-0.705	0.075	-9.4	0.000
log_km_station	0.165	0.049	3.4	0.001	**log_km_station**	0.272	0.063	4.3	0.000
log_km_bigstation	0.125	0.050	2.5	0.012	**log_km_bigstation**	0.177	0.069	2.6	0.010
km_hugecenter	0.162	0.043	3.8	0.000	**km_hugecenter**	0.142	0.058	2.4	0.015
km_bus	0.246	0.085	2.9	0.004	**km_bus**	0.350	0.090	3.9	0.000
Parkingspot	0.252	0.046	5.5	0.000	**Parkingspot**	0.398	0.059	6.8	0.000

Fuel- and weight-based car types

Aspecific Constants	ASC_t	Std err	t-score	P-value	Standard fuel type utility	Coef β_f	Std err	t-score	P-value
Standard_light	0.344	0.166	2.1	0.039	2car Coefficient (β_{2car})	-0.174	0.267	-0.7	0.514
Standard_midlight	1.116	0.135	8.3	0.000	HH_18to39	0.108	0.067	1.6	0.105
Standard_heavy	-1.961	0.302	-6.5	0.000	**inc<20k**	0.221	0.077	2.9	0.004
Diesel_midlight	-1.230	0.168	-7.3	0.000	FracAdultHighedu	-0.071	0.049	-1.5	0.147
Diesel_midheavy	-0.951	0.170	-5.6	0.000	**FracAdultMales**	-0.166	0.057	-2.9	0.004
Diesel_heavy	-1.428	0.227	-6.3	0.000	**km_hugecenter**	-0.228	0.073	-3.1	0.002
HEV	-1.390	0.227	-6.1	0.000	**km_largecenter**	0.149	0.053	2.8	0.005

Diesel fuel type utility	Coef β_f	Std err	t-score	P-value	HEV fuel type utility	Coef β_f	Std err	t-score	P-value
2car Coefficient (β_{2car})	-2.656	0.444	-6.0	0.000	2car Coefficient (β_{2car})	-0.328	0.383	-0.9	0.391
HH_18to39	0.699	0.111	6.3	0.000	HH_60plus	-0.216	0.116	-1.9	0.064
HH_40to59	0.463	0.097	4.8	0.000	inc≥120k	0.067	0.046	1.5	0.146
Workers	0.396	0.099	4.0	0.000	**Higheducated**	0.229	0.097	2.4	0.018
km_largecenter	0.224	0.074	3.0	0.003	**Parkingspot**	0.234	0.096	2.4	0.015
Landuse	-0.121	0.068	-1.8	0.076					
Parkingspot	0.155	0.081	1.9	0.055					

Light weight utility	Coef β_w	Std err	t-score	P-value	Midlight weight utility	Coef β_w	Std err	t-score	P-value
2car Coefficient (β_{2car}/	-0.609	0.324	-1.9	0.060	**2car Coefficient (β_{2car})**	-1.552	0.258	-6.0	0.000
HH_under18	-0.372	0.064	-5.8	0.000	**HH_under18**	-0.220	0.052	-4.3	0.000
HH_40to59	-0.169	0.066	-2.5	0.011	**HH_60plus**	-0.249	0.073	-3.4	0.001
HH_60plus	-0.661	0.085	-7.8	0.000	**inc≥120k**	-0.092	0.045	-2.1	0.040
inc40to60k	-0.116	0.058	-2.0	0.044	**Workers**	0.236	0.068	3.5	0.001
inc60to120k	-0.149	0.064	-2.3	0.020	km_hugecenter	0.123	0.076	1.6	0.109
inc≥120k	-0.198	0.078	-2.5	0.011					
Males	-0.355	0.065	-5.5	0.000					
km_hugecenter	0.201	0.088	2.3	0.022					
NDVI	-0.125	0.061	-2.1	0.039					
Parkingspot	-0.096	0.058	-1.7	0.097					

Midheavy weight utility	Coef β_w	Std err	t-score	P-value	Heavy weight utility	Coef β_w	Std err	t-score	P-value
2car Coefficient (β_{2car})	-1.864	0.567	-3.3	0.001	**2car Coefficient (β_{2car})**	1.194	0.280	4.3	0.000
HH_40to59	0.185	0.112	1.7	0.098	**HH_under18**	0.141	0.057	2.5	0.014
inc60to120k	0.356	0.083	4.3	0.000	**HH_18to39**	-0.309	0.085	-3.6	0.000
Workers	0.267	0.146	1.8	0.067	**HH_60plus**	0.190	0.090	2.1	0.035
NDVI	0.297	0.110	2.7	0.007	Higheducated	0.113	0.070	1.6	0.103
					Males	0.331	0.098	3.4	0.001
					Parkingspot	0.212	0.075	2.8	0.005

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